REPUBLIC OF TÜRKİYE

ALTINBAŞ UNIVERSITY

Institute of Graduate Studies

Electrical and Computer Engineering

ADVANCED 3D FACE ANTI-SPOOFING SYSTEM USING HYBRID DEEP NEURAL NETWORK AND OPTIMIZATION TECHNIQUES

Mohammed Kareem Hussein HUSSEIN

Doctor of Philosophy

Supervisor

Prof. Dr. Osman Nuri UÇAN

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2025

The dissertation titled ADVANCED 3D FACE ANTI-SPOOFING SYSTEM USING HYBRID DEEP NEURAL NETWORK AND OPTIMIZATION TECHNIQUES prepared by MOHAMMED KAREEM HUSSEIN HUSSEIN and submitted on 10/06/2025 has been **accepted unanimously** for the degree of PhD in Electrical and Computer Engineering

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I hereby declare that this dissertation meets all format and submission requirements for a PhD thesis.

I hereby declare that all information/data presented in this graduation project has been obtained in full accordance with academic rules and ethical conduct. I also declare all unoriginal materials and conclusions have been cited in the text and all references mentioned in the Reference List have been cited in the text, and vice versa as required by the abovementioned rules and conduct.

Mohammed Kareem Hussein HUSSEIN

Signature

ABSTRACT

UNDERSTANDING THE EARTHQUAKE RISK REGIONS IN BAĞCILAR VIA KMEANS CLUSTERING FOR URBAN PLANNING STRATEGIES

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Date: June/2025

Pages: 165

Face recognition technology is used everywhere, including mobile security, surveillance, and online payments, to authenticate a person's identity. Spoof faces, like printed photos, videos, 3D masks, and deep fake-generated faces, can mislead such systems. The goal of this research is to improve Face Anti-Spoofing (FAS) techniques to improve facial recognition security, accuracy, and efficiency. The study suggests a 3D Face Anti-Spoofing Model incorporating Dense Squeeze and Excitation Networks and a Neighbourhood-Aware Kernel Adaptation (NAKA) process for identification of fine details and textures on a person's face. A Lightweight Multi-Modal Deep Fusion Network is suggested for fusing different face data modalities such as RGB images, depth maps, and texture information. It is useful in face spoofing detection with higher accuracy even against advanced attacks. Deep Reinforcement Learning (DRL) is also used by the system to learn automatically and keep itself updated at all times, thus able to identify new ways of spoofing. The models are tested using standard datasets like CASIA-SURF, CelebA-Spoof, and GREAT-FASD-S based on a number of performance metrics such as accuracy, precision, recall, and error rates. Experiments demonstrate that models as proposed compare favorably against existing methods and are computationally lightweight for use in real-world applications. The study also confronts fundamental problems such as generalizable good performance over datasets, adversarial attacks resistance, and security vs. usability. Grounded on multi-modal fusion,

attention, and reinforcement learning, the study gives contributions towards robust, light-weight, and explainable face anti-spoofing approaches. These can be applied in high-security applications like banking, border control, and mobile authentication. The outcome will help to introduce biometric security and protect against future face spoofing attacks of novel forms.

Keywords: Deep Learning, Face Spoofing Attacks, 3D Masks, Face Anti-Spoofing, DRL.

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ABBREVIATIONS

3sXcsNet	:	3-Sream Compact Xception Framework
ACA	:	Average Classification Accuracy
ACER	:	Average Classification Error Rate
ACO	:	Ant Colony Optimization
APCER	:	Attack Presentation Classification Error Rate
ASSERT	:	Anti-Spoofing with Squeeze-Excitation and Residual Networks
AUC	:	Area Under the Curve
BO	:	Bayesian Optimization
BPCER	:	Bona Fide Presentation Classification Error Rate
BSO	:	Beetle Swarm Optimization
CASIA	:	Chinese Academy of Sciences
CAFFE	:	Convolutional Architecture of Fast Feature Embedding
CCA	:	Cross-Channel Attention
CDC	:	Central Difference Convolution
CNNs	:	Convolutional Neural Networks
COTS	:	Commercial Off-The-Shelf
CSN	:	Channel-Separated Spatiotemporal Network
DAM	:	Depth-Wise Separable Attention Module
DE	:	Differential Evolution
DNN	:	Deep Neural Network
DSFD	:	Dual Shot Face Detector
DRL	:	Deep Reinforcement Learning
EER	:	Equal Error Rate
ELTCP	:	Extended Local Ternary Co-Relation Pattern

EMO	:	Evolutionary Multi-Objective Optimization
EPBO	:	Enhanced Pity Beetle Optimization
FAS	:	Face Anti-Spoofing
FDDRL	:	Federated Deep Reinforcement Learning
FR	:	Face Recognition
FPR	:	False Positive Rate
FRR	:	False Rejection Rate
GA	:	Genetic Algorithm
GAN	:	Generative Adversarial
GCN	:	Graph Convolutional Network
HOG	:	Histogram Of Oriented Gradients
HTER	:	Half Total Error Rate
IR	:	Infra-Red
LBP	:	Local Binary Patterns
LGS	:	Local Graph Structure
LR	:	Learning Rate
LSTM	:	Long Short-Term Memory
LTP	:	Local Ternary Pattern
MCT- GAN	:	Multiple-Category Image Translation Generative Adversarial Network
M-FoBa	:	Modified Forward–Backward
MIL	:	Multiple Instance Learning
MNV2	:	MobileNetV2
MSRCR	:	Multi-Scale Retinex with Color Restoration
MSRCP	:	Multi-Scale Retinex with Chromaticity Preservation
NAKA	:	Neighborhood-Aware Kernel Adaptation

NIR	:	Near Infra-Red
PCN	:	Point Cloud Network
PIN	:	Postal Index Number
PSO	:	Particle Sworm Optimization
RFID	:	Radio Frequency Identification
ResNet	:	Residual Network
ReLU	:	Rectified Linear Unit
RGB	:	Red Green Blue
ROC	:	Receiver Operating Characteristic
RNN	:	Recurrent Neural Networks
rPPG	:	Remote Photoplethysmography
SE	:	Squeeze-and-Excitation
SE-Net	:	Squeeze-and-Excitation Network
SPSL	:	Single-Pixel Supervision Learning
SVM	:	Support Vector Machines
TN	:	True Negative
TP	:	True Positive
VGGNet	:	Visual Geometry Group Network
VIS	:	Visible Light
XA-CNN	:	aXial Attention CNN network
XA-Net	:	Axial Attention Network

LIST OF SYMBOLS

α	:	Hyper Parameter to Control Sensitivity of Kernel Adaptation
β	:	Weighing Factors
λ	:	Controls the Weight Between Spatial and Temporal Features
γ	:	Focussing Parameter
φ	:	Wavelet Function
θ	:	Gradient Direction
σ	:	Sigmoid Function
δ	:	Correlation Between Successive Points in The Scan or ReLu Function
2^p	:	Weighting Factor That Assigns a Unique Binary Value to Each Comparison.
b	:	Bias
c	:	Channel
d_{ij}	:	Euclidean Distance between Pixel Embedding
f	:	Activation Function
F	:	Mutation Factor
h_t	:	Hidden State at Time t
P	:	Number of Neighbourhood Pixels Considered in Neighbourhood Computation
g_c	:	Gray Value of the Central Pixel

g_p	:	Gray Values of its P Neighbours
G_x	:	Gradient in the Horizontal Directions
G_y	:	Gradient Magnitudes in The Vertical Directions
I_c	:	Grey Value of the Central Pixel
I_i	:	Intensity of the Neighboring Pixels
I_p	:	Grey Values of its P Neighbours
I_t	:	Temporal Image
I_x	:	Spatial Image Gradients in the Horizontal Directions
I_y	:	Spatial Image Gradients in the Vertical Directions
I_s	:	Optimization Problem
P_t	:	Model's Predicted Probability for the Correct Class
s	:	Ternary Function Mapping Pixel Differences to Discrete Values.
U	:	Optical Flow Component Sround X Coordinate
V	:	Optical Flow Component Around Y Coordinate
x_i	:	Feature Vector
x_c	:	Gray Value of the Central Pixel Around X Coordinate
x_t	:	Input at Time t
y_c	:	Gray Values of its P Neighbours Around Y Coordinate
y_i	:	Class Label
h_t	:	Prediction of Each Decision Tree
T	:	Total Number of Trees

w_i	:	Weight Assigned to Each Neighbouring Pixel.
w_1	:	Learnable Weight
w_2	:	Learnable weight
y_1	:	Output of Each Dense layer
F	:	Local Gradient
μ_N	:	Local Mean
σ_N^2	:	Local Variance
ϕ	:	Function that Adjusts the Kernel Weights

1. INTRODUCTION

1.1 BACKGROUND AND MOTIVATION

Biometric authentication is now widely used in security systems, like mobile phones, surveillance cameras, online payments, and even at borders. Unlike passwords or postal index number (PIN) codes, biometric security uses a person's unique physical or behaviours, which makes it safer and easier to use. Amongst various biometric methods, face recognition has become very popular because it doesn't require touch and works instantly. It is extensively used to unlock phones, facilitate digital payments, and control access to secure spaces [1]. There are several security risks involved with face recognition. One of the biggest issues is that attackers can try to trick the system using fake images, videos, or even 3D masks. These methods, known as presentation attacks, can lead to identity theft, unauthorized access, and fraud. If the face recognition systems are weak, they are easily deceived and hence become unsafe and unreliable [2]. Face recognition captures the image of the face of an individual with the assistance of a camera.

It then analyzes important features like shape, texture, and patterns [3]. The system compares the image with stored data to verify the identity. But it also verifies first whether the face is real or not, prior to granting access. This is called an anti-spoofing check. Access is allowed if a real face is detected. But if a spoofed face, like a printed image or a deepfake video, is identified, access is blocked. This added step adds security and prevents hackers from tricking the system [4-7]. Figure 1.1 shows how biometric authentication and the anti-spoofing process work together and add security. The flow of the process of face recognition and anti-spoofing happens in two different ways for detecting forged faces.

There are two, the Parallel Scheme and the Serial Scheme shown in Figure 1.2. The schemes provide a type of combination between face recognition and spoofing detection. Both methods start the same way, where a person presents their face before a sensor, and it captures the image. The system then performs face detection to locate the face on the image. After this step is completed, the two schemes function differently. In the Parallel Scheme, Face Recognition (FR) and Face Anti-Spoofing (FAS) are executed concurrently by the system. Face Recognition checks if the face exists or not in the database, and Face Anti-Spoofing checks if the face is a real face or spoofed face. Both methods generate scores,

which are combined using Score Fusion. Score Fusion is a technique for combining the outputs of face recognition and face anti-spoofing systems to generate a more reliable final decision.

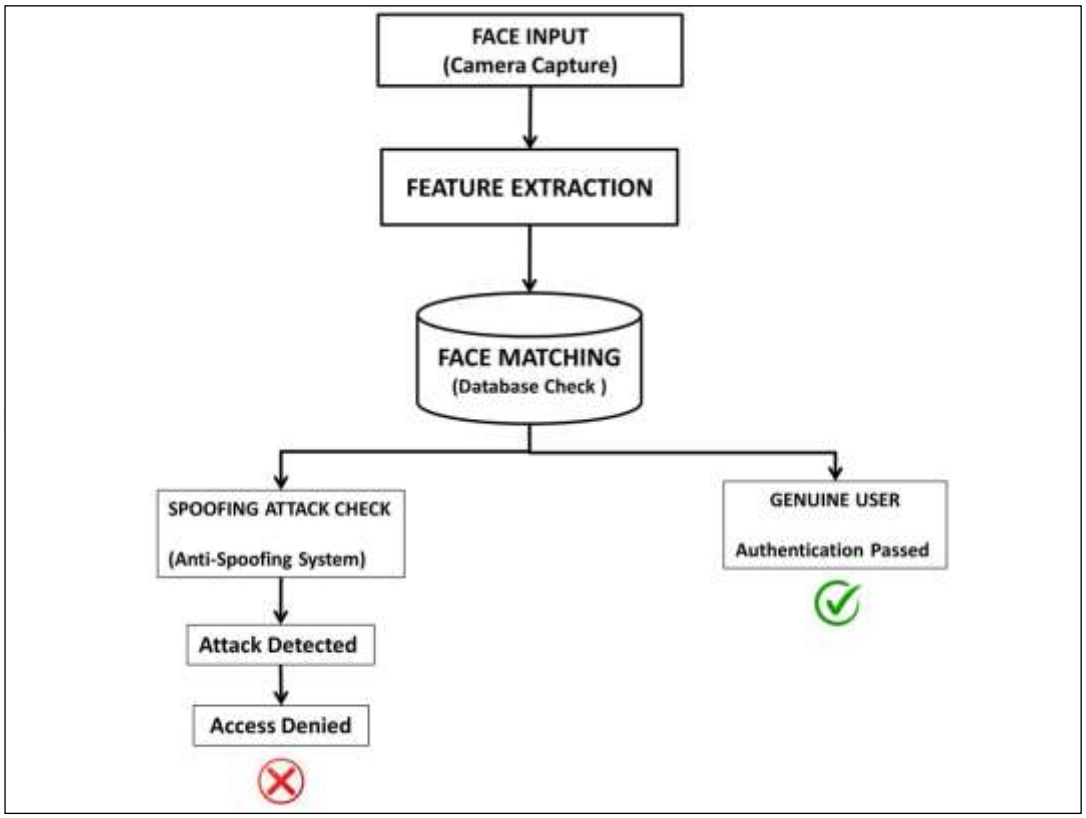


Figure 1.1: Biometric Authentication and Face Anti-Apoofing Process (by Author).

During the face recognition process, the system computes a Face Recognition (FR) score, representing how well the identified face matches a stored identity in the database. Concurrently, the Face Anti-Spoofing (FAS) score identifies whether the face is genuine or not. Rather than taking independent decisions based on these individual scores, the system combines them through score fusion. This combined score helps to provide a better decision for both the identity and authenticity of the face. When the resulting score is higher than a fixed threshold, the identity is accepted; otherwise, the identity is rejected. Score combination increases security by reducing the probability of accepting imposter faces and prevents genuine faces from being falsely rejected. It ensures the tradeoff among accuracy, security, and efficiency in face recognition systems. As discussed, if the combined score is high enough, the system accepts the identity as a Matched ID. If not, the identity is discarded as Not Matched ID. This method is faster but needs more computation. In the Serial Scheme,

the system first authenticates whether the face is real or fake using Face Anti-Spoofing (FAS). If the face is an imposter face, it is rejected immediately as an Attacker. If the face is authentic, it goes to the second step, where Face Recognition (FR) checks if it matches any identity in the database. If it matches, the person is authenticated as a Matched ID; otherwise, they are rejected as Not Matched ID. This method is safer because imposter faces are rejected beforehand, but processing is slower. The Parallel Scheme is useful when time is crucial, while the Serial Scheme suits security needs since it prevents impostors from advancing to the recognition stage.

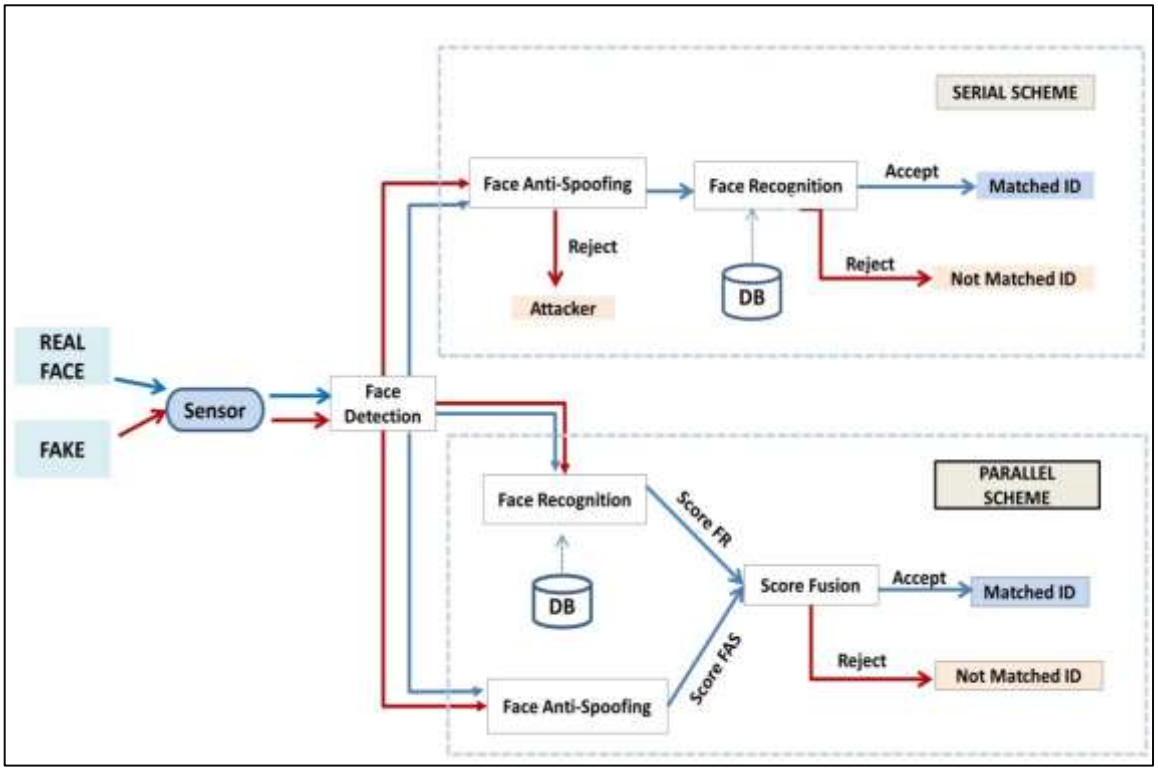


Figure 1.2: Process Flow of Face Recognition and Anti-Spoofing (by Author).

As mentioned, face anti-spoofing is a technique used to stop people from tricking face recognition systems. To make sure the system only allows real people and rejects fake ones, different methods are used to detect if the face is real or fake. Two types of anti-spoofing methods (Hardware based and Software based) are shown in figure 1.3. Hardware-based methods use special tools like infrared sensors, depth cameras, or thermal imaging. Hardware based is mostly likely to sense things like heat from the skin or tiny blood flow movements. These methods are usually accurate, but they can be expensive and need extra equipment, which makes them harder to use everywhere. Software-based methods don't

need extra hardware. Instead, they analyse images and videos to find out if a face is fake or real. Few methods look for tiny details in the texture or skin, track natural movements like blinking, or use AI to catch fake faces. There are some Deep learning models that help a lot by finding tiny details that can be missed by humans [8].

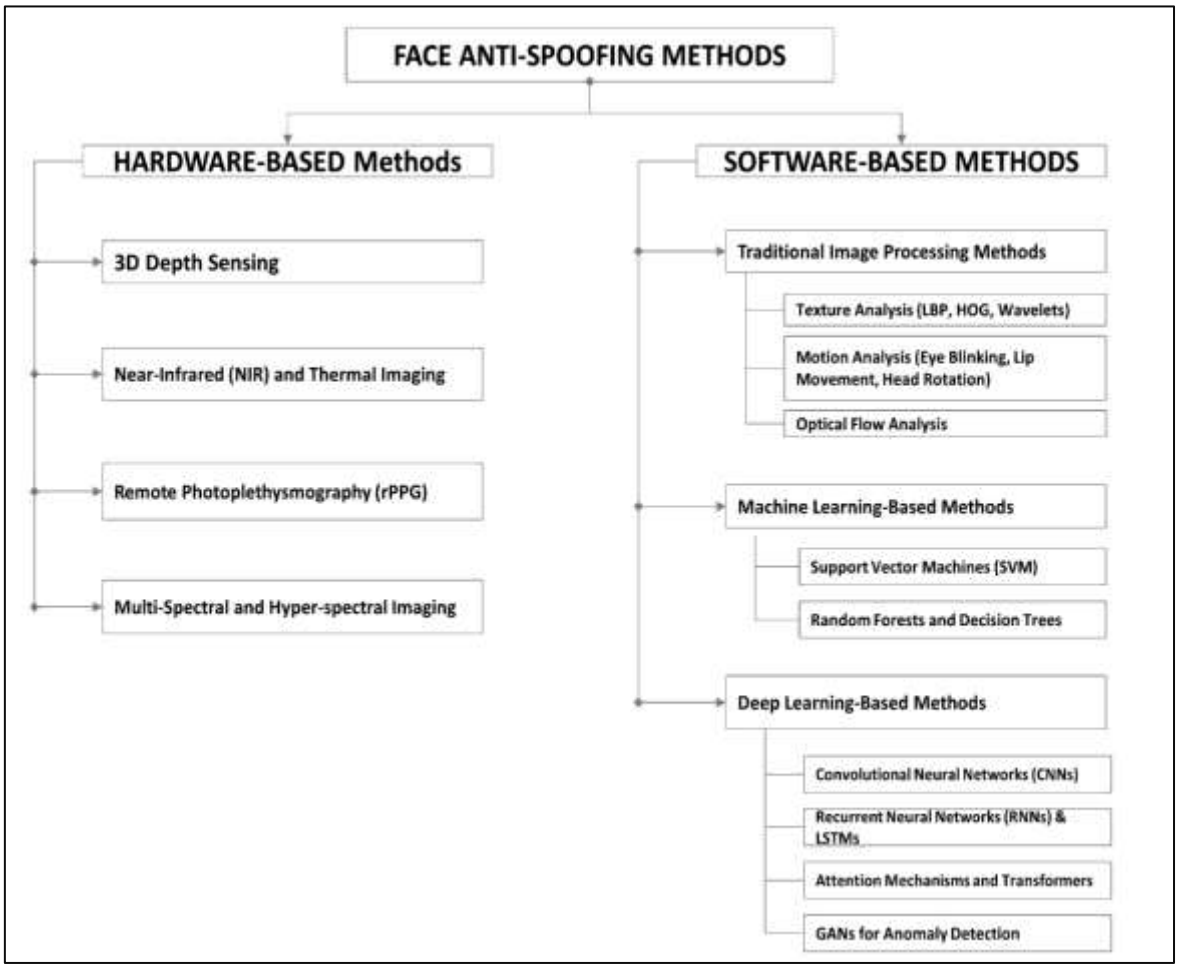


Figure 1.3: Face Anti-Spoofing Methods (by Author).

There are many ways attackers try to fool biometric authentication, such as showing a printed photo, playing a video of a real person's face (replay attack), wearing a 3D mask, or even using deepfake technology. The system uses different detection methods to deal with such threats. Depth-based techniques verify whether the face is truly 3D. A Multi-modal fusion combines RGB images, depth maps, and infrared signals for better accuracy. AI helps by looking at small facial movements, skin texture differences, and other tiny details to tell a real face from a fake one. But as attackers keep finding smarter ways to trick the system, making anti-spoofing models better is still a big challenge.

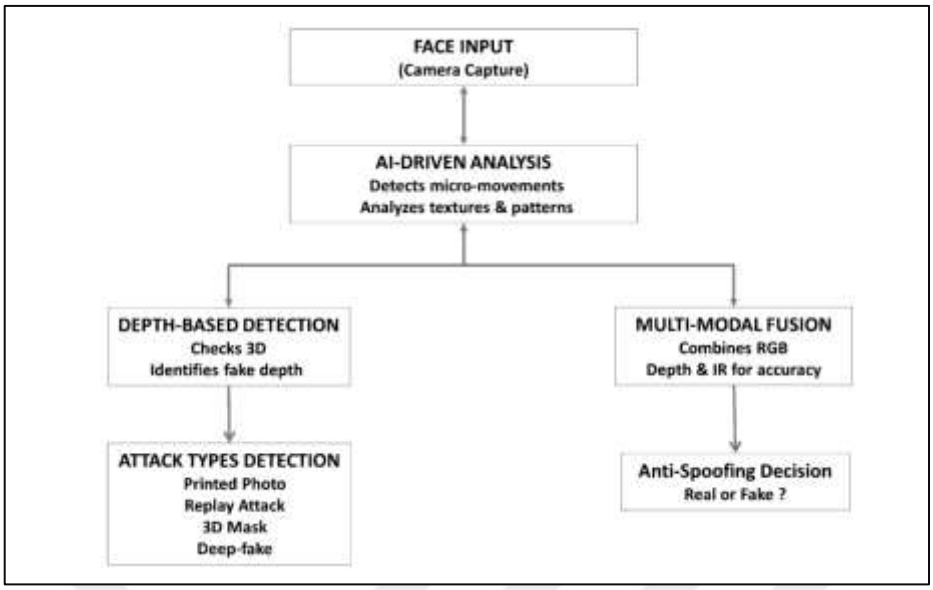


Figure 1.4: Face Anti-Spoofing System Framework (by Author).

Challenges in Face Anti-Spoofing: **-** Face anti-spoofing is still very challenging, even though deep learning has improved face recognition. Many factors make it difficult to distinguish real faces from fake ones. One big issue is that these models don't always work well in different environments. Changes in lighting, background, or attack methods can make them less reliable. Another problem is accuracy. Sometimes real users get wrongly blocked, while fake ones get through. More computing power is required by models which make it hard for them to run on smartphones or other small devices. Deepfake attacks are getting smarter, making them harder to detect. Another problem is that many systems work like a 'black box,' meaning people don't know how they make decisions. To build trust and keep security strong, these systems need to be clearer and easier to understand. Below are the highlights that contribute to the difficulty of face anti-spoofing like:

a. Different Attack Methods: Attackers keep finding new ways to trick face recognition, like using high-quality photos, videos, masks, or AI-generated deep-fakes.
b. Dataset Limitations: There are some models which when tested on new faces, lighting conditions and types of attacks often fail to make them unreliable in real-world scenarios, because these are trained on limited datasets.
c. Speed and Efficiency: Deep learning models require powerful computers to make them fast to use in real-time applications, especially on mobile phones and edge devices.

d. False Detections: For accuracy and better user experience, finding the right balance in detecting real or fake face is important.
e. Advanced Attacks: Many models still cannot detect advanced AI forgeries which make systems vulnerable to attacks.

Motivation: Face recognition is now everywhere from unlocking phones, verifying identity, and to ensuring security. But as it becomes more common, attackers keep finding smarter ways to trick the system. Some use fake photos, videos, or even 3D masks to fool facial recognition, which creates serious security risks. . Several of these methods try to bypass such attacks with some constraints. Texture analysis probes facial detail but is affected by highly realistic duplicates.

Depth-based methods confirm whether a face is 3D or not but are defeated if there are no depth sensors or if there are good-quality 3D masks. Multi-modal fusion offers more precise face detection by combining RGB, depth, and infrared signals. The problem is that it needs expensive sensors, so universal deployment is hard. Deep learning-based models are also useful for detecting fake faces but need large training data. Even when trained on large volumes of data, there is no assurance that they will always work as anticipated. Reinforcement learning allows the systems to learn to fight new threats over time, but it needs plenty of computing power, which may not always be available. Multi-modal fusion improves face detection by combining RGB, depth, and infrared signals. But the need for expensive sensors does not make it convenient to deploy on a massive scale. Deep learning models also come in handy for detecting forgery faces, though they require an enormous quantity of training data. Even if they are trained in huge datasets, there is no assurance that they will always perform flawlessly in real-world environments [12]. These limitations motivate us to construct new deep learning models in order to find subtle distinctions between spurious and real faces and learn and adapt to new attacks.

1.2 PROBLEM STATEMENT

Anti-spoofing of face has developed significantly with deep learning and computer vision but is not problem-free. Facial recognition technology is now everywhere for security purposes, ranging from opening phones to verifying people at banks and borders. The technology itself can be spoofed by attackers with images, videos, 3D masks, or deepfake

AI-generated photos. Researchers have built face anti-spoofing (FAS) systems capable of distinguishing between real human faces and spoof faces. Despite progress in these systems with deep learning and computer vision, there are a number of challenging issues left, and this is still an active research area [13]. Perhaps the biggest challenge in face anti-spoofing is to make models perform well robustly across varied settings.

Most FAS models constructed based on deep learning are trained under pre-defined attack, camera, and lighting conditions. Conditions in the real world are extremely diverse and could affect the model's performance. For example, changes in lighting such as indoor areas with adequate illumination compared to dark outdoor locations would distort facial features and lead to misclassification. Background variations also serve as the cause of challenge in that a model, that performs best in a lab setup, will perform when taken out for use to the office, the road, or home. Methods of spoofing attacks keep on increasing each and every day by new ways such as HD 3D masks and AI-made deepfakes making the task of identifying more difficult [14-16]. The second major issue is the usability vs. accuracy trade-off. Face anti-spoofing systems must be easy to use and secure.

It is difficult to do both because of false positives and false negatives. A system that accepts a counterfeit face by error is a severe security risk. If it rejects an actual user in error, it is frustrating and inconvenient. It is particularly challenging for high-accuracy applications like banking or border control where a low error rate can be catastrophic. To balance security and usability is one of the primary areas of research. Computational complexity also stands in the way of constructing efficient face anti-spoofing systems. Deep learning is computationally heavy, memory-demanding, power-hungry, and implementing it on power-constrained devices like phones or tablets is a challenge. Most facial anti-spoofing algorithms require powerful neural networks difficult to deploy with low latency or power usage on smart phones.

Institutions at scale, like airports or banking institutions, need to verify millions of people every day, so scalability becomes critical. If the anti-spoofing algorithm takes as long to execute, it is not feasible to use it in real life. Deepening technology also aggravates the problem. Traditional spoofing threats like printed images or replaying video are simple to identify. Deepfake attacks today use AI-generated faces that replicate real human expressions, eye blinks, and head movements with extremely high fidelity. Attackers keep

refining their attack mechanisms so that it becomes increasingly harder for face anti-spoofing mechanisms to differentiate between real faces and spoofed faces.

It's possible to generate deepfake attacks that can bypass existing defenses, so researchers have to continually update their models to keep ahead of new vulnerabilities. Face anti-spoofing with deep learning is not interpretable. There are many kinds of models that are "black boxes." If an authorized user is blocked, the system typically can't say why. Similarly, when an attack avoids security, it is difficult to determine the flaw of the model. Without explanations, users lose trust in the technology, and security teams cannot improve the models. Developing explainable AI models with insights into how they arrive at their conclusions is extremely crucial to provide greater confidence and reliability to face anti-spoofing technology [17-18]. Anti-spoofing face is a challenging task because it has multiple challenges like variability of the environment, variety of attacks, limited computation, adaptive deepfake attacks, and AI-based decision-making explainability. Researchers need to develop models that are accurate, light, flexible, and explainable without sacrificing performance in actual situations. All this requires humongous advances in areas of deep learning, feature engineering, adversarial training, and real-time processing. As security attacks become more advanced, the necessity for efficient and robust face anti-spoofing solutions will also continue to be on the rise, and hence it is a significant area of research in biometric verification.

1.3 RESEARCH OBJECTIVES

The objective of this study is to develop a robust and efficient face anti-spoofing system that should address various attack types retaining time performance as a priority. The major objectives are as follows:

a. To develop a 3D Face Anti-Spoofing Model that focuses on major facial features via Dense Squeeze and Excitation Networks. To bring about this improvement in feature extraction by identifying deep patterns in real faces and removing the counterfeit ones. To accomplish this, use a mechanism that will render the system more adaptable in identifying novel attack techniques. The goal is to develop a model that is highly accurate and also computationally efficient, such that it can be implemented in the real world. ii. To developing a Lightweight Multi-Modal Deep Fusion Network to combine

different modalities of facial information, such as RGB images, depth maps, and texture features. To detect sophisticated spoofing attacks, such as high-quality 3D masks and deepfakes by exploiting multiple data sources. To developing a technique to enhance the relationship between these features and make the system more reliable.

b. iii. Incorporating Deep Reinforcement Learning for Adaptive Learning so that model can learn to adapt towards new and emerging spoofing attacks. To utilize Deep Reinforcement Learning (DRL) techniques to learn and improve system's detection ability on a continuous basis with the progression of time. To allow system to adjust its parameters dynamically to identify new emerging threats, thus make it more secure against unknown attack methods.
c. To enhancing Real-Time Performance for Practical Use. One of the biggest challenges in face anti-spoofing is balancing accuracy and speed. To create optimizing the model's computational efficiency so that it can work in real-time applications such as smartphones, biometric access systems, and banking security. To design a system for low-power devices while maintaining high detection rates.
d. Developing a Transparent and Explainable Model. Most deep learning-based security systems function as black boxes, meaning users do not understand how decisions are made. To creating an explainable AI model that provides clear justifications for its classifications. The goal is to build user trust by ensuring that when a face is rejected or accepted. This will help security teams refine the model and make better-informed decisions.
e. Testing and Validating the System across Different Environments. For the purpose of reliability, the face anti-spoofing system will be tested on several real-world scenarios including different lighting, different backgrounds, and different attacks. The study will test the system on more than one dataset and real-world test scenarios to ensure its performance on a large variety of spoofing methods. The ultimate system will be reliable, flexible, and deployable in the real world on multiple industries.

1.4 CONTRIBUTION OF THESIS

The thesis makes a novel contribution to face anti-spoofing. The fundamental anti-spoofing problems are solved and new strategies are given to solve the constraints. The thesis aims to render face recognition systems more reliable in actual application scenarios. Different face

anti-spoofing datasets are utilized to evaluate how well the models can detect spoofed faces. Some of the datasets used are CASIA-SURF [184], CelebA-Spoof [157], and GREAT-FASD-S [185]. These data sets are utilized to evaluate the models under different conditions, including different illumination and types of attacks. The models are evaluated based on accuracy, precision, recall, and error rates. The high accuracy reveals the capability of the models to identify real versus synthetic faces. Evaluation with different data sets is employed to ensure that the models perform well in the real world. The principal contributions are:

a. DenseNet is combined with a 3D-FAS, SE mechanism, NAKA scheme, cross-channel attention, and MIL in the architecture proposed to construct an effective and efficient anti-spoofing system.
b. A novel "Neighbourhood-Aware Kernel Adaptation" method is introduced to adaptively modify 3D convolution kernels according to spatial similarities in the voxel's neighbourhood to improve the model's ability to identify intricate spatial patterns in 3D facial data.
c. For the first time, MIL is introduced in facial anti-spoofing for enabling the model to learn temporal and spatial abnormalities across face regions and enhance the spoof detection over dynamic and local regions.
d. d. An explicit cross-validation evaluation was conducted via a five-fold cross-validation and achieved performance over baseline models based on Classification accuracy, Precision, Recall, F1-score, ACER, APCER, and BPCER.
e. e. In the initial stage, we employ the aXial Attention Network (XA-Net) model. The model is employed to achieve deep hidden features of multi-modal images for enhancing the system's capacity to differentiate between real faces and spoof attacks.
f. f. Once the feature extraction process has been completed, we employ a bidirectional fusion technique. It is direction-aware in the aspect that it is able to seamlessly merge features from all modes. The bidirectional fusion method is beneficial in realizing a finer-grained representation of the input information.
g. Feature optimization is further carried out using the improved pity beetle optimization (EPBO) algorithm [24]. It is utilized to solve data dimensionality issues through feature optimization and selection, leading to efficiency in handling high-dimensional and complicated data.

h. The model used in the subsequent face anti-spoofing phases is the hybrid federated reinforcement learning (FDDRL) method. The hybrid exploits the maximum trade-off between the detection and the false positives to drive the system for improved performance. The reinforcement learning aspect provides flexible learning and decision-making, leading to the model being robust under different anti-spoofing situations.anti-spoofing scenarios.

1.5 THESIS STRUCTURE

The thesis is structured in a logical way to provide a deep understanding of face anti-spoofing, from fundamentals to state-of-the-art approaches and experimental evaluations. Each chapter flows from the previous one in a continuous logic of research and findings.
Chapter 1 provides a comprehensive background on biometric authentication and face recognition security concerns. It highlights the importance of face anti-spoofing and the challenges. In Chapter 2 literature study of existing face anti-spoofing techniques, including traditional image processing methods, machine learning approaches, and deep learning-based solutions are presented. Recent advancements along with the research gaps in multi-modal fusion, attention mechanisms, and reinforcement learning for face anti-spoofing are presented. Chapter 3 introduces the hybrid model, which is effective in determining masked and true face scans. Chapter 4 presents a lightweight multi-modal approach to detect various types of spoofing attempts. Chapter 5 is the experimental setup and evaluation. It represents the datasets used for evaluation, pre-processing techniques, and benchmark methodologies. Chapter 6 summarizes the key findings of the thesis. It discusses the limitations of the proposed models and areas for improvement. It suggests potential future research directions, including real-time deployment strategies and adversarial attack resilience.

2. LITERATURE REVIEW

Face recognition systems are increasingly used in real-time applications like access control, surveillance, and user authentication, and paramount security issues are raised [21]. To enumerate, one of the extensive threats to these systems is presentation attacks, also known as spoofing attacks, whereby the attacker tries to mimic a legitimate user by presenting an artificial image, for instance, a picture, a video clip, or even a three-dimensional mask [22]. These attacks exploit facial recognition weaknesses, enabling identity theft, criminal access, and financial fraud. This compromises the system's credibility and reliability. As a result, users face increased security risks and loss of trust.

2.1 OVERVIEW

In past two decades, researchers have explored multiple FAS (face anti-spoofing) methods. From traditional image processing-based approaches to machine learning and deep learning architectures, several studies have shown that deep learning-based techniques perform better than traditional methods. It is because deep learning-based techniques automatically learn important facial features. However, to further improve detection, a combination of adaptive architectures, multi-modal approaches, and optimization techniques is needed. Literature review explores the major advancements in face anti-spoofing by covering traditional, machine learning, and deep learning methods. The limitations, effectiveness and possible future research directions are also covered.

To address these risks, analysts have devoted a lot of time to carefully creating very strong face anti-spoofing solutions that are designed to differentiate between authentic face samples and fake artifacts [23-25]. Of all the approaches, the 3D face anti-spoofing is greatly focused because it can capture the depth and tap into the live face structures, including the surface texture and movement. Traditional 3D face anti-spoofing relies on hand-crafted features, often failing to capture complex patterns and temporal dependencies needed for detecting advanced attack models. Previous studies have revealed several strategies for dealing with presentation attacks [26], [27]. For example, Zhao et al. [28] utilized local binary patterns (LBP) and support vector machine (SVM) for the detection of 2D face spoofing attacks. These methods performed well on development data but struggled to generalize due to limited feature representation and shallow model architectures.

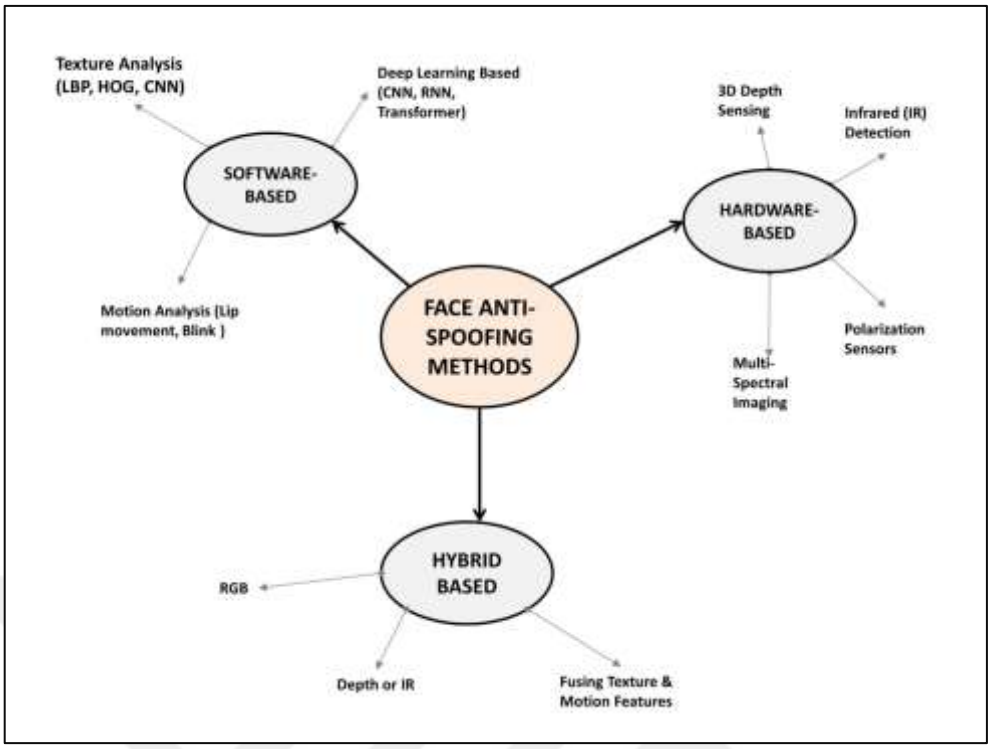


Figure 2.1: Classification of Face Anti-Spoofing Methods (by Author).

Despite making progress, the existing methods emphasize either the spatial or the temporal domains while focusing limited attention on 3D face data's potential fusion capability. Generic 3D methods based on visual saliency and facial motion [29], convolutional auto-encoders [30], stereo matching [31], and dual stream deep neural networks have shown remarkable performance on various public and private anti-spoofing datasets [32].

Several approaches influence various representation learning techniques to capture depth and texture features. It boosts their ability to distinguish between genuine and spoofed faces. But, their dependency on pre-defined feature extraction mechanisms limits their adaptability toward complex and diverse spoofing scenarios. Furthermore, most of these models suffer from generalization in the presence of variations in lighting, poses, and environmental conditions and often lack the dynamism to adapt to neighbourhood variations in 3D facial data. The figure 2.1 provides a clear classification of Face Anti-Spoofing Methods, dividing them into three main categories: Software-Based, Hardware-Based, and Hybrid-Based approaches. Software-Based Methods rely on analysing facial images and videos using computer algorithms. Texture analysis such as LBP (Local Binary Patterns), HOG

(Histogram of Oriented Gradients), and CNN is used to detect fake patterns. Deep learning techniques like CNN, RNN and Transformer are used to enhance detection rates.

Hardware-Based techniques employ specialized hardware. More detail and spectral information like 3D depth sensing, infrared (IR) sensing, multi-spectral imaging, and polarization sensors can be readily acquired. It is helpful in differentiating real faces from spoofing attacks like masks or printed images by capturing unique physical characteristics. Hybrid-Based Methods is the combination of both software and hardware approaches. Using combination of different methods, face anti-spoofing systems can provide robust security against various spoofing attacks, ensuring accurate and reliable facial authentication.

2.1.1 Traditional Image Processing-Based Methods

This section explains how early image processing techniques were used to detect fake faces. The basic idea is that real faces have natural variations, while fake ones—such as printed photos, videos, or masks often have visible differences. The original image processing methods work by selecting the specific features from a face image to specify if it is real or fake. These features might include texture, colour, or patterns on the skin.

One of the first techniques used for face anti-spoofing is Local Binary Patterns (LBP). It captures small texture differences in facial images [33]. The LBP operator tags pixels of an image by keeping threshold as neighbourhood pixels and convert them into a binary number. The standard LBP function is mathematically defined in Eq. 2.1. Where, 'I_c' is the grey value of the central pixel. 'I_p' are grey values of its P neighbours. If $x \geq 0$ then $s(x) = 1$, else $s(x) = 0$. The patch-pooling operation aggregates local textural features. This function assigns a binary value based on the difference between 'I_p' and 'I_c'. 'P' is the number of neighbourhood pixels considered in neighbourhood computation. '2^p' is a weighting factor that assigns a unique binary value to each comparison.

$$extLPB_P\ , R = \sum_{p=0}^{P-1} s\left(I_p - I_c\right)2^p \tag{2.1}$$

The final LBP value is obtained by summing the weighted binary values of all neighbourhood pixels as shown in figure 2.2. This method effectively encodes local texture patterns, making it robust for detecting facial spoofing attempts. Maatta et al. applied LBP

(figure 2.2) to analyses these variations and successfully differentiate real from fake faces, including printed photos and video replays.

$$LBP\ (x_c\ , y_c) = \sum_{p=0}^{P-1} s\left(g_p\ , g_c\right).\ 2^p \tag{2.2}$$

Here, g_c is the gray value of the central pixel, g_p are the gray values of its P neighbors, $s(x) = 1$ if $x > 0$, else 0 and P is the number of neighborhood pixels One of the major drawbacks of LBP is that it is highly sensitive to changes in lighting and struggles to detect high-resolution spoofing attempts.

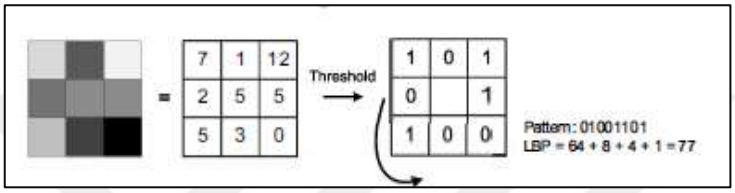


Figure 2.2: The Basic LBP Operator [34].

Peixoto et al. found that HOG-based features improved the detection of print attacks. HOG (Histogram of Oriented Gradients) is also another commonly used method which focuses on detecting edges and structural differences in facial images. As shown in Eq. 2.3 and Eq. 2.4, the HOG feature is computed by evaluating the orientations of gradient $G_x\ , G_y$ respectively as follows.

$$G_x = I\ (x + 1, y) -\ I\ (x - 1, y) \tag{2.3}$$

$$G_y = I\ (x, y + 1) -\ I\ (x, y - 1) \tag{2.4}$$

$$\theta = tan^{-1}\left(\frac{G_y}{G_x}\right) \tag{2.5}$$

Here $G_x\ , G_y$ are gradient magnitudes in the horizontal and vertical directions, $I\ (x, y)$ is the intensity of the image at pixel(x, y). Here, 'θ' represents the gradient direction in Eq 2.5. When it comes to 3D mask attacks, HOG does not perform well because it cannot capture depth information [35]. Optical Flow Analysis is one method that helps detect motion differences in replay attacks. Kollreider et al. observed that real faces have small, natural movements that are missing in video-based spoofing attempts. Optical flow is used to estimate motion between two consecutive frames. The Horn-Schunck method formulates it

as $I_x u + I_y v + I_t = 0$. Here I_x, I_y are the spatial image gradients, $I_t$is the temporal image gradient and u, v are the optical flow components.

Wavelet Transform analyses texture patterns at multiple scales to identify fake faces [30]. Wavelet decomposition is used to analyse texture patterns at different scales as shown in Eq. 2.6.

$$W_\varphi(a,b) = \int_{-\infty}^{\infty} f(x)\ \varphi_{a,b}(x)dx \tag{2.6}$$

Here, $\varphi_{a,b}(x)$ is the wavelet function, a is the scaling parameter, b is the translation parameter and $f(x)$ is the signal (image intensity values).

Traditional methods offer some advantages but they have limitations also. They struggle against more advanced spoofing techniques, such as deepfake attacks, which can generate highly realistic fake faces. A model trained on one dataset may fail when tested on another. They do not perform well across different datasets. Due to these challenges, researchers have shifted their focus toward machine learning techniques to improve the accuracy of face anti-spoofing.

2.1.2 Machine Learning Approaches

Machine learning approaches uses statistical models to classify facial images as real or spoofed based on extracted features. One of the most widely used techniques is SVMs (Support Vector Machines), where LBP and HOG-based feature descriptors are fed into a classifier for decision-making [36]. SVM aims to look for the optimal hyper-plane that separates two classes by maximizing the margin between them. The optimization problem is formulated as in Eq.2.7. Where, 'w' is the weight vector,' b' is the bias, 'x_i' are the feature vector and 'y_i' are the class labels.

$$y_i(w.x_i + b) \geq 1,\ \forall i \quad \mid min_{w,b}\ \frac{1}{2}\ \|w\|^2 \tag{2.7}$$

SVM models have shown improved accuracy over traditional methods. SVM leads to increased computational costs as it requires manual feature selection. Its adaptability to diverse attack types is thus limited [37]. Random Forest classifiers use multiple decision trees, it has been applied to improve classification robustness [38]. The prediction of random forest model is given by following Eq. 2.8.

$$\hat{y} = \frac{1}{T} \sum_{t=1}^{T} h_t(x) \tag{2.8}$$

Where, '$h_t\ (x)$' represent the prediction of each decision tree. 'T' is the total number of trees. Random Forests can handle a variety of spoofing scenarios and require large feature sets for training. To detect replay and deepfake attacks, temporal variations in face videos could be analysed using motion-based machine learning methods. Sun et al. developed a model that captures subtle facial motion patterns to distinguish between real and spoofed faces [39]. Models can be trained on both real and artificially generated spoofed images to enhance generalization using adversarial feature learning which is an emerging trend in machine learning-based FAS. Generative Adversarial Networks (GAN) based methods improve spoof detection by generating adversarial samples [35]. The loss function for a GAN is represented by Eq.2.9

$$min_G max_D E_{x \sim p_{data}(x)}[\log D(x)] + E_{z \sim p_z(z)}[\log(1 - D(G(z)))] \tag{2.9}$$

Here, $D(x)$ is the discriminator that classifies real vs. fake samples, $G(z)$ is the generator that creates synthetic images, $p_{data}(x)$ is the distribution of real images and $p_z(z)$ is the distribution of latent variables. One of the main drawbacks of machine learning methods is their dependence on feature engineering. Since handcrafted features may not always capture complex attack strategies, these models struggle when deployed in real-world scenarios with unseen spoofing techniques.

Xu et al. [40] introduced a MIL-based approach for face anti-spoofing systems, which considers each face sample as a bag of instances (for example, patches or frames, etc). The framework uses multi-instance CNN, in which instance-level decisions are employed to make the final decision for spoofing classification; it can capture the local spoofs successfully. Some of the techniques used in adversarial learning are used for data augmentation and to create synthetic data. Xu et al. [41] proposed a privacy-preserving anti-spoofing system named RFace, which extracts both the 3D geometry and inner biomaterial features of faces using a COTS RFID (Commercial Off-The-Shelf Radio Frequency Identification) tag array. These features are difficult to obtain and forge and, hence, are resistant to spoofing attacks. However, the global performance of the proposed system was prone to overfitting because of high dimensionality and limited data validation.

Birla et al. [42] developed a face anti-spoofing method for short-duration videos by utilizing statistical features to compactly represent the correlation between pulse signal and a large number of local rPPG signals. However, the performance of the model was superior to existing methods but limited to specific datasets. It achieved lower performance on the CASIA-SURF 3DMask dataset than the 3DMAD and HKBU-MARsV1+ datasets. Kumar and Bansal [43] addressed the problem of masked and unmasked face detection in images and real-time video streams. The approach employs a hybrid model based on Caffe-MobileNetV2 for feature extraction and mask identification with extra layers added for enhanced classification accuracy. The proposed approach shows excellent results with 99.64% accuracy, 100% precision, and 99.28% recall values. Kumar and Mishra [44] proposed a multiclass masked face age and gender identification model by integrating a convolutional architecture of fast feature embedding (CAFFE) with the modified MobileNetV2 (MNV2). This model was trained and evaluated on 12,160 masked face images with 96.54% accuracy and a 3.46% error rate.

2.1.3 Deep Learning-Based Methods

Deep learning-based techniques have gained popularity due to their ability to learn complex feature representations from raw facial data. These techniques have transformed FAS. Deep learning techniques eliminate the need for manual feature extraction.

Yu et al. extended this work by incorporating pixel-wise supervision, allowing models to learn fine-grained facial details that distinguish real and fake faces. Advancement in deep learning-based anti-spoofing is the use of Recurrent Neural Networks (RNNs) for video-based analysis [45]. RNNs process sequential data to analyse temporal inconsistencies in video-based face anti-spoofing. The hidden state update is given in Eq. 2.9. In the equation h_t is the hidden state at time t, x_t is the input at time t, W_h, W_x are weight matrices, b is the bias and f is the activation function.

$$h_t = f(W_h\, h_{t-1} + \, W_x\, x_t + b) \tag{2.10}$$

Generative Adversarial Networks (GANs) have been used to generate synthetic spoofing attempts for training more robust models. Liu et al. proposed an adversarial learning approach that improves a model's ability to detect AI-generated deepfake attacks. Deep learning-based methods still face challenges like high computational costs, dataset biases,

and vulnerability to adversarial perturbations [47]. Table 2.1 provides a structured comparison of Face Anti-Spoofing techniques based on their methodologies, advantages, limitations, and key references. The evolution from traditional methods to deep learning and adaptive architectures has improved the effectiveness of spoof detection.

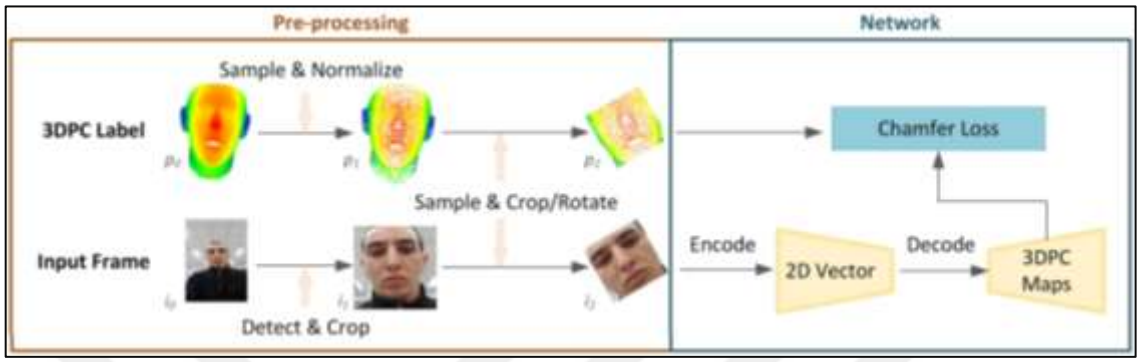


Figure 2.3: Overview of 3DPC-Net [48].

Few other advanced methods, such as 3D Point Cloud Network (3DPC-Net) as shown in figure 2.3 and Factorized Bilinear Coding [49], have shown remarkable performance on 3D samples but often struggle to generalize across diverse attack scenarios and environmental conditions. Apart from high classification accuracy, the performance was noise-sensitive and exhibited limited robustness to variations in rotation, scale, and incomplete data, highlighting the need for improved pre-processing and augmentation techniques to enhance generalization. The emergence of 3D-based spoofing attacks further exacerbates this challenge, as they exploit depth and texture details to deceive detection systems. Moreover, existing approaches cannot adapt dynamically to neighbourhood variations in input data, resulting in performance degradation under varying lighting, poses, and background conditions. Therefore, a completely new 3D anti-spoofing framework must be devised to enhance the performance claimed by existing methods.

Raghavendra et al. [50] suggested a face anti-spoofing approach based on extended local ternary co-relation pattern (ELTCP). ELTCP transforms the ternary edges co-relation of an image given. The method demonstrates significantly better performance compared to conventional methods such as LBP (Local Binary Pattern), LTP (Local Ternary Pattern), and LGS (Local Graph Structure). ELTCP transforms a ternary edge of an image and forms a co-relation pattern as shown in Eq.2.10.

$$ELTCP\ (x, y) = \sum_{i=1}^{n} w_i . s\ (I_i - I_c) \quad (2.11)$$

Where, 'I_i' represent the intensity of the neighboring pixels. 'I_c' is the center pixel intensity, 'w_i' is the weight assigned to each neighbouring pixel, 's' is the ternary function mapping pixel differences to discrete values. This approach utilizes luminance and chrominance channels from a color image, employing high-level descriptors from different color spaces to represent facial color textures, which proves more robust in unknown conditions than grayscale counterparts. The algorithm also has block-wise division of the frame, and block-wise Haralick video features are extracted. Dimension of the Haralick texture feature is reduced using PCA and classified using SVM later on.

Jiang et al. [61] proposed a face anti-spoofing method that leverages information from both visible light (VIS) images and near-infrared (nIR) images without requiring near-infrared equipment during testing. They introduced a multiple-category image translation generative adversarial network (MCT-GAN) to generate corresponding NIR images for both live and spoof VIS face images. A CNN is employed to learn fused features from both VIS images and the generated NIR images, facilitating live and spoof face classification. Experimental results demonstrate the effectiveness of extracting color texture information from luminance and chrominance channels in enhancing face anti-spoofing performance. However, variations in illumination conditions, spoofing mediums, and manufacturing processes introduce texture differences even for the same sample.

Bousnina et al. [52] analysed differential evolution-based adversarial attacks using a VGG16-based face liveliness detection model. The study focuses on practical criteria to enhance defence strategies for deep learning-based anti-spoofing systems against such attacks. The adversarial attack model uses the differential evolution (DE) optimization approach which is represented as below in Eq. 2.11.

$$x_i^{(t+1)} = x_r^t + F\ .\ (\ x_a^t - x_b^t) \quad (2.12)$$

Table 2.1: Summary of Traditional Image Processing, Machine Learning, and Deep Learning Based Methods for Anti-Spoofing

Authors Details	Key Challenges	Proposed Approach	Findings
Maatta et al. (2011) [33]	Sensitivity of LBP to lighting changes and inability to detect high-resolution spoofing attempts.	Used Local Binary Patterns (LBP) for texture analysis to differentiate real and fake faces.	LBP is effective for simple spoofing but struggles with advanced attacks.
Peixoto et al. (2017) [34]	HOG cannot capture depth information, making it ineffective against 3D mask attacks.	Utilized Histogram of Oriented Gradients (HOG) to detect print attacks.	Improved detection for print attacks but failed against 3D mask attacks.
Freitas et al. (2013) [35]	Video-based spoofing attacks lack natural face movements.	Optical Flow Analysis to detect motion differences in replay attacks.	Could detect replay attacks but struggled with subtle face manipulations.
Xu et al. (2021) [40]	Feature engineering limitations and difficulty in detecting unseen spoofing techniques.	MIL-based approach using multi-instance CNNs for local spoof detection.	Successfully captured localized spoofs but prone to overfitting due to limited data.
Kumar & Bansal (2023) [43]	Masked and unmasked face detection in real-time video streams.	Hybrid Caffe-MobileNetV2 model for feature extraction and mask detection.	Achieved 99.64% accuracy, high precision, and recall values.
Kumar & Mishra (2024) [44]	Need for accurate age and gender identification with masked faces.	Integrated CAFFE with MobileNetV2 for multi-class classification.	96.54% accuracy with a 3.46% error rate.
Liu et al. (2021) [46]	Vulnerability to deepfake attacks.	Combined CNNs and RNNs for detecting temporal inconsistencies.	Enhanced ability to detect deepfake and replay attacks.
Raghavendra et al. (2020) [50]	Traditional LBP, LTP, and LGS methods fail under unknown conditions.	Proposed ELTCP-based algorithm using luminance and chrominance features.	More robust than grayscale-based methods in varying conditions.
Jiang et al. (2021) [51]	Dependence on near-infrared equipment for testing.	Introduced MCT-GAN for generating NIR images from visible light images.	Improved face anti-spoofing but faced illumination variation challenges.
Bousnina et al. (2022) [52]	Adversarial attacks on face liveness detection models.	Used differential evolution-based adversarial attacks on VGG16 models.	Showed trade-offs between attack robustness and defense strategies.
Katika et al. (2023) [53]	Need for identity-independent face spoof detection.	Random correlated scans with one-class SVM for spoof detection.	Achieved an EER of 2.02% for inter-database evaluation.

Katika et al. [53] introduced an identity-independent architecture based on random correlated scans applied to natural face images. This innovative approach involves scanning the same natural face image multiple times through independent correlated random walks, generating simple differential features on the resulting 1D scanned vector are randomly chosen individuals from the population, the feature extraction using random walks can be modelled as shown in Eq. 2.12.

$$RCS(x) = \sum_{i=1}^{n} f\left(I(x_i)\right).\delta(x_i - x_{i-1}) \tag{2.13}$$

Here, $RCS(x)$ represents random correlated scan function. The pixel function mapping intensity to feature space is given by $f\left(I(x_i)\right)$. The correlation difference between successive points in the scan is given by $\delta(x_i - x_{i-1})$. The method is designed to capture pixel correlation statistics with minimal interference from content, particularly when trained on natural face datasets. Utilizing a one-class SVM and cross-validation on various databases, the framework demonstrates promising performance. The detection of spoof faces achieved an EER of 3.8291% with random scan features and 2.02% with auto-populated samples for inter-database evaluation.

2.2 ADAPTIVE ARCHITECTURES IN FACE ANTI-SPOOFING

Adaptive Architectures in FAS (Face Anti-Spoofing) dynamically adjust model parameters and feature selection strategies to improve spoof detection across different conditions. These architectures, such as Meta-Learning Models, Domain Adaptation Networks, and Multi-Modal Fusion Systems, enhance generalization, robustness, and efficiency. Meta-learning allows the model to quickly familiarize to unseen spoofing attacks, while domain adaptation reduces dataset bias for cross-dataset performance. Multi-modal fusion combines RGB, depth, and infrared features for better detection accuracy. By learning adaptive patterns, these models improve real-world performance in biometric security applications.

2.2.1 Convolutional Neural Networks (CNNs)

CNN-based face anti-spoofing has seen significant advancements through various state-of-the-art approaches. CNN-based models such as VGGNet and ResNet extract hierarchical facial features, enabling improved spoof detection. To improve the robustness of FAS methods, researchers have proposed adaptive architectures that enhance feature extraction and generalization. But, these architectures are sometimes expensive in terms of computational cost [53]. The CNNs (Convolutional Neural Networks) have been widely adopted for detecting spoofing artifacts in face images. Figure 2.4 presents the architecture of FAS proposed by Atoum et al. A CNN-based approach is introduced that analyses texture and depth information, significantly improving detection accuracy. The convolution operation is defined as given in Eq. 2.13.

$$F(i,j) = \sum_m \sum_n I\,(i-m, j-n).K(m,n) \tag{2.14}$$

Here, $I(i,j)$ is the input image, $K(m,n)$ is the convolutional kernel (filter) and $F(i,j)$ is the feature map output at position (i,j). Eq. 2.14 shows ResNet skipping connections to address vanishing gradients where x is the input to the residual block, $f(x)$ is the transformation applied by convolutional layers and y is the output to ensure gradients can flow easily.

$$y = f(x) + x \tag{2.15}$$

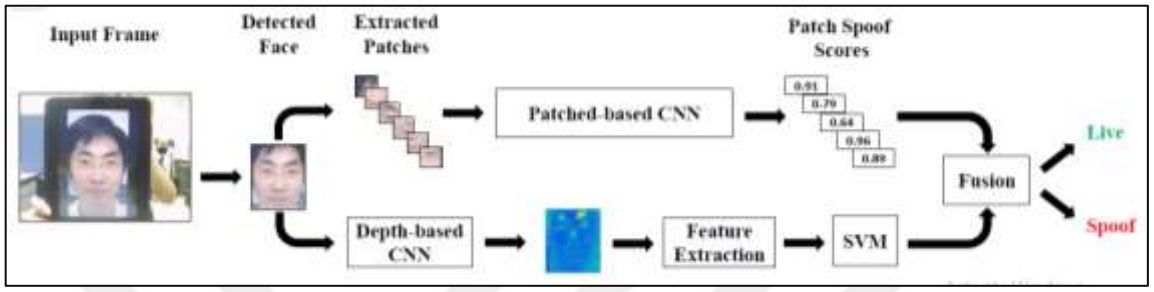


Figure 2.4: Architecture of the Proposed FAS Approach by Atoum et al. [9].

Y. Liu, J. Zhang, and X. Wang proposed an adaptive face anti-spoofing model using multi-modal fusion and a self-learning mechanism for better spoof detection. It faces challenges like high computational complexity and reduced effectiveness against new attack methods [54]. Similarly, Z. Luo, H. Li, and F. Wu introduced a deep multi-modal fusion framework combining RGB, depth, and infrared (IR) features. Their model improves robustness against various spoofing attacks but requires specialized hardware and has high computational costs [55].

Cai et al. [56] proposed a face anti-spoofing detection network employing a CNN and a brightness equalization model. The multi-task CNN comprises three cascaded networks, namely P-net, R-net, and O-net, which work together to precisely position the face. Subsequently, the detected face bounding box is cropped by a specified multiple, and brightness equalization is applied to perform brightness compensation on different areas of the face image with varying brightness. Data features are then extracted, and classification is carried out using a 12-layer CNN. The results demonstrate relatively high classification accuracy, with the Half Total Error Rate (HTER) reaching 1.02%. MobileNet was introduced as a lightweight alternative for real-time applications. Residual and Dense Networks have been explored to improve feature propagation and minimize information loss [57]. Dense

Network improves feature reuse by connecting each layer to every subsequent layer as represent by Eq. 2.15.

$$x_l = H_l([x_0, x_1, \ldots\ldots, x_{l-1}]) \tag{2.16}$$

Here, x_l is the feature map at layer l, H_l is the transformation function (e.g., convolution, activation) and $([x_0, x_1, \ldots\ldots, x_{l-1}]$ represents concatenation of all previous feature maps.

Liu et al. demonstrated that combining CNNs with RNNs enhances the ability to detect temporal inconsistencies in replay attacks [46]. They also proposed the DeepTree framework. It utilizes a hierarchical decision tree model built on CNN features to enhance generalization across different spoofing attacks. The probability of classification at each node is given as follows in Eq.2.16. Here, X is the CNN-extracted feature vector, y is the predicted class (real or spoof), $P(y_i|X_i)$ is the probability of a decision at node i and N is the total number of nodes in the tree.

$$P(y|X) = \prod_{i=1}^{N} P(y_i|X_i) \tag{2.17}$$

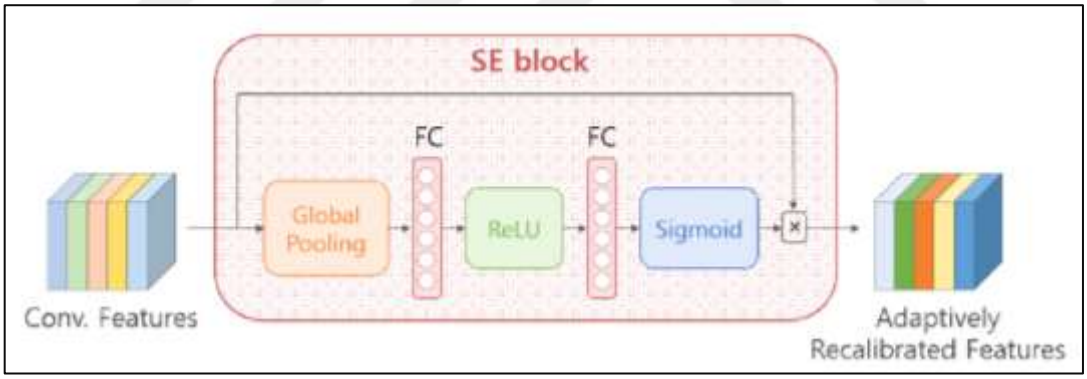


Figure 2.5: Attention Module Architecture Used by Boulkenafet et al. [12].

CNN extracts feature from input face images. Instead of using a single classification layer, the features are passed through a decision tree structure, where each node specializes in detecting specific types of spoofing attacks. Using hierarchical approach, the model handles multiple attacks separately for better generalization [58]. Boulkenafet et al. also explored colour texture analysis combined with CNNs to improve robustness against cross-dataset variations. In the proposed colour texture analysis, the LBP and Colour Histograms are

extracted from different colour spaces (RGB, HSV, YCrCb). Figure 2.5 shows details of the attention module architecture used.

These features are fused with CNN-extracted deep features to capture both shallow and deep-level texture patterns in real vs. fake faces. Eq. 2.17 shows the fusion of LBP and colour histogram where F_{LBP} is the LBP-based texture features, $F_{colorHist}$ represents colour histogram features, F_{CNN} represents deep CNN features and (α, β, γ) are the weighing factors.

$$F = \alpha F_{LBP} + \beta F_{colorHist} + \gamma F_{CNN} \tag{2.18}$$

Addressing dataset bias, Zhang et al. introduced FaceDs, a domain adaptation-based CNN model that enhances cross-dataset generalization. As per their research, traditional CNN models overfit to specific datasets and fail to generalize to new data distributions. FaceDs applies domain adaptation techniques such as adversarial training to align feature distributions across different datasets. A domain discriminator is used to reduce dataset-specific bias and encourage learning of generalized facial spoofing features [59-60].

To improve video-based spoof detection, Liu et al. developed "FaceGuard", a framework that integrates both spatial and temporal cues for better detection accuracy. FaceGuard integrates CNN (spatial features) and RNN/LSTM (temporal features) as follows:

$$F_{final} = \lambda F_{CNN} + (1 - \lambda) F_{RNN} \tag{2.19}$$

Here, λ controls the weight between spatial and temporal features. As represented in Eq 2.18 the FaceGuard extracts spatial features (face textures, skin tone variations) using CNNs. The temporal features (blinking, micro-expressions) using Recurrent Neural Networks (RNNs) or Long Short-Term Memory (LSTM) networks are extracted to improve FAS. Liu et al incorporated both spatial and temporal feature types to differentiate static spoof attacks (print, digital screens) from dynamic live face interactions [61].

George and Marcel proposed SPSL (Single-Pixel Supervision Learning), which leverages CNNs to learn fine-grained texture details in spoofing attempts, achieving high performance with minimal labelled data. SPSL focuses on individual pixel differences between real and fake textures. Eq 2.19 shows how SPSL uses pixel-wise contrastive learning to learn fine-grained differences at a microscopic level (e.g., subtle texture differences, micro-reflections,

or diffusion patterns). The Euclidean distance between pixel embedding is represented by d_{ij}, the label is depicted by y_{ij} (1 if same class, 0 if different), and m is the margin hyper parameter.

$$L = \sum_{i,j}[y_{ij}\, d_{ij}^2 + (1 - y_{ij}) \max(0, m - d_{ij})^2] \quad (2.20)$$

SPSL technique achieves higher accuracy even by using less labelled data which is its advantage over other techniques [3]. Zhang et al. introduced the STASN (Spatial-Temporal Anti-Spoofing Network) captures both spatial features and dynamic motion cues. It enhances real-time spoof detection accuracy. This can detect deepfake-based attacks, where pixel-level inconsistencies reveal synthesized images. STASN works well with limited labelled data, making it useful for low-resource environments [62-63].

A work based on a graph convolutional network (GCN) framework was developed for 3D face recognition from facial meshes described as graphs by Dai et al. [64] It uses spatial and spectral graphs and convolution to capture local and global geometric features, which has helped yield better face recognition performance.

The face de-spoofing framework relies on CNNs to model attack-specific noise and is effective against print and replay attacks, but struggles with 3D mask attacks and real-world variations. In contrast, Auto Spoof leverages GANs to generate adversarial representations, making it more robust against 3D mask attacks, but it requires large-scale training data and may fail against evolving spoofing techniques [65] [66].

Cao et al. [67] have also used a spatio-temporal attention network for face anti-spoofing, where spatial and temporal attentions have been integrated into the network. Temporal attention focuses on dynamic cues extracted from the video sequences, while the spatial attention module zooms into discriminative facial areas, giving the model a unique opportunity to learn from both temporal and spatial domains for spoofing detection. However, the model was limited only to 2D facial images and therefore couldn't validate on 3D anti-spoofing attacks.

Biswas et al. [68] introduced a novel 3-stream compact Xception framework (3sXcsNet) consisting of four input streams RGB, MSRCR (Multi-Scale Retinex With Color Restoration), MSRCP (Multi-Scale Retinex With Chromaticity Preservation), and a depth map to form two specific 3-stream fusion to mitigate the illumination scenarios. These

streams provided highly discriminative features, such as RGB images having rich texture features. Here, MSRCR and MSRCP images are illumination invariant and preserve better chromaticity when applied to a color or intensity channel, respectively. This approach realized a very low equal error rate (EER) on various datasets but suffered from the high-dimensional behaviour of fused feature sets.

Kong et al. [69] devised a novel two-branch framework that combines the global and local frequency clues of input signals to distinguish inputs, live vs. spoofing faces accurately. The authors validated their approach on the self-proposed acoustic-based FAS 18 database, Echo-Spoof, and realized more than 98.0% accuracy in all conditions. Another model was proposed by Zhou et al. [70], which is PointXD, a deep learning-based approach that directly deals with filter point clouds and 2D characteristics for 3D facial recognition purposes. It employs PointNet++ to learn point cloud elements and CNN to learn the patterns of 2D features that include geometric and texture information. Nathan et al. [71] utilized the modified squeezed residual blocks and attention mechanisms to enhance the facial expression representation by recalibrating channel-wise responses to emphasize informative features incorporating global average pooling and channel-wise excitation. This approach was validated on multiple datasets, including CelebA-spoof datasets, and revealed superior performance over baseline models.

2.2.2 Residual and Dense Networks

Residual Networks (ResNets) and Dense Networks (DenseNets) address the limitations of vanishing gradients and feature redundancy. ResNets use skip connections that allow gradients to flow smoothly across layers, improving the learning capability of deep networks. Figure 2.6 presents the building block of the work done by He et al. DenseNets, proposed by Huang et al. [73], enhance feature propagation by connecting each layer to all subsequent layers, thereby maximizing information reuse. Researchers have applied ResNet-based architectures in face anti-spoofing to improve depth estimation and spatial feature extraction.

Liu et al. applied ResNet-based models to enhance depth estimation for 3D spoof detection. They demonstrated that ResNet-based models effectively distinguish real and fake faces by leveraging multi-scale feature fusion [74]. For depth estimation in 3D face anti-spoofing, a multi-scale feature fusion is calculated as given in Eq. 2.20. The estimated depth map is

given by D. The feature map from i[th] layer ResNet is given by F_{ResNet}^{i}, and α_i is the weighing factors.

$$D = \sum_{i}^{N} \alpha_i F_{ResNet}^{i} \tag{2.21}$$

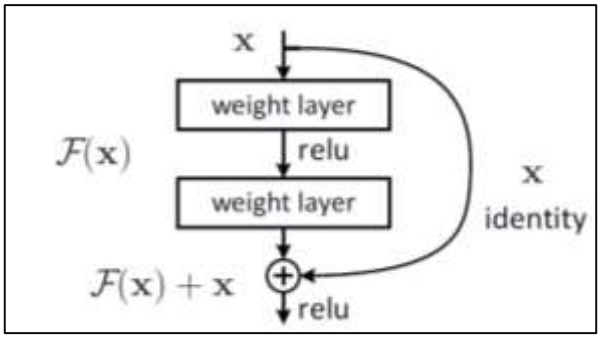


Figure 2.6: Building Block of Residual Learning [72].

DenseNets shows superior feature reuse across network layers. George et al. surveyed DenseNet architectures to enhance fine-grained texture analysis in spoof detection. Other studies have further refined these models for improved performance [75]. Li et al. proposed ResNet-based attention mechanisms that focus on discriminative spoofing patterns, increasing robustness against adversarial attacks. The attention weight A for a given feature map F is computed as shown in Eq. 2.21. Where, the trainable weights are given by W_a, b_a, the sigmoid activation is represented by σ and F_{att} is the refined attention-weighted feature map.

$$A = \sigma\left(W_a \times F + b_a\right) \tag{2.22}$$

$$F_{att} = A.F$$

Kim et al. introduced a hybrid DenseNet-ResNet model that balances feature extraction efficiency and computational cost [76]. A hybrid model that combines DenseNet and ResNet features is given below in Eq. 2.22. The feature maps extracted from respective networks are represented by $F_{DenseNet}$ and F_{ResNet}. The balance between two feature maps is given by λ.

$$F_{hybrid} = \lambda F_{DenseNet} + (1 - \lambda) F_{ResNet} \tag{2.23}$$

Sun et al. developed a lightweight ResNet variant optimized for real-time mobile applications, addressing the challenge of computational complexity [77]. More recently,

Zhang et al. integrated self-supervised learning with ResNet-based architectures to enhance generalization across unseen spoofing datasets. These networks provide strong feature representations, making them robust against various spoofing techniques. However, computational complexity remains a challenge, prompting the need for lightweight architectures [78].

2.2.3 Attention Mechanisms

Face anti-spoofing models are integrated with attention mechanisms to improve feature selection and focus on discriminative facial regions. Attention mechanisms help by directing computational focus toward the most relevant facial regions.

Hu et al explained how Squeeze-and-Excitation (SE) Networks enhance the model's ability to focus on important feature channels rather than treating all features equally. SE networks introduce a "squeeze" operation that compresses global information across spatial dimensions. It is followed by an "excitation" operation. The model assigns different importance scores to each feature channel which contains important facial details like skin texture, lighting reflection, and depth variations [79]. These channels are given higher weights and unrelated features like lighting variations or image artifacts are dropped. The Squeeze-and-Excitation (SE) mechanism follows two steps where it calculates global average pooling followed by activation of fully connected layers.

a. Global Average Pooling is calculated as mentioned in Eq. 2.23 (a), where, $X_c(i,j)$ is the activation at spatial location (i,j) in channel c.

$$z_c = \frac{1}{H \times W} \sum_{i=1}^{H} \sum_{j=1}^{H} X_c(i,j) \qquad (2.24) - (a)$$

b. Activation of Fully Connected Layers is given in Eq. 2.23 (b). Here W_1 and W_2 are learnable weights. 'δ' is the ReLu function and σ is the sigmoid function.

$$s = \sigma\,(W_2\,\delta(W_1\,z)) \qquad (2.24) - (b)$$

Yu et al. introduced a CNN model with spatial attention, which selectively focuses on facial regions disposed to spoofing artifact [80]. The attention map is computed as given in Eq. 2.24. Where, 'X' represents input feature map, 'W_1' and 'W_2' are learnable weights. Symbol '*' represents convolution. 'σ' is the sigmoid activation function and 'A_s' is the spatial

attention map. This model struggles with generalization to unseen spoofing techniques and is sensitive to variations in lighting conditions.

$$A_s = \sigma(W_2 . ReLU(W_1 * X)) \tag{2.25}$$

Lai et al. (2019) [81] introduced Anti-Spoofing with Squeeze-Excitation and Residual network (ASSERT) with four DL components i.e., feature engineering, DNN models, network optimization, and system combination, where the DNN models are variants of squeeze-excitation and residual networks. The Squeeze-Excitation (SE) module enhances feature representation by recalibrating channel-wise feature responses. Eq. 2.25 represents its calculation. In the equation 'X' is the input feature map. 'W_1' and 'W_2' are fully connected layers. '$\delta(.)$' is the ReLu activation function. 'σ (.)' is the sigmoid function. '$S(X)$' can be calculated using Eq. 2.26.

$$F_{SE\ (X)} = X.\sigma\ (W_2\ \delta\ (W_1\ S(X))) \tag{2.26}$$

$$S(X) = \frac{1}{H \times W} \sum_{i=1}^{H} X(i,j) \tag{2.27}$$

Liu et al. [82] developed a GAN framework for 3D face anti-spoofing in which synthetic depth maps and rPPG data are regenerated to enlarge the training data. The synthetic data is utilized to train the CNN-based anti-spoofing model and increase its effectiveness against diverse types of spoofing attacks. George and Marcel [83] proposed a channel-wise attention model for face anti-spoofing, which adjusts feature maps to focus on spoof-specific features. Integrated into a CNN framework, this module enhances detection performance. A comparative study by Gezawa et al [84] tested multiple anti-spoofing models on various benchmarks and suggested an adversarial approach to reduce the domain shift differences between the datasets. Attention-based models have been developed further to include spatial and temporal features as well. Kotwal and Marcel [85] proposed a patch-pooling mechanism to learn complex textural features from the lower layers of a CNN. The patch-pooling operation aggregates local textural features and it's mathematically calculated as given in Eq. 2.27. The proposed patch pooling layer was used with a pre-trained face recognition CNN without fine-tuning. This approach was validated on mask attacks in Near InfraRed (nIR) channels from WMCA and MLFP datasets.

$$P(X) = \sum_{i=1}^{N} \sum_{j=1}^{M} w_{ij} X_{ij} \tag{2.28}$$

Here, 'X_{ij}' represents local feature response. 'w_{ij}' is the weight associated with each part. Zhang et al. combined channel attention with ResNet architectures to enhance feature representation. By dynamically adjusting attention to critical regions, these models improve both interpretability and generalization. Although this approach improves interpretability, it requires extensive training data and is computationally expensive which makes it less suitable for real-time applications [86]. Li et al. extended these approaches by incorporating a dual-branch attention mechanism that simultaneously extracts spatial and frequency-based features for improved spoof detection. However, the model has high computational costs and may overfit to specific datasets, reducing its cross-dataset adaptability [87]. Sun et al. introduced a transformer-based attention model that effectively captures long-range dependencies in facial textures, making it robust against 2D and 3D spoofing attacks. But, transformers demand substantial computational resources and large-scale datasets which limit their deployment in resource-constrained environments [88]. Liu et al. proposed approach "attention-guided" advancement in hybrid attention-based architecture, depth estimation network that enhances live face detection by distinguishing subtle depth cues. Despite its effectiveness, it may perform poorly in cases where high-resolution depth information is unavailable or distorted [89].

Kim et al. introduced a multi-scale attention fusion model that integrates information from different feature hierarchies, increasing resilience to illumination variations. But, the fusion process can introduce redundancy, leading to inefficiencies in feature selection [90]. Feature fusion across scales is formulated as below in Eq. 2.28, where, 'F_s' is the feature map at scale 'S'. 'w_s' is the weighting factor.

$$F_{fusion} = \sum_{s=1}^{S} w_s \, . F_s \tag{2.29}$$

Wu et al. developed a cross-modal attention framework that combines RGB and infrared cues for improved generalization across datasets. One limitation is the dependency on infrared data, which may not always be available in real-world scenarios [91]. Recently, Chen et al. applied a vision transformer with adaptive attention weighting, achieving state-of-the-art performance on multiple anti-spoofing benchmarks. While this model excels in feature learning, it suffers from high computational complexity and may require significant fine-tuning to adapt to different datasets [92]. Kong et al. [93] merged the residual network and the channel attention mechanism to extract the shadow and edge-based feature

differences between features in face images. The experiments were performed on Replay-Attack and CASIA-FASD datasets and realized classification accuracy of 99.98% and 97.75%, respectively.

The integration of attention mechanisms like Channel Attention Networks and Vision Transformers improves feature selection by prioritizing discriminative facial regions. In literature Vision Transformers (ViTs) for face anti-spoofing has been explored well. Vision Transformers (ViTs) use self-attention mechanisms to learn relationships between different parts of an image. It looks for local features to capture long-range dependencies, for effective FAS. ViTs can find out deepfake and 3D mask artifacts that CNNs might miss [94]. As compared to CNNs, ViTs process facial images as a sequence of patches, capturing long-range dependencies and spatial relationships more effectively. ViTs process images as sequences of patches and apply self-attention [95]. The self-attention mechanism is given in Eq 2.29.

$$Attention\ (Q,K,V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right) V \tag{2.30}$$

Here Q,K,V are query, key, and value matrices respectively, d_k is the scaling factor (dimension of key vectors) and $softmax$ function ensures proper weighting of attention scores. Table 2.2 provides a structured summery of different FAS approaches across CNNs, Residual/Dense Networks, and Attention Mechanisms, highlighting their contributions, benefits, and challenges.

2.3 OPTIMIZATION TECHNIQUES FOR MODEL ENHANCEMENT

Optimization techniques play a crucial role in improving the robustness and efficiency of face anti-spoofing models. Several loss functions have been introduced to refine feature discrimination. Meta-heuristic Optimization like Genetic Algorithms and Particle Swarm Optimization optimizes the hyper-parameters and improve learning efficiency [96]. Loss functions are fundamental in training deep learning models, guiding the optimization process toward higher accuracy. Several loss functions have been introduced to improve feature discrimination in anti-spoofing models. Hadsell et al. applied Contrastive Loss in tasks where the objective is to learn embedding that separate dissimilar samples while bringing similar samples closer together. It is commonly applied in Siamese networks for face

verification and anti-spoofing. In face anti-spoofing, Contrastive Loss ensures that the embedding of real faces is closer together, while those of fake faces are pushed apart. Eq. 2.30 represents the calculation of contrastive loss. 'Y' is 1 if the pair is from different classes (real vs. fake) and 0 otherwise. Here, 'D' is the Euclidean distance between features embedding, 'm' is the margin that ensures dissimilar samples remains apart.

Table 2.2: Summary of Adaptive Architectures in Face Anti-Spoofing

Authors Details	Key Challenges	Proposed Approach	Findings
Atoum et al. (2017) [9]	Difficulty in analyzing texture and depth information for spoof detection.	CNN-based approach that extracts both texture and depth features.	Improved detection accuracy in face anti-spoofing.
Cai et al. (2020) [56]	Variations in facial brightness affecting classification.	Multi-task CNN with brightness equalization and 12-layer CNN classification.	Achieved high classification accuracy with HTER of 1.02%.
Liu et al. (2016) [59]	Generalization of FAS models to multiple spoofing attacks.	DeepTree framework using hierarchical decision tree with CNN features.	Enhanced generalization across different spoofing techniques.
Boulkenafet et al. (2022) [12]	Difficulty in handling cross-dataset variations.	Colour texture analysis combined with CNNs, extracting LBP and Colour Histograms.	Improved robustness in real vs. fake face detection.
Zhang et al. (2022) [60]	CNN models overfitting to specific datasets.	FaceDs, a domain adaptation-based CNN with adversarial training to reduce dataset bias.	Enhanced cross-dataset generalization.
Liu et al. (2021) [61]	Differentiating between static and dynamic spoof attacks.	FaceGuard framework integrating CNN for spatial features and RNN/LSTM for temporal features.	Improved accuracy in video-based spoof detection.
Zhang et al. (2021) [63]	Challenges in detecting deepfake attacks.	STASN (Spatial-Temporal Anti-Spoofing Network) capturing spatial and motion cues.	Effective real-time detection of deepfake-based attacks.
Dai et al. (2024) [64]	Limited feature extraction in 3D face recognition.	Graph Convolutional Network (GCN) framework applied to facial meshes.	Improved performance in 3D face recognition.
Cao et al. (2024) [67]	Limited validation for 3D anti-spoofing.	Spatio-temporal attention network integrating spatial and temporal attention.	Effective for 2D facial images but not validated for 3D.
Biswas et al. (2021) [68]	Variability in illumination conditions.	3sXcsNet using RGB, MSRCR, MSRCP, and depth maps for feature fusion.	Low Equal Error Rate (EER) but suffered from high-dimensional fused features.

Table 2.2: Summary of Adaptive Architectures in Face Anti-Spoofing (Table Continued).

Authors Details	Key Challenges	Proposed Approach	Findings
Kong et al. (2024) [69]	Need for improved real vs. spoof detection accuracy.	Two-branch framework combining global and local frequency clues.	Achieved over 98% accuracy on Echo-Spoof dataset.
Zhou et al. (2024) [70]	Combining 3D and 2D facial recognition.	PointXD model integrating PointNet++ and CNN.	Improved recognition using both geometric and texture information.
Authors Details	Key Challenges	Proposed Approach	Findings
Nathan et al. (2024) [71]	Enhancing facial expression representation.	Modified squeezed residual blocks and attention mechanisms.	Superior performance on CelebA-spoof datasets.
Liu et al. (2022) [74]	Computational complexity in ResNet models.	ResNet-based multi-scale feature fusion for depth estimation.	Improved depth estimation and robustness in 3D face spoofing.
Kim et al. (2021) [76]	Balancing efficiency and computational cost.	Hybrid DenseNet-ResNet model.	Optimized feature extraction while reducing computational cost.
Sun et al. (2023) [77]	Real-time application constraints.	Lightweight ResNet variant.	Optimized for mobile applications.
Zhang et al. (2024) [78]	Need for enhanced generalization in spoof detection.	Self-supervised learning integrated with ResNet architectures.	Improved robustness across unseen spoofing datasets.
Hu et al. (2018) [79]	Difficulty in selecting relevant features.	Squeeze-and-Excitation (SE) Networks enhancing feature focus.	Improved focus on discriminative facial features.
Yu et al. (2019) [80]	Sensitivity to lighting variations.	CNN with spatial attention mechanism.	Improved feature selection but struggled with unseen spoofing techniques.
Lai et al. (2019) [81]	Need for better feature extraction.	ASSERT model using squeeze-excitation and residual networks.	Achieved over 93% accuracy on ASVspoof 2019 datasets.
Liu et al. (2022) [82]	Need for effective training on diverse spoofing attacks.	GAN-based framework regenerating synthetic depth maps and rPPG data.	Improved CNN anti-spoofing model effectiveness.
George & Marcel (2020) [83]	Focus on spoof-specific features.	Channel-wise attention model integrated into CNN.	Enhanced detection performance.
Kotwal & Marcel (2020) [85]	Learning complex textural features.	Patch pooling mechanism combined with pre-trained CNN.	Improved performance on mask attacks in NIR channels.
Li et al. (2024) [86]	High computational costs.	Dual-branch attention mechanism extracting spatial and frequency-based features.	Improved spoof detection but suffered from dataset overfitting.
Sun et al. (2021) [88]	Capturing long-range dependencies in textures.	Transformer-based attention model.	Effective against 2D and 3D spoofing but resource-intensive.
Liu et al. (2022) [89]	Need for enhanced depth cues.	Attention-guided depth estimation network.	Effective in distinguishing subtle depth cues but struggled with low-resolution data.
Kim et al. (2021) [90]	Handling illumination variations.	Multi-scale attention fusion model.	Increased resilience but introduced feature redundancy.

$$L_{contrastive} = (1 - Y)\frac{1}{2} D^2 + Y \frac{1}{2} \max(0, m - D)^2 \quad (2.31)$$

This enhances model robustness against spoofing attacks by making it easier to differentiate between real and spoofed faces [97]. Qi et al. used Contrastive Loss with Siamese networks to improve robustness against adversarial attacks.

Bera et al. [98] introduced a two-stage human verification scheme to address vulnerabilities to attacks and bolster security. HandCAPTCHA serves as an initial defence against automated bot attacks before progressing to the subsequent biometric stage. The finger biometric verification of a legitimate user incorporates presentation attack detection using authentic hand images from individuals who have completed a random HandCAPTCHA challenge. The electronic screen-based presentation attack detection is evaluated using image quality metrics. A modified forward–backward (M-FoBa) algorithm is devised to select relevant features for biometric authentication. The average accuracy for correctly solving HandCAPTCHA is 98.5%, with a false accept rate of 1.23% for bots. Presentation attack detection is tested on 255 subjects from the BU dataset, achieving the best average error rate of 0%.

Lin et al. used Focal Loss to address the class imbalance problem in classification tasks by assigning higher importance to hard-to-classify examples while reducing the weight for well-classified ones. Since real faces are more frequent than spoofed faces in datasets, Focal Loss ensures that difficult spoofing attempts (such as high-quality printed masks or digital screen replays) receive more attention during training, improving detection accuracy [99].

$$L_{focal} = -\alpha(1 - p_t)^{\gamma} \log(p_t) \quad (2.32)$$

Eq. 2.31 represents how focal loss is calculated. Here, 'p_t' is the model's predicted probability for the correct class, 'γ' is the focusing parameter (typically set to 2) and 'α' is the weighting factor for class balancing. Li et al. demonstrated that Focal Loss which enhances deep model ability to detect challenging spoofing scenarios [100].

Schroff et al designed Triplet Loss that improved feature learning by ensuring that embedding of real faces remain distinct from those of fake faces by comparing three samples (Anchor, Positive and Negative) at a time i.e. the original image (α), a sample from the same class as the anchor (p) and a sample from a different class (n) respectively. Triplet Loss

enhances deep model's ability to learn fine-grained differences between real and fake faces, leading to better feature discrimination. The Eq. 2.32 represents triplet loss. Here '$d(x, y)$' is the distance function (e.g., Euclidean distance) and 'α' is a margin to enforce separation [101].

$$L_{triplet} = \sum_{i=1}^{N} \max(0, d(a, p) - d(a, n) + \alpha) \tag{2.33}$$

Centre Loss introduce by Wen et al to improve intra-class compactness by reducing variations among samples of the same class. It minimizes the Euclidean distance between embedding of a class and their class centre. Centre Loss helps maintain compact clusters of real and fake faces, ensuring that intra-class variations (such as different lighting conditions or camera angles) do not affect classification performance [68]. Zhang et al. integrated centre loss with ResNet to enhance feature separation, improving spoof detection in real-world applications [102]. In Eq.2.33 'x_i' is the feature representation of the i^{th} sample and 'c_{y_i}' is the centre of the corresponding class.

$$L_{center} = \frac{1}{2}\sum_{i=1}^{N}\left\|x_i - c_{y_i}\right\|^2 \tag{2.34}$$

Goodfellow et al. designed Adversarial Loss to be used in Generative Adversarial Networks (GANs) to make models more robust by training against adversarial examples. Adversarial Loss is used in GAN-based spoof detection models, where the generator creates synthetic spoofing attacks, and the discriminator learns to detect them, leading to stronger generalization against unknown spoofing methods [103].

Wang et al. proposed a hybrid loss function combining Triplet Loss and Adversarial Loss, achieving better generalization across diverse datasets. Calculation in Eq. 2.34 is used in GANs to train models against adversarial examples. Where, '$D(x)$' is the discriminator network output, which predicts whether a sample is 'x_r' (real) or 'x_f' (fake) samples. 'P_r' and 'P_f'are the real and fake data distributions respectively. First term ($E_{x_r \sim P_r}[\log D\ (x_r)]$) in Eq. 2.34 ensures that the discriminator assigns high probabilities to real samples. The second term ($E_{x_f \sim P_f}\left[\log(1 - D)\ \left(x_f\right)\right]$) penalizes the discriminator when it incorrectly classifies fake samples as real.

$$L_{adv} = E_{x_r \sim P_r}[\log D\ (x_r)] + E_{x_f \sim P_f}\left[\log(1 - D)\ \left(x_f\right)\right] \tag{2.35}$$

This adversarial loss function helps to train the discriminator and generator in a min-max game. A realistic fake sample is created by generator tries to fool the discriminator. The discriminator improves in distinguishing real from fake which in-turn enhances the model's robustness against adversarial examples. Binary Cross-Entropy Loss (BCE) is one of the most commonly used loss functions for binary classification developed by Rubinstein & Kroese, including face anti-spoofing. BCE Loss is widely used in deep learning-based spoof detection systems as it effectively penalizes incorrect classifications and provides smooth gradient updates [104]. Following equation represents BCE computation. Here, 'y_i' is the true label (1 for real, 0 for fake), '$\widehat{y_i}$' is the predicted probability.

$$L_{BCE} = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log(\widehat{y_i}) + (1 - y_i)\log(1 - \widehat{y_i})] \tag{2.36}$$

2.3.1 Regularization and Generalization Strategies

Regularization techniques help prevent over-fitting and improve the generalization of deep learning models. Srivastava et al. introduced Dropout, a technique that randomly deactivates neurons during training. This prevents the model from over-relying on specific features, reducing over-fitting and improving generalization to unseen spoofing attacks. By encouraging the network to learn diverse feature representations, Dropout enhances robustness against dataset biases and variations in spoofing techniques. It has been effectively integrated into CNN-based architectures for Face Anti-Spoofing (FAS), improving accuracy, especially in low-data scenarios [105]. Eq. 2.36 and Eq.2.37 represents mathematical formulation, which describes how neurons are randomly dropped during training. Here, y_i is the output of the neuron after applying Dropout, 'x_i' is the input to the neuron, 'w_i' is the weight associated with the neuron, 'r_i' is a binary mask where each element is sampled from a Bernoulli distribution. 'p' is the probability of keeping a neuron active (typically between 0.5 and 0.8 during training). During inference, the network uses a scaled version of the weights to compensate for the dropped neurons during training:

$$y_i = w_i.(x_i \,.\, r_i) \tag{2.37}$$

$$\widetilde{w_i} = p.w_i \tag{2.38}$$

Batch Normalization (BN) normalizes activations within a mini-batch to accelerate training and stabilize deep networks. It reduces internal covariate shifts, making training more stable

and efficient. BN helps models adapt to variations in lighting, camera quality, and face angles, improving spoof detection. However, its effectiveness depends on batch size—very small batches can lead to unstable training, especially in resource-limited environments. Additionally, BN assumes mini-batches represent the overall data distribution, but in face anti-spoofing, variations in lighting, pose, and occlusions can reduce its performance [106]. Santurkar et al. analysed Batch Normalization (BN) and provided new insights into its effectiveness beyond reducing internal covariate shift. BN also improves model robustness against environmental variations, such as lighting conditions and camera quality. BN may fail to generalize well when tested on datasets with significantly different distributions, requiring additional fine-tuning or domain adaptation [107].

Zhang et al. explored impact of BN on deep learning model. The result output shows it reduces reliance on large batch sizes, making training more efficient even on resource-constrained devices. BN introduces additional computation due to mean and variance calculations for each batch, which can slow down training in large-scale models. George & Marcel presented a FAS model to enhance feature consistency across different face datasets. During inference, BN uses estimated population statistics, which may differ from training statistics, leading to performance inconsistencies [108].

Li et al. leveraged adversarial data augmentation, introducing perturbations to training samples to improve model robustness against adversarial attacks, but at the cost of increased computation time. In contrast, Galbally and Marcel's approach focused on image quality assessment (IQA) features to detect spoofing attacks based on distortions like blurriness and noise, making it computationally efficient. However, their method struggles with high-resolution spoofing materials and 3D mask attacks, whereas Li et al.'s model is more resilient to adaptive spoofing techniques [109][110]. George et al. explored the impact of elastic transformations and Gaussian noise augmentation, showing improved accuracy in face anti-spoofing detection. While the technique improves robustness, it does not always account for complex real-world variation, such as changes in sensor quality, aging effects, or makeup application [111]. Wang et al. proposed Mixup augmentation, where synthetic training samples are generated by blending multiple real and fake face images, resulting in a smoother decision boundary [112]. Zhang et al. applied CutMix, a technique that replaces regions of an image with patches from another image, improving the model's ability to

recognize spoofing patterns under occlusions [113]. Deb et al. investigated domain adaptation techniques using style transfer-based augmentation to improve cross-dataset generalization. Despite using adversarial augmentation strategies, spoofing attacks like high-resolution 3D masks can still fool the model, necessitating additional countermeasures [114]. Zheng et al. studied the impact of spectral regularization, where frequency-based constraints are imposed on deep networks to prevent over-fitting to texture artifacts. Spectral regularization applies frequency-domain constraints to prevent over-fitting and is calculated as below:

$$L_{SR} = \sum_i \left\| F(x_i) - F(x_j) \right\|^2 \tag{2.39}$$

Huang et al. introduced stochastic depth regularization in face anti-spoofing models, allowing layers to be randomly skipped during training, which enhances model robustness [115]. Further, Xu et al. explored the use of feature de-correlation regularization to minimize redundant information in deep feature maps, leading to improved performance in detecting sophisticated spoofing attacks [116].

2.3.2 Meta-Heuristic Optimization in Deep Learning

Meta-heuristic optimization techniques have been explored to fine-tune deep learning models. These include Genetic Algorithms and Particle Swarm Optimization. Sun et al. applied Genetic Algorithms to optimize CNN parameters, achieving better detection accuracy. Zhang et al. (2022) introduced a reinforcement learning-based approach that dynamically adjusted feature extraction settings to improve generalization. RL-based feature extraction is computationally expensive and requires extensive training data. The approach may struggle with unstable training due to reward signal sparsity as it requires domain-specific tuning to adapt to different datasets effectively [117]. Figure 2.7 represents flow of how meta-heuristic optimization methods enhance face anti-spoofing models. The meta-heuristic optimization framework for face anti-spoofing enhances deep learning models by optimizing feature extraction and classification. In the input data pre-processed facial images are fed into a feature extraction module. It generally uses convolutional neural networks (CNNs) to capture texture and pattern details. Thereafter, meta-heuristic optimization techniques such as genetic algorithms (GA), particle swarm optimization (PSO), differential evolution (DE), and ant colony optimization (ACO) are applied to fine-tune hyper-parameters, improve feature selection, and optimize network structures. Then classifier is

fed with the optimized features like support vector machine (SVM) or SoftMax. It makes a final binary decision which identifies the face as either live (genuine user) or spoofed (fake attempt). This framework improves accuracy, enhances adaptability to various spoofing attacks, and ensures robust performance across different datasets.

Additionally, Li et al. explored the use of Differential Evolution (DE) to fine-tune loss functions, leading to improved convergence and stability in face anti-spoofing models. DE can be slow to converge when dealing with large-scale optimization problems. The performance is sensitive to parameter selection, requiring manual fine-tuning. DE may not be as effective in high-dimensional spaces with a large number of variables. [118].

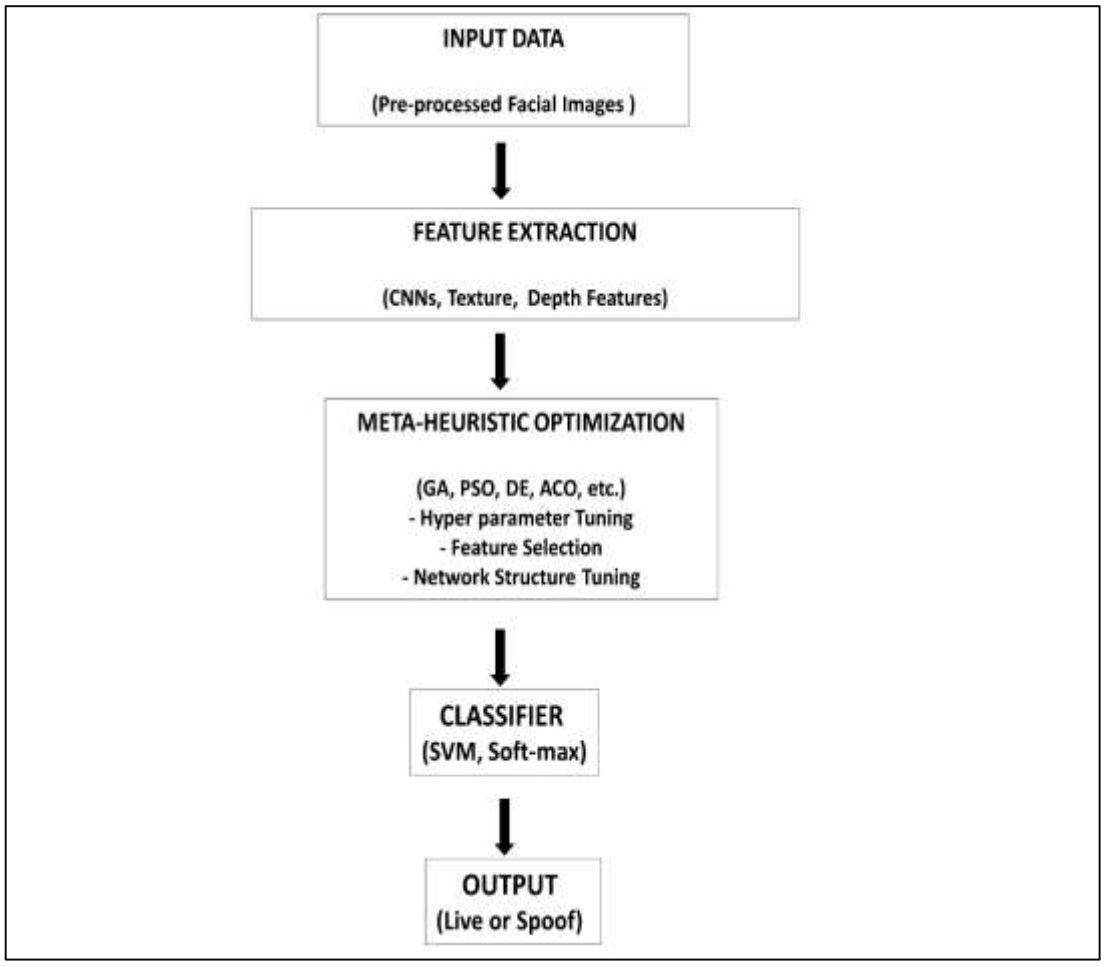


Figure 2.7: Meta-Heuristic Optimization Framework for Face Anti-Spoofing (By Author).

Wang et al. integrated Ant Colony Optimization (ACO) for selecting optimal network architectures, demonstrating improved performance in deep feature learning. However, ACO struggles with high-dimensional search spaces and requires careful parameter tuning.

In another study, Chen et al. applied Simulated Annealing method to reduce computational overhead while preserving accuracy, making face anti-spoofing models more efficient. The method does not leverage gradient information, making it inefficient for deep learning tasks. [119].

Hu et al. used Bayesian Optimization (BO) to tune hyper-parameters in Face Anti-Spoofing (FAS) models. Their approach optimized parameters like learning rate and batch size. This reduced over-fitting, improved cross-dataset generalization, and minimized computational costs, enhancing model accuracy. However, BO requires predefined prior distributions, which may not always be suitable for deep learning applications [120].

Luo et al. introduced an Evolutionary Multi-Objective Optimization (EMO) framework that simultaneously optimized feature extraction and decision threshold for improved robustness. Using Genetic Algorithms (GA) and Particle Swarm Optimization (PSO), EMO method balanced accuracy, efficiency, and adaptability. Through adjusting model thresholds dynamically and based on environmental conditions, EMO approach reduced false positives and improved real-time performance [121-129]. These advancements make FAS models more resilient against diverse spoofing attacks and ensure better generalization [130].

Tang et al. introduced a swarm intelligence-based approach that dynamically adapts learning rates based on the complexity of spoofing patterns, leading to more adaptive models. The approach requires frequent parameter tuning to adapt to different datasets [131]. Additionally, Zhou et al. implemented Firefly Algorithm-based optimization to enhance feature selection, demonstrating superior performance in real-world face anti-spoofing scenarios. It requires a large number of evaluations to find an optimal solution, leading to high computational costs. Also, the performance is highly dependent on initial parameter settings, which can be challenging to determine [132]. Table 2.3 shows structured description of several Optimization Techniques for Model Enhancement.

Table 2.3: Summary of Optimization Techniques for Model Enhancement

Authors Details	Key Challenges	Proposed Approach	Findings
Boulkenafet et al. (2017) [12]	Poor model generalization to unseen conditions	Applied data augmentation techniques	Enhanced adaptation but increased computation time
Hadsell et al. (2006) [97]	Difficulty in distinguishing between real and fake faces	Applied Contrastive Loss in Siamese networks for better feature discrimination	Improved robustness against spoofing attacks
Bera et al. (2019) [98]	Vulnerability to automated bot attacks	Introduced HandCAPTCHA and biometric verification with M-FoBa algorithm	98.5% accuracy in HandCAPTCHA, 0% error rate in biometric verification
Lin et al. (2017) [99]	Class imbalance in datasets	Used Focal Loss to assign higher importance to hard-to-classify examples	Improved spoof detection, especially for challenging cases
Wang et al. (2020) [100]	Poor generalization across datasets	Hybrid loss combining Triplet Loss and Adversarial Loss	Achieved better performance across diverse datasets
Schroff et al. (2015) [101]	Need for fine-grained feature learning	Implemented Triplet Loss for distinguishing real and fake faces	Enhanced feature separation and model accuracy
Wen et al. (2016) [102]	High intra-class variation in feature representations	Introduced Centre Loss to reduce intra-class variations	Improved classification performance and spoof detection
Goodfellow et al. (2014) [103]	Weaknesses in detecting adversarial attacks	Applied Adversarial Loss in GAN-based models	Strengthened generalization against unknown spoofing methods
Rubinstein & Kroese (2004) [104]	Inconsistent model penalization in binary classification	Used Binary Cross-Entropy Loss	Improved gradient updates and classification performance
Srivastava et al. (2014) [105]	Overfitting in deep learning models	Implemented Dropout regularization	Enhanced generalization and robustness
Santurkar et al. (2018) [107]	Variability in environmental conditions affecting performance	Utilized Batch Normalization	Improved stability and training efficiency
Zheng et al. (2018) [109]	Overfitting to texture artifacts	Introduced Spectral Regularization	Reduced model dependency on texture features
Sun et al. (2019) [115]	Difficulty in optimizing CNN parameters	Applied Genetic Algorithms	Improved detection accuracy
Authors Details	Key Challenges	Proposed Approach	Findings
Zhang et al. (2020) [114]	Unstable training due to sparse reward signals	Used Reinforcement Learning for dynamic feature extraction	Improved generalization, but required extensive data

Table 2.3: Summary of Optimization Techniques for Model Enhancement(Table Continued).

Li et al. (2021) [118]	Inefficient loss function optimization	Used Differential Evolution (DE)	Achieved better convergence but required manual fine-tuning
Chen et al. (2021) [119]	High computational costs	Applied Simulated Annealing	Reduced computation overhead while maintaining accuracy
Wang et al. (2022) [130]	Complexity in selecting optimal network architectures	Integrated Ant Colony Optimization (ACO)	Improved feature learning, but struggled with high-dimensional search spaces
Hu et al. (2020) [120]	Need for efficient hyperparameter tuning	Used Bayesian Optimization (BO)	Improved cross-dataset generalization and reduced overfitting
Luo et al.(2021) [130]	Trade-off between accuracy and efficiency	Developed Evolutionary Multi-Objective Optimization (EMO)	Achieved balanced accuracy, efficiency, and adaptability
Tang et al. (2023) [131]	Dynamic adaptation to varying spoofing patterns	Used swarm intelligence for adaptive learning rates	Enhanced model flexibility but required frequent tuning
Zhou et al. (2023) [132]	Feature selection optimization challenges	Implemented Firefly Algorithm	Improved feature selection, but required high computational resources

2.4 CHALLENGES IN FACE ANTI-SPOOFING

The continual development of adaptive architectures confirms that face anti-spoofing techniques remain effective against emerging attack methods while balancing computational efficiency and real-time applicability. However, there are challenges such as dataset bias, adversarial robustness, and real-time performance [21].

2.4.1 Intra-Dataset and Cross-Dataset Generalization

One of the major challenges in face anti-spoofing is achieving generalization across different datasets. This can be categorized into Intra-dataset generalization and Cross-dataset generalization. Intra-dataset generalization is ability of a model to perform well within a single dataset. Cross-dataset generalization is the ability of a model to maintain high performance across different datasets. Challenges in Generalization are dataset bias and limitation of existing datasets [23]. Many face anti-spoofing models achieve high accuracy on the dataset they were trained on but fail on unseen datasets due to domain gaps [24]. Variations in lighting, camera specifications, demographics, and spoofing materials cause performance degradation [22]. Datasets like CASIA-FASD, MSU-MFSD, and OULU-NPU

contain controlled environments with limited variations [12]. Models trained on these datasets struggle with real-world variations, reducing their reliability.

2.4.2 Robustness Against Real-World Attacks

Ensuring robustness against real-world spoofing attacks remains a significant challenge in face anti-spoofing. Attackers continuously refine their methods, making it difficult for models to detect all possible threats effectively. Challenges in real-world spoof detection are evolving spoofing techniques and variability in real-world conditions [25].

Traditional spoofing techniques, such as printed photos, replayed videos, and 3D masks, are well-documented in research datasets. However, attackers continuously develop more sophisticated spoofing methods, making it difficult for models to detect all possible threats effectively [55]. Real-world scenarios present numerous challenges that make spoof detection harder. Variations in facial expressions, head poses, illumination conditions, and occlusions can affect the performance of anti-spoofing models [62]. Apart from high-quality screens, adaptive masks, and deep fake bundles, an attacker can also use them to create more convincing attack spoofs. Most existing approaches utilize handcrafted features like movement detection and texture analysis, which can be outsmarted by good-quality attacks.

2.4.3 Computational Efficiency and Model Complexity

Model size and computational cost are of the highest importance in face anti-spoofing, especially for real-time scenarios. The majority of state-of-the-art deep learning models are computationally costly and demand an enormous computational resource such that it is not possible to execute them on edge devices such as smartphones, surveillance cameras, and embedded systems. There must be a compromise between accuracy and computation cost in keeping anti-spoofing models deployable at a much wider scale [11].

Deep and complex models with large parameter sizes will probably perform best for face anti-spoofing [9]. These models do, nonetheless, incur higher inference time and power usage that may deter real-time usage. Moreover, their execution on low-power devices may rely on application-specific hardware accelerators such as GPUs or TPUs that are not always readily available [10]. Training deep learning models both for effectiveness and efficiency is thus still a research endeavor [32]. [32].

2.5 LIMITATIONS AND RESEARCH GAPS

Face anti-spoofing (FAS) techniques have increased tremendously in preventing presentation attacks, but some of the limitations and research shortcomings still exist. These challenges include dataset generalization, robustness, and computational efficiency, adaptability, and evaluation standards [27]. Addressing these issues is crucial for improving the reliability of FAS systems.

i. Dataset Generalization Issues: Models perform well within the same dataset but fail on unseen datasets due to domain gaps (lighting, camera quality, attack types, environmental factors) [28]. Existing datasets lack sufficient diversity, leading to models over-fitting dataset-specific artefacts rather than learning general anti-spoofing features [12]. Domain adaptation and domain generalization remain suboptimal, requiring more diverse datasets and robust algorithms [110].
ii. Robustness against Real-World Attacks: Most models are evaluated against common attacks (printed photos, replayed videos, 3D masks) but struggle against high-quality deep fake videos, adversarial perturbations, and advanced 3D masks [29]. Adversarial training and anomaly detection have been explored but remain inadequate against evolving attack strategies [65]. Continuous updates in datasets and models are needed for better real-time adaptability [55].
iii. Computational Efficiency and Model Complexity: CNNs and transformer-based models achieve high accuracy but come with high computational costs, making them impractical for smartphones, surveillance systems, and embedded IoT applications [40]. Lightweight models and optimization techniques (knowledge distillation, quantization, and pruning) help, but balancing efficiency and accuracy remains a challenge [26]. Over-fitting, interpretability issues, and training stability still affect optimization techniques like loss function tuning and regularization [42].

iv. Limitations in Optimization Techniques: Loss function optimization, regularization techniques, and meta-heuristic approaches improve performance. However, it does not eliminate few issues like class imbalance and adversarial vulnerability [34]. Attention mechanisms and advanced architectures improvise feature extraction but vary in effectiveness across different spoofing attacks and conditions [69]. There is need of more

research on adaptive learning strategies which can adjust model behaviour based on real-world contextual inputs [62].

v. Lack of Standardized Evaluation Metrics: Different benchmarks use varied metrics that makes the comparison of FAS models difficult [32]. A universal evaluation framework is necessary for standardizing research and performance assessment [111].

In this chapter, a comprehensive literature review of FAS techniques in past decade is presented. The survey indicates adaptive architectures and optimization strategies which can enhance performance and efficiency is still active research area. Future advancements in these domains will segregate significantly assist in increasing the solidity and security of face anti-spoofing systems in real applications. Regarding improving techniques, subsequent chapter suggests a model based on highlighting key face details through Dense Squeeze and Excitation Networks. It employs a new approach towards improving its feature in better face spoof detection.

3. 3D FACE ANTI-SPOOFING WITH DENSE SQUEEZE AND EXCITATION NETWORK AND NEIGHBORHOOD-AWARE KERNEL ADAPTATION SCHEME

3.1 OVERVIEW OF THE PROPOSED 3D FACE ANTI-SPOOFING MODEL

The application of face anti-spoofing is necessary in order to deliver security in biometric authentication frameworks. The focal point of this chapter is to introduce an effective and strong 3D Face Anti-Spoofing (3D-FAS) model that utilizes the latest deep learning techniques to improve the detection rate of spoof attacks, i.e., 3D masks attack and photo-based spoofing attack. The main goal of this approach is to improve the performance and robustness of face anti-spoofing systems by applying new deep learning approaches. Traditional methods are vulnerable to 3D mask attacks if attackers utilize real-like 3D masks for manipulating face recognition systems. A better approach is proposed to overcome the problem of spatial feature improvement extraction and discriminate more between real and spoof faces [133-145]. MIL is used for face anti-spoofing for the first time [146].

This allows the model to learn spatial and temporal variations in irrelevant facial regions. In contrast with typical single-instance learning-based methods, MIL guarantees the system can effectively detect local spoofing attempts in changing facial regions with an outstanding improvement in detection performance. A five-fold cross-validation experiment is implemented to validate the effectiveness of the proposed method. This rigorous validation process ensures generalization of the model across multiple datasets and real-world scenarios and makes the model more reliable and deployable in real life. The current model leverages DenseNet, Squeeze-and-Excitation (SE) blocks, Neighborhood-Aware Kernel Adaptation (NAKA), and Cross-Channel Attention to facilitate improved spatial feature learning, thereby making the system robust against sophisticated spoofing attacks.

Dense Squeeze and Excitation Networks is the core element of the proposed approach, which includes dense connections in SE blocks. Such inclusion makes feature recalibration more effective because channel-wise feature responses are re-calculated, hence the model becomes more efficient to focus on informative features. The fusion approach enhances

face anti-spoofing systems to be more efficient and robust since it is capable of excavating discriminative spatial 3D spatial features from 3D face data. The whole architecture of the proposed work starts with four phases: (1) Preprocessing, (2) Feature Engineering, (3) Classification, and (4) Model Validation. Figure 3.1 shows the exact flowchart. A step-by-step overview of the scheme suggested for anti-spoofing is discussed more elaborately in the following sections.

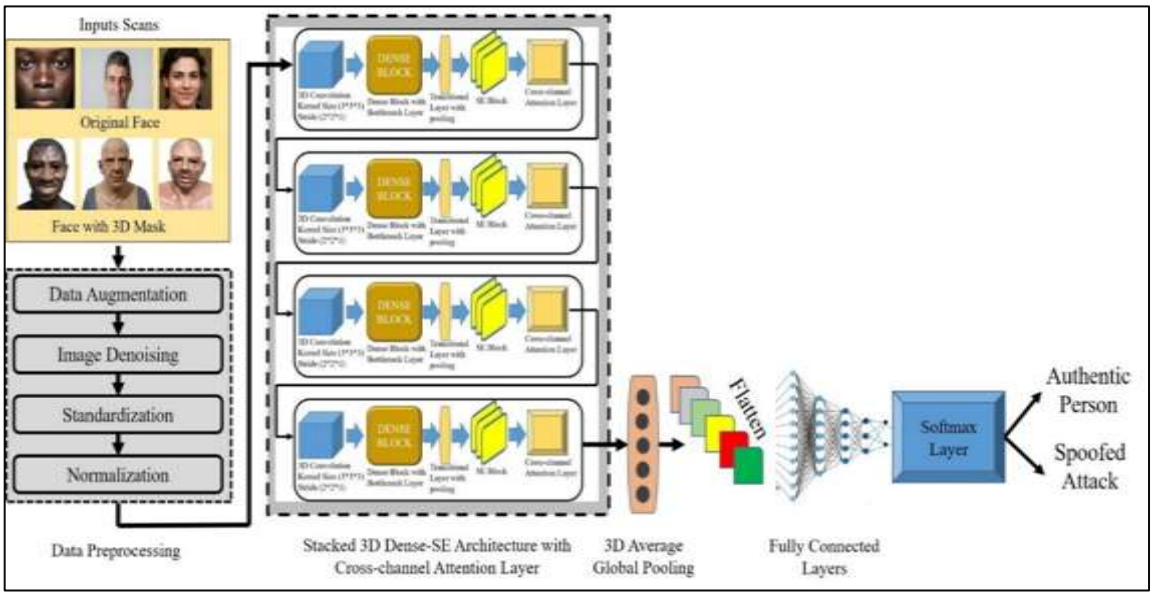


Figure 3.1: The Pipeline Architecture of the Proposed Methodology for Anti-Spoofing Crop Operations in Data Augmentations (By Author).

3.2 DENSE SQUEEZE AND EXCITATION (SE) NETWORK

Dense Squeeze and Excitation Networks (Dense-SE Networks) in this case denote the integration of Dense Networks with Squeeze-and-Excitation Networks to improve feature acquisition. This hybridization process boosts 3D face recognition by adopting dense connections for efficient feature reuse and SE blocks for channel-wise recalibration, allowing more discriminative features to be showcased. Together, it enhances the model's accuracy and ability to recognize finer details of faces.

3.2.1 Enhancement of Feature Representation

The section primarily discusses how the proposed 3D Dense-SE Architecture enhances feature representation using several advanced mechanisms, including 3D convolutions, Dense blocks, Squeeze-and-Excitation (SE) blocks, and Cross-Channel Attention

mechanisms. The proposed 3D Dense-SE Architecture involves a key hybrid block figure 3.2 including (1) a 3D convolution layer, (2) a Denseblock with bottleneck layer, (3) a Transitional layer with pooling, (4) a Squeeze and Excitation block, and (4) Cross-channel attention module.

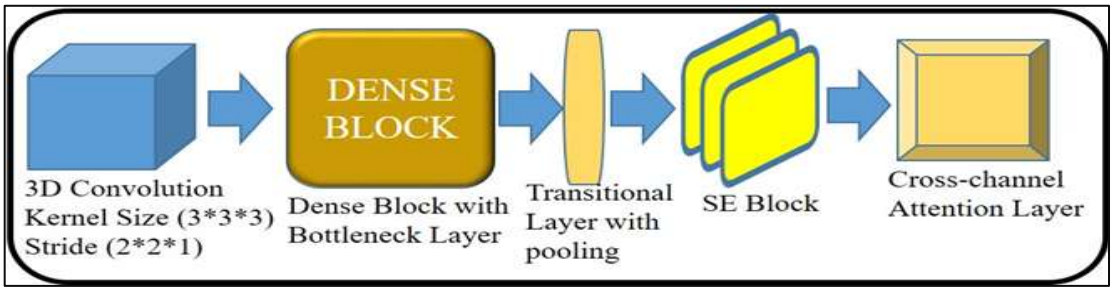


Figure 3.2: Visualization of Key Block Used as Basis for the Proposed Hybrid Dense-SE Architecture (By Author).

The 3D convolution layer involves the convolution operator where the adaptive kernel is applied across three dimensions ($Height, Widh, and\ Depth$). Let $X \in \mathbb{R}^{H*W*D*C}$ refers to the input feature map where $H, W, and\ D$ refers to the height, width, and depth, respectively, and C denotes the number of channels [149] [150]. The proposed 3D convolutional kernel operates on X by sliding across the 3D spatial dimensions with a specified stride, generating an output feature map $Y \in \mathbb{R}^{H'*W'*D'*C_{out}}$ where C_{out} shows the number of output channels. Eq. 3.1 shows operations in mathematical terms:

$$Y(H', W', D', n) = \sum_{c=1}^{C} \sum_{i=1}^{k_H} \sum_{n=1}^{K_W} \sum_{p=1}^{K_D} K\ (i, j, l, c, n).X(i + h', j + \ w', l + d', c, n) \tag{3.1}$$

Where $H', W', D',$ and n refer to the spatial coordinates and number of output channels, respectively. The 3D convolution helps the network learn some spatial dependencies across the depth dimension, which is quite important for undertaking 3D face anti-spoofing. It uses a kernel of size 3×3×3, meaning that the filter moves across the input volume in three dimensions: the color and the shapes also, like the height, width, and depth. This design is useful in capturing spatial features from the input 3D face data. The stride is 2, 2, and 1, which means the filter moves 2 pixels in height, 2 in width, and 1 in-depth, thus shrinking the spatial size of the input while keeping depth.

The proposed stacked hybrid Dense-SE architecture incorporates dense connections, whereby each layer in a dense block receives connections from all prior layers, reducing the vanishing gradient problem in deep architectures. In this architecture, Eq. 3.2 presents the output of each dense layer Y_l as follows.

$$Y_l = F_l([Y_0, Y_1, \dots Y_{l-1}]) \tag{3.2}$$

Where, F_l stands for the 3D convolutional process, which is performed at layer l, and [.] represents the concatenation of feature maps. The inclusion of the Squeeze-and-Excitation (SE) block introduces a channel-wise attention mechanism, where the channel-wise dependencies are modelled by first performing a global average pooling over the spatial dimensions as shown in Eq. 3.3:

$$z_c = \frac{1}{HWD} \sum_{h=1}^{H} \sum_{w=1}^{W} Y(h, w, d, c) \tag{3.3}$$

This step is succeeded by several fully connected layers that enable the computation of scaling factors s_c for each channel as mentioned in Eq 3.4.

$$s_c = \sigma(W_2 . \delta\ (W_1 * z_c)) \tag{3.4}$$

where W_1 and W_2 are the weight matrices corresponding to fully connected layers, $\delta(\cdot)$ is the ReLU activation, and $\sigma\ (.)$ is the sigmoid activation. The final output in Eq. 3.5 is shown, the SE block is computed by rescaling the input feature map:

$$y'(h, w, d, c) = \ s_c * Y(h, w, d, c) \tag{3.5}$$

Dense blocks are the type of layers that are highly connected, as each layer gets connected to all the previous layers. The bottleneck layer, which requires a smaller number of input features, usually employs a 1×1×1 convolution to make the network run lighter. As shown in the DV, dense blocks can maximize the number of feature parameters reused from the previous layer, which also combines both internal and external features necessary for spoof attack detection. Moreover, the Transitional Layer with the Pooling layer enables the extraction of features between the dense blocks while down-sampling the feature maps by pooling operation, which decreases the dimensions of height and width. The max-pooling

layers are used to reduce dimensionality and emphasize the significant characteristics in each area of the feature maps.

Finally, the channel attention layer is used to recalibrate the feature map, where the model paid more attention to the relationships between different channels. This assists the network in focusing more on the discriminative features of real facial images, including texture changes or depth variations, which are keys in spoofing detection. A coordinated attention mechanism for cross-channel is designed to enhance the feature representation through the identification of which of the channels needs to be boosted or muted depending on the information from the neighbouring channels. This cross-referencing ensures that the network can notice the signs of spoofing that are more likely to be seen across different channels.

The architecture repeats the pattern of 3D Convolution, Dense Block, Transitional Layer, SE Block, and Cross-Channel Attention four times. These repeated stacking enable the network to gradually enhance the features at multiple levels of abstraction and, therefore, increase the ability of the network to capture sophisticated spoofing patterns. As the architecture goes deeper, it captures even higher levels of patterns and begins focusing on the primary aspects of the scenes with the help of SE blocks and cross-channel attention layers. The final feature maps of the Cross-Channel Attention Layer are concatenated and passed into fully connected (dense) layers. These layers convert these inputs through linear transformations coupled by non-linear activations (for example, ReLU) to learn abstract representations. The number of neurons in these layers reduces as the network goes deeper toward the output layer while compressing the information in the domain, maintaining discriminative characteristics that can be used to classify features. The output of the last fully connected layers is then taken and fed into a SoftMax layer. The SoftMax layer transforms the Weights either directly obtained from the dense layer or, also known as logits, into a probability distribution. Finally, the class with the maximum probability score is regarded as the predicted class for the input 3D face image. The network output of the SoftMax layer measures the preciseness of a face or spoof based on the features and patterns learned by the previous layers.

3.3 NEIGHBORHOOD-AWARE KERNEL ADAPTATION SCHEME

A novel "Neighbourhood-Aware Kernel Adaptation" (NAKA) adjustment policy is introduced to enhance the performance of the defined 3D kernel structure. This approach uses the spatial and contextual similarities within the neighbourhood of a given voxel to adaptively change the convolutional kernel, allowing for enhanced detection of complex spatial structures in 3D data. The key hypothesis for this proposed adjustment policy can be defined using the following definitions:

Neighborhood Policy: Unlike the conventional methods in which only voxel value is considered, the NAKA method adapts the kernel by invoking the neighbourhood, which is a local region in the 3D space. Local texture, gradient, and spatial distribution of this neighbourhood define the characteristics of the area and help to tweak the kernel for more accurate filtering.

Adaptive Kernel Shaping: As previously discussed in the process of neighbourhood analysis, the convolutional kernel has size, weight, and orientation dimensions. This scaling enables the kernel to take into consideration the architecture of the spatial distribution of the data and improve its capability to identify intricate patterns in three-dimensional space.

Contextual Weighting: The weights allocated to the neighbour voxels in a neighbourhood are based on the significance of the voxel in a specific context. Areas of high contrastive texture and steep gradation (edges), for instance, are highlighted to a higher degree than the more even or much less contrastive areas.

3.3.1 Adaptive Feature Learning Mechanism

The Adaptive Feature Learning Mechanism is targeted at meaningful context and spatial information extraction from 3D facial data based on neighbourhood-based calculation of the features. For every voxel in a 3D space, a neighbourhood region within a pre-specified radius is defined so as to efficiently take local structural variation into account. To describe features more effectively, three most significant features local gradient, local mean, and local variance are computed. Local gradient (∇F) computes spatial intensity differences in different directions, which are used to find edges and textures useful in spoofing pattern detection. Local mean (μ_N) eliminates noise by computing the average of pixel intensity

in a neighborhood, removing noise and preserving strong facial features. The local variance ($\sigma\_N\hat{}2$) estimates the scatter of intensity values and allows discriminating between the texture difference of real faces and spoofing attacks, i.e., printed replicas or masks. The fusion features increase the ability of the model in capturing dynamic fine-grained spatial mismatches in 3D face scans and improving progressively in distinguishing real and fake faces. By integrating neighbourhood-aware feature extraction, the process not only enhances the robustness of 3D face anti-spoofing but also facilitates computational efficiency. The approach allows the system to adaptively alter feature learning according to spatial variations, which provides enhanced classification accuracy. For an input feature map F with dimensions $H * W * D * C_{in}$, define the neighborhood region $\mathcal{N}(i,j,k)$ for a given voxel position (i,j,k) as a 3D region surrounding that voxel.

Neighborhood Definition and Feature Extraction: In this phase, the computation of local, regional neighborhood $N(i,j,k)$ with the center of the voxel (i,j,k) is performed, and it includes all the data points within a fixed radius r from (i,j,k). In this case, Eq. 3.6 represents the neighborhood size which is determined by as follows:

$$\mathcal{N}(i,j,k)=\{(i',j',k'): |i'-i| \leq r \ AND \ |j'-j| \leq r \ AND \ |k'-k| \leq r\} \quad (3.6)$$

Experimentally, the radius r is set to 3 voxels to ensure an optimal balance between capturing local contextual information and maintaining computational efficiency. It allows the model to adopt neighbor-aware feature adaptations in a way that it effectively bypasses excessive computational cost. Based on the calculated neighborhood, three regional features are extracted that establish the spatial and contextual nature of the region. The nature of these features is outlined below:

i. Local Gradient (∇F): The local gradient ∇F(i,j,k) is the rate of change of a function F in a 3D neighborhood. It is computed for each voxel (a point in a 3D space) and is given by:

$$\nabla F(i,j,k) = \left(\frac{\delta F(i,j,k)}{\delta x}, \frac{\delta F(i,j,k)}{\delta y}, \frac{\delta F(i,j,k)}{\delta z}\right) \quad (3.7)$$

The Eq. 3.7 is three partial derivatives, which measure how the function F changes in the x, y, and z directions. The gradient helps in edge, texture, and depth variation detection in

3D data, which is crucial for detecting structural differences in face anti-spoofing applications.

ii. Local Mean (μ_N) : The local mean, denoted as '$\mu_{N(i,j,k)}$' represents the average intensity or value of function F within a neighbourhood $\mathcal{N}\ (i,j,k)$ surrounding a voxel at position (i, j, k). It is mathematically defined as below in Eq. 3.8.

$$\mu_{N(i,j,k)} = \frac{1}{|\mathcal{N}\ (i,j,k)|}\sum_{\mathcal{N}\ (i',j',k') \in \mathcal{N}\ (i,j,k)} F(i',j',k') \tag{3.8}$$

The local neighbourhood of voxel (i, j, k) $|\mathcal{N}\ (i,j,k)|$ represents the number of voxels in the neighbourhood '$F(i',j',k')$' is the function value at a neighboring voxel. This operation helps to smooth data by removing noise and highlighting salient features in an image. In face anti-spoofing, it can be utilized in average pixel intensity change analysis for detecting abnormalities in texture or lighting.

iii. Local Variance (σ_N^2): The local variance, denoted as '$\sigma_N^2(i,j,k)$' quantifies the spread or dispersion of the function values within the neighborhood N(i, j, k). It is given by:

$$(\sigma_N^2) = \frac{1}{|\mathcal{N}\ (i,j,k)|}\sum_{\mathcal{N}\ (i',j',k') \in \mathcal{N}\ (i,j,k)}(F(i',j',k') - \mu_{N(i,j,k)})^2 \tag{3.9}$$

The Eq. 3.9 calculates how different the values within the neighbourhood are from the mean $'\mu\_(N(i,j,k))'$. The greater variance, the more pixel intensity differences, which is useful to detect edges, textures, and patterns in 3D images. In face anti-spoofing, local variance is also crucial to discriminate real faces from spoof attacks as real faces usually have changing textures, whereas imposter faces (e.g., masks or printed photos) present unnatural uniformity or artefacts.

All the above three mathematical parameters gradient, mean, and variance are used to obtain major spatial features from 3D face scans. Gradient highlights structural variation, mean smoothens data, and variance detects variation in texture. Together, they enhance the detection of spoofing attempts by analysing fine-grained spatial inconsistencies in 3D facial data.3D facial data.

3.3.2 Local Feature Enhancement through Kernel Adaptation

Kernel Adaptation Policy is explained in this sub section. The convolutional kernel K is modified in each layer for the features of the neighbourhood '$N(i,j,k)$'. The process of kernel adaptation requires changing the kernel's weights, width, and orientation to make them more appropriate to the local environment.

Let K be the original 3D convolutional kernel of size ($K_h \times K_w \times K_d \times C_{\text{in}} \times C_{\text{out}}$), where K_h, K_w, K_d, the height, width, and depth of the kernel, and C_{in}, C_{out} are the number of input and output channels, correspondingly. The adaptive kernel $K_{adapted}(.)$ is computed as:

$$K_{adapted}(m,n,p,Cin,Cout) = \emptyset\,(K(m,n,p,C_{in},C_{out}), \nabla \mathrm{F}(i,j,k), \mu_{N(i,j,k)}, \sigma_N^2) \tag{3. 10}$$

Where, "$\emptyset\,(.)$" is a function that adjusts the kernel weights depending on the neighbourhood characteristics. The weights of the kernel are adjusted proportionally to the local gradient magnitude and variance. The Neighborhood-Aware Kernel Adaptation (NAKA) dynamically adjusts convolutional kernels for improved sensitivity to spoof-specific textures. Eq. 3.11 shows the combination of 3D convolution operator and CCA boosts model accuracy, generalization, and computational efficiency, making it highly effective for static images.

$$K_{adapted}(m,n,p,C_{in},C_{out}) = K(m,n,p,C_{in},C_{out}) * \exp\left(-\frac{\alpha * \nabla \mathrm{F}(i,j,k)^2 + \beta * (\sigma_N^2)}{\tau}\right) \tag{3.11}$$

Where, α, β, and τ are hyper-parameters controlling the sensitivity of the kernel adaptation. The kernel orientation is shifted in the direction that is most dominant in the direction of the gradient in the neighbourhood, improving the edge detection.

Neighbourhood-Aware Convolution: The induced kernel adaptation scheme makes the convolution operator respond to the spatial relations and hence boosts the identification of the pattern of data in 3D. The convolution operation with the adapted kernel is performed as shown in Eq. 3.12.

$$Y(i,j,k) = \sum_{C_{in}=1}^{C_{in}} \sum_{m=1}^{K_h} \sum_{n=1}^{K_w} \sum_{p=1}^{K_d} K_{adapted}(m,n,p,C_{in},C_{out}).\ F(i+m, j+n, k+p, C_{in}, C_{out}) \tag{3.12}$$

This operation generates an output feature map Y, which is a convolution operation with the inclusion of local neighbourhood context, making it easy to detect spatial variations and/or complex spatial patterns in the 3D data. The detailed pseudo code of the feature extraction procedure is given in Algorithm 3.1.

Algorithm 3.1: Pseudo-Code of Proposed Neighbourhood-AWare Kernel Adaptation Scheme

Input : 3D feature map F with dimensions $H * W * D * C_{in}$ (Height, Width, Depth, Number of Channels)
Output: Adapted feature map Y

#Step 1: Define Neighbourhood and Extract Features
For each voxel (i, j, k) in F:

N(i, j, k) = {voxels within radius r of (i, j, k)}
local_gradient = ∇F(i, j, k)) # Compute gradient within N(i, j, k)
local_mean = mean(N(i, j, k)) # Calculate the mean within the neighborhood
local_variance = variance(N(i, j, k))) # Calculate variance within the neighborhood

 # Step 2: Adaptive Kernel Shaping
For each voxel (i, j, k) in F:
K = InitializeKernel (K_h×K_w×K_d×C_{in}×C_{out}), # Kernel dimensions
For each element (m, n, p) in K:
$K_{adapted}$ $(m, n, p, C_{\text{in}}, C_{\text{out}})$ =

$$K(m, n, p, \text{Cin}, \text{Cout}) * \exp(-\frac{\alpha * \nabla \text{F}(i,j,k)^2 + \beta * (\sigma_N^2)}{\tau})$$

$K_{adapted}$ = AlignKernel($K_{adapted}$, local_gradient)

 # Step 3: Neighbourhood-Aware Convolution
For each voxel (i, j, k) in F:
$Y(i, j, k)$ = 0 # Initialize the output feature map Y
For each channel c_in in F:
For each element (m, n, p) in Adapted:

Y(i, j, k)+= $K_{adapted}$ $(m, n, p, \text{Cin}, \text{Cout})$ * $F(i\ \ m, j + n, k + p, C_{in},\ C_{out})$

3.4 MODEL IMPLEMENTATION AND TRAINING PROCESS

The model implementation and training process starts with comprehensive dataset pre-processing and augmentation. It enhances the robustness of the deep learning-based anti-

spoofing system. Techniques such as flipping, rotation, zooming, translation, brightness, and contrast adjustments are applied to improvise model generalization. Image denoising is performed using multi-scale wavelet decomposition, adaptive thresholding, and anisotropic diffusion to preserve crucial facial details while reducing noise. Intensity normalization further stabilizes variations due to illumination changes. Feature extraction is achieved using a dynamic 3D convolution operator integrated with DenseNet and a Squeeze-and-Excitation mechanism to enhance spatial feature representation for improved classification accuracy. Following subsection discusses data pre-processing and augmentation in detail.

3.4.1 Dataset Pre-processing and Augmentation

Data pre-processing is a crucial step in DL-based anti-spoofing model to ensure high-quality input for training and inference. The applied pre-processing is discussed in the subsequent sections.

i. Data Augmentation: Various data augmentation techniques are used in the proposed work to enhance the robustness and generalization capability of the model in deep learning-based anti-spoofing.

Figure 3.3: A Sample Set of Generated Images After Applying Translation, Brightness, and Crop Operation in Augmentation [47].

Flipping, both horizontal and vertical, to create a mirror image is applied to make the model invariant to change in orientation. Rotation is constrained within the range ±20° to introduce angular variation, and zooming up to 20% is applied to simulate changes in focal length. Translation in both horizontal and vertical directions (up to 20%)

helped in handling positional shifts in facial images. Contrast and brightness adjustment: It adjusted contrast and brightness with a factor of 0.2 to counter changing lighting conditions. Cropping is done by randomly shifting the width and height in the range of ±20% to enhance partial face region detection. Height and width transformation within ±20% is also utilized for different aspect ratios. Finally, a middle crop operation is used where resized images are provided at 80 % of their dimensions to focus on more central facial characteristics. A sample of randomly selected images after applying translation, brightness, and crop operations is shown in figure 3.3, where the '0' annotation refers to the pre-processed original image and '1' indicates a spoofed image sample.

ii. Image Denoising: Image denoising is a crucial step to minimize the effect of random variations in the intensity values of pixels in an image. It may reduce the quality of the image, making it difficult to analyse or interpret the visual information accurately. Here, the objective is not to remove useful texture but to reduce irrelevant or harmful noise that may obscure critical facial features, especially in real-world scenarios where noise due to lighting conditions, occlusions, or other artefacts is common. Original 2D biased filter methods such as Gaussian, Median, and Laplacian filters cannot be properly applied to 3D images since they are incapable of reconstructing the spatial structure in the 3rd dimension and result in loss of structural information and improper segmentation across different slices. The applied steps are discussed in subsequent points.

Multi-scale Wavelet Decomposition: For a given 3D facial image $f(x, y, z)$ where $x, y,$ and z refer to spatial dimensions of the input scan. The 3D wavelet transforms [147] decomposes f into a set of coefficients representing different scales and orientations. The wavelet decomposition can be mathematically expressed as following in Eq. 3.13.

$$W(f) = \{LL_n, LH_n, HL_n, HH_n\}_{n=1}^{N} \tag{3.13}$$

Where, LL_n refers to the approximation coefficient at scale n and $LH_n, HL_n, \ and \ HH_n$ indicate detail coefficients.

Adaptive Thresholding: To minimize noise, adaptive thresholding is implemented to the wavelet coefficients. Let $Coeff_{i,j,k}$ indicate the wavelet coefficient at coordinate

(i, j, k) with scale n. The noise standard deviation σ is estimated using the coefficients of the maximum scale as shown below in Eq. 3.14.

$$\sigma = \frac{MAD(Coeff_{max})}{0.8431} \tag{3.14}$$

where MAD is the median absolute deviation. Further, the adaptive threshold parameter (λ) is calculated in Eq 3.15 based on the noise level as shown below.

$$\lambda = \sigma\sqrt{2\log(N)} \tag{3.15}$$

Where, N indicates the number of coefficients. Finally, a thresholding operator (T) to the wavelet coefficients is represented in Eq. 3.16.

$$W_{threshold}(f) = \{T(Coeff, \ \lambda)\} \tag{3.16}$$

Inverse Wavelet Transform: This step mainly focuses on reconstructing the denoised image from the threshold coefficients using the inverse wavelet transform defined in Eq. 3.17.

$$f_{denoised} = W^{-1}(W_{thresh}(f)) \tag{3.17}$$

Anisotropic Diffusion for Image refinement: This step uses anisotropic diffusion to improve the denoised image and maintain edges. Eq. 3.18 is the partial differential equation (PDE) which represents the applied anisotropic diffusion process.

$$\frac{\delta(I)}{\delta\,(t)} = \nabla.((\mathrm{c}.\nabla\,\mathrm{I})\nabla\,\mathrm{I}) \tag{3.18}$$

Where, I is the image, ∇ denotes the gradient operator. '$(\mathrm{c}.\nabla\,\mathrm{I})$' is the diffusivity function defined in Eq. 3.19 mentioned below.

$$\mathrm{c}.\nabla\,\mathrm{I} = e^{-\frac{|\nabla\,\mathrm{I}|^2}{Kappa^2}} \tag{3.19}$$

where kappa is constant, governing the sensitivity to gradients. Eq. 3.20 represents the image gradients along each axis. It is computed as:

$$\nabla_x(I) = \frac{\delta I}{\delta x}, \nabla_y(I) = \frac{\delta I}{\delta y}, \nabla_z(I) = \frac{\delta I}{\delta z} \tag{3.20}$$

The diffusivity is then applied to these gradients individually, and image I is iteratively implemented according to Eq. 3.21:

$$I^{t+1} = I^t + \gamma\,[\nabla . (\mathrm{c}\,(\nabla I^{(t)})I^{(t)}\,] \tag{3.21}$$

where γ is the time step size parameter. The pseudocode of the proposed denoising method is given in the Algorithm 3.2.

iii. Intensity Normalization: Intensity normalization is another important data preparation stage that is performed to reduce the impact of different types of facial images caused by illumination. The techniques used to achieve stable normalization are incorporated under a multistage, multi-technique method. Histogram equalization techniques [148] improve the contrast of images by distributing the occurrences of intensity values. Here, transformation function defined in Eq. 3.22 for intensity normalization is applied.

$$I_{eq}(x,y) = \frac{cdf\ I\ (x,y) - cdf\ (I_{min})}{(M*N) - cdf\ (I_{min})} * (L-1) \tag{3.22}$$

Where, $I_{eq}(x,y)$ is the equalized intensity value at the position(x,y). $cdf\ I\ (x,y)$ is the cumulative distribution function of the intensity value at the position (x,y). $cdf\ (I_{min})$ is the minimum value of the cumulative distribution function. $M * N$ is the number of pixels in the image. L is the number of possible intensity levels.

iv. Feature Extraction and 3D Convolution Operator: Feature extraction and classification leverages three concepts: (1) Designing a dynamic 3D convolution operator, (2) Combining DenseNet and Squeeze and Excitation Networks, and (3) Introducing a channel attention mechanism. The proposed dynamic 3D convolution operator is incorporated into DenseNet to perform feature propagation across layers and also preserve spatial information in three dimensions. The squeeze and excitation (SE) mechanism adds to this by rescaling the feature maps to highlight the features that are most important in terms of the same spatial depth and depth.

The proposed 3D convolution operator enhances feature extraction by capturing spatial correlations and depth variations crucial for 3D face anti-spoofing. The integration of Dense-SE networks and Cross-Channel Attention (CCA) ensures refined and discriminative feature learning. The mathematical and theoretical details of all concepts are discussed in the subsequent subsections. To enhance the conceptual understanding of proposed 3D

convolution operator, mathematical formulation without explicitly including the channel size is defined below. This representation focuses on the core spatial convolution process while maintaining clarity for theoretical analysis.

Algorithm 3.2: Pseudo-Code of the Proposed Image Denoising Algorithm Using 3D Wavelet Transform and Anisotropic Diffusion

Step 1: Function Denoise3DImage(image_3D):

wavelet_denoised = WaveletThresholding (image_3D, wavelet='db2', level=2, threshold_method='soft')

diffusion_denoised = Anisotropic Diffusion (wavelet_denoised, num_iter=20, kappa=30, gamma=0.1)

Return diffusion_denoised

Step 2: Function Wavelet Thresholding (image, wavelet='haar', level=3, threshold_method='soft', sigma=None):

coeffs = Wavelet Decomposition (image, wavelet, level)

If sigma is None:

sigma = MedianAbsoluteDeviation(coeffs[-1]) / 0.8431

threshold = sigma * sqrt(2 * log(size(image)))

coeffs_thresh = ApplyThreshold (coeffs, threshold, threshold_method)

denoised_image = InverseWaveletTransform([coeffs[0]] + coeffs_thresh, wavelet)

Return denoised_image

Step 3: Function Anisotropic Diffusion (image, num_iter=15, kappa=50, gamma=0.1):

For i from 1 to num_iter:

dx = Sobel(image, axis=0)

dy = Sobel(image, axis=1)

dz = Sobel(image, axis=2)

c = exp(-($dx^2 + dy^2 + dz^2$) / $kappa^2$)

grad_x = Gradient(c * dx)[0]

grad_y = Gradient(c * dy)[1]

grad_z = Gradient(c * dz)[2]

image += gamma * (grad_x + grad_y + grad_z)

Return image

Function Sobel(image, axis):

return sobel(image, axis=axis)

Function Gradient(image):

return np.gradient(image)

Mathematical Definition (Without Channel Size): Given an input tensor X with dimensions $H * W * D$ (Height, Width, Depth), the 3D convolution operation with a kernel W of size $K_h * K_w * K_d$ is expressed as below in Eq. 3.23.

$$Y(i,j,k) = \sum_{m=1}^{K_h} \sum_{n=1}^{K_w} \sum_{p=1}^{K_d} W(m,n,p).X(i+m-1, j+n-1, k+p-1) \quad (3.23)$$

Where, $Y(i,j,k)$ is the output feature map at a 3D spatial location (i,j,k). $W(m,n,p)$ is a weight at random 3D spatial location (m,n,p) of the given kernel. $X(i+m-1, j+n-1, k+p-1)$ refers input feature map at location $(i+m-1, j+n-1, k+p-1)$

Mathematical Definition (With Channel Size): For completeness, the full 3D convolution operation considering multiple channels is shown in Eq. 3.24.

$$Y(i,j,k,C_{out}) = \sum_{C_{in=1}}^{C_{in}} \sum_{m=1}^{K_h} \sum_{n=1}^{K_w} \sum_{p=1}^{K_d} W(m,n,p,C_{in},C_{out}). \quad X(i+m-1, j+n-1, k+p-1, C_{in}) \quad (3.24)$$

Where, $Y(i,j,k,C_{out})$ is the output feature map at 3D spatial location (i,j,k) for the ${C_{out}}^{th}$ channel. $W(m,n,p,C_{in},C_{out})$ is a weight at random 3D spatial location (m,n,p) of the given kernel for ${C_{in}}^{th}$ input channel and ${C_{out}}^{th}$ output channel. $X(i+m-1, j+n-1, k+p-1, C_{in})$ refers to the input feature map at location $(i+m-1, j+n-1, k+p-1)$ for the ${C_{in}}^{th}$ channel.

3.4.2 Training Pipeline and Hyper-Parameter Tuning

Training pipeline of the proven 3D face anti-spoofing model involves a sequence of steps to obtain maximum convergence, generalization, and adversarial resilience of the model. Training pipeline of the provided 3D face anti-spoofing model involves a sequence of preparatory processes to attain maximum performance.

i. Train, Validation, and Test Set Splitting Strategy for Dataset: With the aim to make the model evaluation unbiased, the dataset is divided into train, validation, and test sets in the proportion 70:15:15, respectively. The training set is used to train the model, the validation set is used to optimize the hyper-parameter and prevent overfitting, and the test set is kept entirely unseen to facilitate a final model performance assessment.

ii. Model Training Process: Training is performed carefully, e.g., optimization methods and loss monitoring for better generalization and avoiding overfitting.

a. Optimizer Selection - The model is trained using the Adam optimizer, which provides an adaptive learning rate based on the current state of the model and supports fast convergence. Initial Learning Rate (LR) = 0.001. Learning Rate (LR) = 0.1 reduced each 10 epochs for slow convergence.

b. Batch Size and Epochs - batch size of 32 for a balance between computation speed and stable updates of gradients. Training up to 50 epochs with early stopping when validation loss is not reducing for 5 or more consecutive Batch size of 32 is employed to strike a balance between computation speed and gradient stability. Dropout layers with dropout rate 0.5 are incorporated to prevent over-fitting and early stopping is implemented if validation loss does not improve for 5 consecutive epochs

iii. Overfitting Prevention Strategies: To prevent overfitting, the following regularization techniques are incorporated. To enhance the generalization capability of the 3D face anti-spoofing model and prevent overfitting, multiple regularization techniques are implemented. Dropout is applied with a rate of 0.5 in fully connected layers to randomly deactivate neurons during training, ensuring that the model does not rely too heavily on specific features and improves robustness. Additionally, L2 regularization with a weight decay parameter (λ) of 0.0001 was incorporated into the convolutional layers to penalize large weight values, promoting smoother and more stable learning. The data augmentation techniques such as flipping, rotation, and brightness adjustments are used to artificially expand the dataset. It helps in improving the model's ability to handle variations in real-world facial images. The regularization strategies helped in maintaining high performance while mitigating the risk of overfitting. The combination of dropout and L2 regularization helps prevent overfitting by ensuring the model does not rely too heavily on specific features.

iv. Hyper-parameter Tuning: Proposed 3D face anti-spoofing model training procedure includes some time-consuming Hyper-parameter tuning is carried out by a combination of grid search and random search. Some of the important hyper-parameters are dense block counts, 3D convolutional kernel size, and layer-wise channels. The optimal configuration is selected based on best F1-score on validation

set. Moreover, robustness of the model in accuracy, precision, recall, and ROC-AUC for detection of spoofing attack is also tested. Explanation is given in chapter 5 where entire experimental setup and results of suggested methodology are presented.

a. Grid Search for Major Hyper-parameters: Grid Search is applied to find the best combination of key model parameters. The hyper-parameter tuning process involved evaluating multiple configurations to identify the optimal settings for the 3D face anti-spoofing model. The number of dense blocks was tested with values of 2, 3, and 4, where a configuration of 3 blocks demonstrated the best balance between feature extraction and computational efficiency. For the 3D convolutional kernel size, three options (3×3×3), (5×5×5), and (7×7×7) were assessed. The (5×5×5) kernel was selected as it provided the best trade-off between capturing spatial details and maintaining model complexity. To prevent overfitting, different dropout rates (0.3, 0.5, and 0.7) were evaluated, with 0.5 emerging as the most effective in ensuring generalization while retaining important feature representations. Finally, the learning rate was fine-tuned among 0.001, 0.0005, and 0.0001, with 0.001 being chosen as it facilitated stable convergence without causing rapid fluctuations in model performance. These hyper-parameter values were set based on the best F1-score on the validation set in such a manner that spoof detection would be both robust and accurate.

b. Random Search for Fine-Tuning - Random search fine-tunes on more sensitive parameters such as: Kernel adaptation sensitivity Number of filters per layer Batch normalization Momentum This union provides macro-level and micro-level tuning both.

The model's performance is assessed in terms of metrics such as precision, recall, accuracy, and ROC-AUC to make spoofing attack detection resilient. The new model structure based on Dense-SE Networks and Neighbourhood-Aware Kernel Adaptation requires carefully adjusted values of hyper-parameters such as number of dense links and sensitivity of kernel adaptation. Such parameters are adjusted for enhancing model capacity for encoding high-level spatial fine-grained features as well as increasing the level of accuracy for spoofing detection.

Experimental arrangement and discussions regarding result on suggested methodology are included in chapter 5. The problems regarding enhance decision-making and learning are discussed in the following chapter. Sophisticated attention mechanism for key feature selection, sharpening optimization strategy, and learning technique to generate correct classification have been introduced in it. In the next chapter, another approach for face detection by combined utilization of other image types is discussed.

4. A LIGHTWEIGHT MULTI-MODAL DEEP FUSION NETWORK FOR FACE ANTI-SPOOFING WITH CROSS-AXIAL ATTENTION AND DEEP REINFORCEMENT LEARNING

4.1 OVERVIEW OF THE MULTI-MODAL DEEP FUSION APPROACH

The Multi-Modal Deep Fusion Approach is an intelligent method to identify real and fake faces from diverse kinds of images together. Instead of a single kind of image as in the case of a normal color multi modal fusion, the method in this case encompasses different kinds of images such as infrared (IR) and depth images. Different kinds of images yield different kinds of beneficial information. For instance, a normal photo captures the shape and color of the face, an infrared photo captures heat signatures, and a depth photo is useful to realize the 3D shape of the face.

The system becomes enhanced with the assistance of multi modal deep fusion process through the step of first acquiring several images of an individual's face. Thereafter, the principal feature from one of them is identified out by a deep learning model. Features can include skin texture, face shape, and even tiny details like light reflection. After extracting the features, the system merges or "fuses" them. This fusion helps the model understand the face in a better way than using just one type of image. By combining information from multiple sources, the model can find patterns that a single type of image might miss. For example, a printed photo may look real in an RGB image, but an infrared image can show that it has no heat signature, which proves it is fake [151- 165].

Similarly, a 3D mask might look like a real face in one image, but a depth image can reveal its unnatural shape. The Multi-Modal Deep Fusion Approach improves the accuracy of face anti-spoofing. It reduces mistakes and helps security systems make better decisions. This method is very useful for places where high security is needed, like banking apps and airport check-ins. However, it also needs more computing power and good training data to work well. In this chapter a new multi-modal model XA-Net (aXial Attention network) is proposed to optimize feature interaction which makes the system highly resistant to spoofing attempt. Model enhances the system's ability to discern genuine faces from spoof attempts. A bidirectional fusion technique in the model facilitates the effective combination of features from each mode. This bidirectional fusion approach contributes to a more comprehensive

representation of the input data [165-169]. Feature optimization is also refined using the enhanced pity beetle optimization (EPBO) algorithm [170]. A new method FDDRL (Federated Deep Reinforcement Learning) is used to improve face anti-spoofing. It helps to balance accuracy and reducing errors. The model learns from different cases and adapts over time to become better at spotting fake attempts [171-173].

A Multimodal deep fusion network consists of four steps: (1) Feature extraction using XANet, (2) Feature amalgamation using bi-directional fusion scheme, (3) Feature optimization using enhanced pity beetle optimization (EPBO) algorithm, (4) Classification using FDDRL classifier. The performance of the proposed architecture is presented on both the benchmark datasets using multi-fold cross validation scheme. The detailed discussion on all the steps is given in subsequent subsections.

4.2 CROSS-AXIAL ATTENTION MECHANISM

The multi-modal deep fusion network integrates with the axial attention mechanism and federated reinforcement learning to design a secure and efficient FAS framework. The figure 4.1 illustrates a face anti-spoofing framework that leverages multi-modal data (Depth, Infrared (IR), and RGB) and employs an advanced Cross-Axial Attention Mechanism for effective feature extraction. The framework is divided into two main phases: training and testing. The central theme of this model is the Axial Attention Network (XANet), which enhances feature extraction by focusing on spatial dependencies along both horizontal and vertical axes separately. It makes it highly efficient in detecting spoofing attempts. During the training phase, Depth, IR, and RGB images from datasets such as CASIA-SURF [174] and GREATFASD-S [175] are passed through XANet, which applies the cross-axial attention mechanism to extract meaningful features. XANet allows the model to focus on spatially relevant features while ignoring redundant information. The extracted features from each modality are then fused using a bidirectional fusion mechanism, ensuring that the most critical spatial and contextual information is retained. This combined representation is input to feature optimization, where significant discriminative features are optimized.

The final training step incorporates classification using Feature Disentanglement and Dynamic Representation Learning (FDDRL) to render the model highly adaptive in the case of any attack. New test samples proceed through the identical pipeline. XANet extracts features, fuses them bidirectionally, and sends it through the trained classifier for real and

spoof face classification. Use of the Cross-Axial Attention Mechanism in XANet enables the model to attend to different regions of the face. It delivers improved accuracy and 3D mask, printed photo, and replay attack resistance.

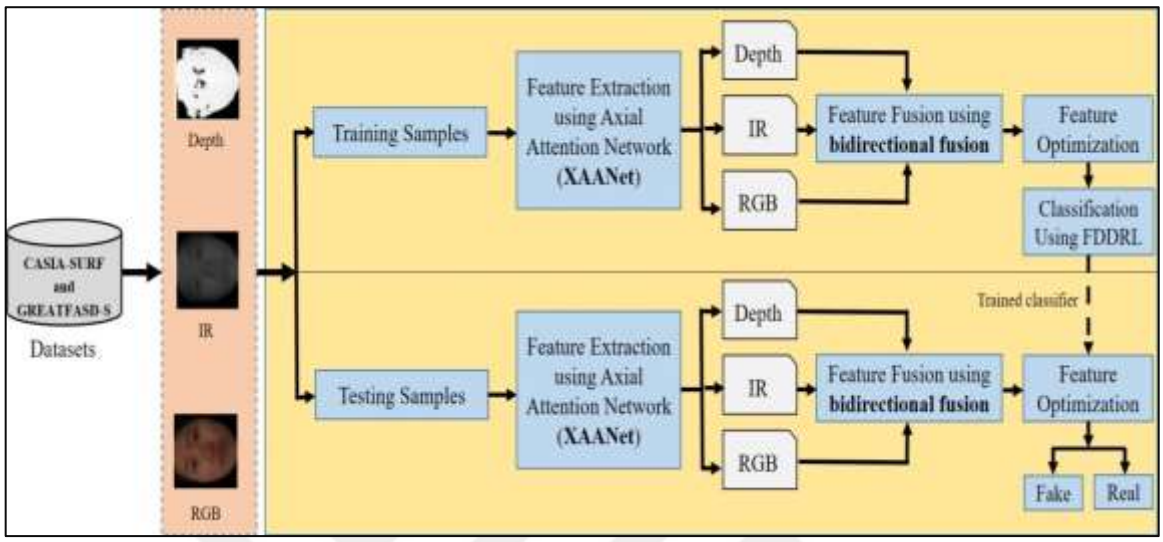


Figure 4.1: Overall System Architecture of Proposed Multimodal Deep Fusion Network (By Author).

In the proposed work, an axial attention network (XANet) is employed for deep feature extraction from the multimodal datasets. By placing cross-axial attention at the core, this framework ensures efficient feature extraction reduces computational complexity. It also improves face anti-spoofing performance in real-world scenarios.

4.2.1 Enhancing Feature Interactions

Feature extraction refers to the process of capturing and representing distinctive characteristics or patterns from facial images that are relevant for distinguishing between genuine faces and spoof attempts. This step is crucial for building effective models that can discern the subtle differences between live faces and various presentation attack methods. In our work, we employed both manual and deep features for characterization of input face scans. Here, four type of manual face imaging attributes: (1) Dimensional attributes (5 features), (2) Facial characteristics (7 features), (3) Image statistics (5 features), and (4) Texture features (4 features) are extracted from all three image modalities (RGB, IR, Depth). Therefore, total 63 (21*3) features were used for further data processing. In the research study, Skimage library [176] is used for feature extraction purpose.

The details of all the extracted features from above-mentioned categorized are listed in the Table 4.2. A novel an aXial Attention CNN network (XA-CNN) is introduced for extracting deep features. The details of developed XA-CNN architecture are introduced in next subsection. The figure 4.2 (a) and 4.2 (b) represents a face anti-spoofing framework that is divided into two main stages i.e. Deep Feature Extraction and Hybridization and Optimization, and Classification. Each of these components plays a crucial role in ensuring an accurate and robust face anti-spoofing mechanism. This framework efficiently combines deep learning and manual feature engineering for face anti-spoofing. Stage (A) extracts rich deep features using CNNs and Axial Attention Mechanisms, while Stage (B) optimizes and classifies these features using bidirectional fusion and the FDDRL classifier. The incorporation of Axial Attention makes the model robust against diverse spoofing attacks.

a. Deep Feature Extraction Using XA-CNN Architecture

The primary objective of introducing XA-CNN Architecture is to extract deep hidden features, from multi-modal facial images. The proposed XA-CNNet model is a type of attention-based neural network used in computer vision tasks, particularly for image understanding. Axial attention refers to the mechanism of attending to different axes (rows and columns) of an input tensor separately. The XANet model incorporates this idea to capture long-range dependencies in both the row and column directions of the input data.

The proposed network combines conventional Residual network (RESNet) [170] as a base CNN model with axial attention mechanism to extract deep face imaging features. It starts out with an Input Layer corresponding to a 32x32 RGB image, laying the ground for next steps. In the Initial Convolution and Pooling phase, a 64-filter Conv2D layer with 7×7 kernel size, 2 strides and ‘same’ padding is used. Batch Normalization and ReLU activation improve the model’s resilience, followed by MaxPool2D with a 3×3 kernel, 2 strides and ‘same’ padding for spatial subsampling.

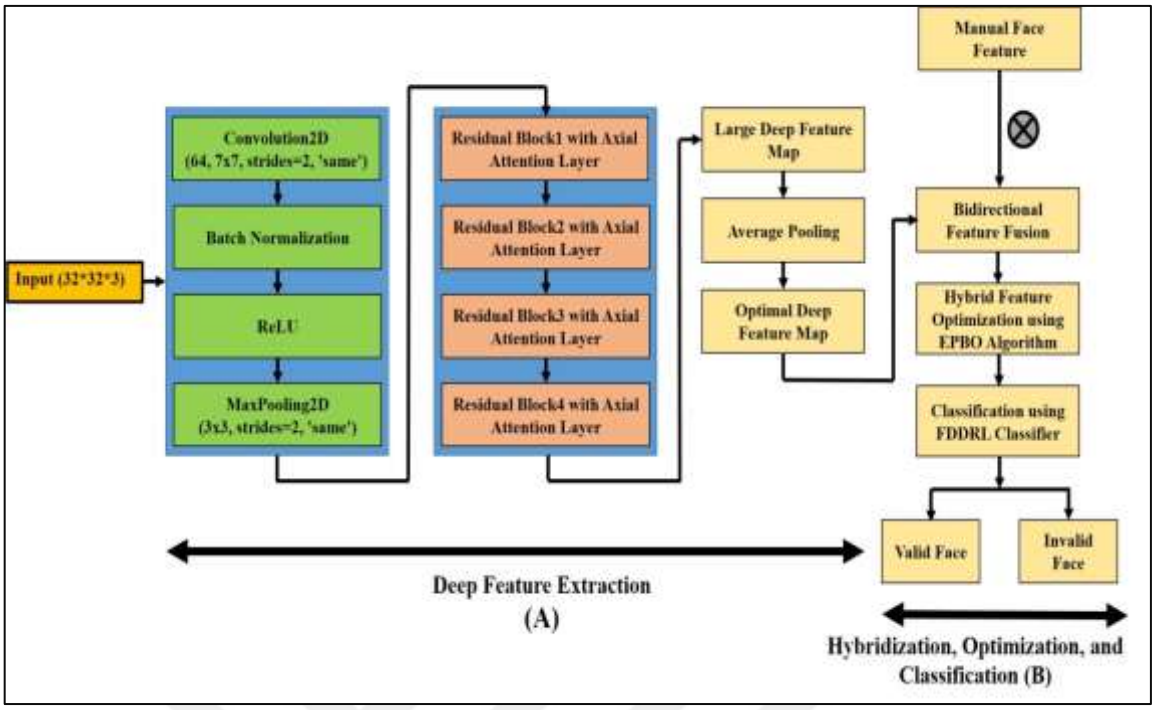


Figure 4.2: The Proposed Anti-Spoofing Classification Framework (By Author).

The main components of the model are Residual Blocks with Axial Attention. Consisting of four stacks, every stack containing a certain number of residuals blocks, an AxialAttention layer is cunningly embedded in the middle of each block. Each stack has its own number of residual blocks, determined by the num_blocks_list variable where the value is [2, 2, 2, 2]. The model's capacity increases with every stack, multiplying the numbers of filters in each block from 64. The Axial Attention Layer (AxialAttention) [165] is a new mechanism, and it combines both row-wise and column-wise axial attention. The row_attention and col_attention layers apply MultiHeadAttention [177] with a key dimension of dim "num_heads". The outputs of these attention mechanisms are also concatenated along the last axis which gives the model capability to capture relations along rows and columns separately. The Residual Block (resnet_block) in every stack follows the standard residual architecture. Batch Normalization and ReLU activation follow Conv2D layers of varying filter numbers, 3x3 kernel size and 'same' padding. A shortcut connection, is introduced either through a convolutional layer (first block in a stack or first stack) by an addition of the input to output. Each block is finalized with the ReLU (Rectified Linear Unit) activation layer. The details of the deep feature extraction process are shown in the Figure 4.4(A).

b. Bidirectional Feature Fusion

In previous step, a large size deep feature set with multiple zero entries is extracted. To resolve this issue, an average pooling procedure is applied to minimize the sparsity level in deep feature set. The updated features were merged with manual features using bidirectional feature fusion technique [178]. This approach ensures that the fusion process takes into account not only the interaction from one source to another but also the reciprocal interaction in the opposite direction. In this context, bidirectional fusion is applied to effectively combine features from different modes. Feature fusion involves combining information from different sources to create a more comprehensive and informative representation. This is often done to enhance the understanding or performance of a model. Bidirectional attention ensures that the fusion process considers the interaction not only from one mode to another but also from the other mode back to the first. It captures the reciprocal influence between the modes. Bidirectional attention ensures that the combination process accounts not only for interaction from one to the other but also from the other to the first. Bidirectional attention includes the bidirectional impact between the modes. Figure 4.4(B) is the bidirectional combination scheme aimed at effective integration of features. This means resulting combined features better represent the input data, describing both direct and the mutual interrelations. By also considering bidirectional information flow, the model can better capture more complex patterns, dependences, and interactions between features of different modes. Bidirectional feature combination is particularly critical where the task to be solved can be aided by a balanced representation of the relationship between the various modalities or information sources.

4.2.2 Spatial and Channel-Wise Attention Strategies

Channel and spatial attention methods help computers to focus on major areas of an image without regarding trivial things. They are applied to deep models, especially to face anti-spoofing and other kinds of tasks wherein the system has to specify if a face is genuine or forged. Spatial attention helps the model focus on most vital areas of an image. For example, when detecting a forged face, there may be subtle variations within certain regions like the eyes, nose, and the mouth in the genuine versus the forged pictures. The model gives more value to these places and less value to other zones like the hair and background. This makes detection more accurate as the system never wastes time with unimportant aspects. Channel-wise attention is otherwise.

Instead of focusing on some regions of an image, it forces the model to pay attention to more useful features across different color channels. There are many channels of an image, e.g., red, green, and blue (RGB). Some channels carry more useful information in order to discriminate between forged and genuine faces. For example, forged images can have conflicting patterns of textures within some color channels. Channel-wise attention makes sure that the model puts more weight on the correct channels and less on the incorrect ones. When both these methods are applied together, they improve the performance of face anti-spoofing systems. Spatial attention makes sure that the model looks at the correct areas, whereas channel-wise attention makes sure that it looks at the correct features. Together, they assist the system in identifying fake faces more effectively, even if lighting, camera quality, or face positions vary.

4.3 DEEP REINFORCEMENT LEARNING FOR FACE ANTI-SPOOFING

Deep Reinforcement Learning (DRL) is a machine learning process where a model learns from decision-making and rewarding for the good decisions. In face anti-spoofing, DRL helps an automatic system make decisions on whether a face is real or not by learning from experience. The system does not follow set rules but learns with time by experimenting with various methods of detecting fake faces and using the best ones based on reward.

There needs to be face anti-spoofing since one can spoof facial recognition systems using photos, video, or mask attacks. Hand-crafted features are of old-school times but will generalize much less to other lighting or video quality. DRL avoids that by training on automatically distinguishing between imposter and real faces in different environments.

There are three basic components of DRL: the agent, the environment, and the reward system. The model of decision-making is the agent, the environment is a set of simulated and actual face images, and the reward system gives positive rewards for correct classification and negative rewards for incorrect classification. The model will start making random decisions, but the more feedback, the better it is at identifying spoofed faces. Another advantage of using DRL in face anti-spoofing is that it can generalize over a wide range of attack classes. Since it learns by trial and error, it can be trained on novel spoofing approaches that it hasn't seen before. This also makes it even more efficient and effective than any other traditional machine learning method. But DRL has its disadvantage as well.

First, it needs gigantic amounts of data and computation. The model must attempt several different methods towards identifying artificial faces before it figures out how to do it in the best manner possible, and that takes resources. Second, training is unstable because the agent is not always receiving good-defined rewards, therefore slow learning. Third, DRL models need fine-tuning so that they perform appropriately on other data sets as well as on real-world scenarios.

Researchers are enhancing DRL for face anti-spoofing by its steadier training and reduced data requirement. One approach is the use of hybrid models, where DRL is combined with other machine learning techniques to gain higher accuracy. Another enhancement is the use of pre-trained models, where a DRL model is pre-trained on general features from a huge dataset in advance before fine-tuning it especially for face anti-spoofing.

Although it has its own set of challenges, DRL is potentially a reliable face anti-spoofing method. With progress, technology has the potential to enhance the security and reliability of facial recognition technologies. With ongoing research, DRL can become an essential building block in eradicating forgery of identities and protecting information.

4.3.1 Learning-Based Decision-Making for Spoof Detection

Learning-based decision-making allows a computer to decide whether a face is real or not. The computer does not have predetermined rules. Instead, it learns by analyzing many images of real and fake faces. It recognizes minute details that differentiate real and fake faces. The computer uses a machine learning model, which is like an intelligent program. The model is trained through many face images. There are some pictures where actual faces are shown, and other pictures show false faces from photographs or videos. The model sees these pictures and learns patterns. For example, an actual face can have the natural texture of skin, and a false face will look too smooth or too shiny. When the system gets to see a new face, it compares the new face to what it learned. It looks at features like skin texture, eye movement, and lighting. If the face looks real, the system accepts it. If it looks fake, the system rejects it. This method is good because it improves over time. If the system makes mistakes, it can learn from them. But it needs a lot of training data to work well. If the data is not good, the system may not make correct decisions.

Spoof Detection and Face Anti Spoofing Classification: Federated reinforcement learning generally involves training a reinforcement learning model across multiple decentralized devices or servers without exchanging raw data. Instead, the models are trained locally on individual devices, and only model updates or aggregated information is shared among them. This approach is often used to maintain privacy and security, especially when dealing with sensitive data. In face anti-spoofing, the hybrid federated reinforcement learning (FDDRL) model could potentially combine reinforcement learning techniques with other approaches to enhance the overall performance. FDDRL model is used to analyse and classify the images, decide whether they are real or fake, and improve its decision making over time based on feedback and reinforcement learning.

The Eq. 4.1 and Eq. 4.2 define the communication and computation constraints in federated learning, focusing on query delay, local training delay, and upload time. In Eq. 4.1, ' $I_{S,Y}^{d}$ ' denote the query preparation delay for client b∈B in circuit $s \in S$. This means the time taken by client b (where b is a client in the set of clients B) to prepare a query in communication round s (where s belongs to the set of communication rounds S). This delay includes the time required to fetch local data, pre-process it, and generate the necessary query for model training or update. ' $I_{S,Y}^{d}$ ' is the detailed local exercise delay in round *s* for client *n* i.e. computational time spent by client n (one of the participating devices) to train its local model using its own data in round s. This depends on hardware capabilities, data volume, and model complexity. After computing local updates, client n needs to upload its locally trained model to the Federated Learning (FL) server. This upload time depends on network bandwidth, latency, and data size. The term ' $I_{S,Y}^{U}$ ' denotes the time for consumer *n* to upload the local model to the FL server. A binary variable '*φ (s,b)*' determines whether a client n is selected by the Feature Disentanglement and Dynamic Representation Learning (FDDRL) algorithm for training in the current round. If φ(s,b) = 1, client n is chosen and participates in training. If φ(s,b) = 0, client n is not included in the current round. This term ' $I_{S,Y}^{d}$ ' represents the sum of all delays encountered in the federated learning communication process, including query preparation, local training, and model upload times. The ' I_{S} ' in message round t quantifies the total cost in terms of data transmission, computational effort, and

communication overhead required to exchange information between clients and the FL server during a particular round.

Since FL focuses on decentralized learning, the optimization problem does not explicitly include transmission delay as a primary objective. Metadata Upload Delay Ignored: The delay in uploading client metadata to the server is not considered in this optimization framework. Client Termination and Local Epoch Correction: The $T \times N$ matrix (where T represents training rounds and N represents participating clients) is computed by the FDDRL algorithm to optimize the federated training process.

$$I_S = \underset{1 \le Y \le y}{Max} (I^d_{S,Y} + I^U_{S,Y}) M^S_Y \tag{4.1}$$

$$n_S = \sum_{Y=1}^{y} n^S_Y \phi^S_Y \tag{4.2}$$

Because FL is not part of the 'I_S' optimization problem, transmission delay $I^N_{S,Y}$ is not involved. Also, the delay in uploading the client metadata to the server is ignored $I^A_{S,Y}$. Hence, $I^A_{S,Y}$ from is ignored and client m_S termination and local epoch correction $I^P_{S,Y} >> i^U_{S,Y}$, $T \times N$ matrix is compute by FDDRL. The problematic is expressed as weighted sum optimization problematic as shown in Eq. 4.3.

$$\underset{\phi_s, e_s}{Max} e \left[\sum_{S=1}^{s} W_1 [U(m_S) - U(m_{S-1})] - (W_2 n_s + W_3 i_S) \right] \tag{4.3}$$

Where, W_1, W_2 and W_3 are the masses that control the position of each objective. A utility meaning m_S denoted U(·) is used to recalibrate the global model, although small, it can optimize FL at the end of the process m_S. As defined in FedMarl $V(m_S)$.

$$V(m_S) = \frac{20}{1 + E^{0.35(1-m_S)}} - 10 \tag{4.4}$$

One problematic with the novel $V(m_S)$ as shown in Eq 4.4 is that it lone tells us the different worth of m_S . The complete $W_1[V(m_S) - V(m_{S-1})]$ can be re-parameterized into solitary $w_1[v(\Delta M_s)]$ face, which might stanchly tell us the gain/penalty for ΔM_s. Primary, the $V(m_S)$

calculation is easy in the assumed range $0 \leq M_s \leq 1$ since at is restricted among 0 and 100%. To estimate $V(m_S)$ a traditional line within a given range, we need the slope and q-intercept of the graph $V^{'}(m_S)$. $V^{'}(m_S)$ can be mathematically calculated as follows in Eq. 4.5.

$$V^{'}(m_S) = \frac{7E^{0.35(1-M_s)}}{(1+E^{0.35(1-M_s)})^2} \tag{4.5}$$

The hostile of the incline, $\overline{V^{'}(m_S)}$, within the series can be calculated as in Eq. 4.6 below.

$$\overline{V^{'}(m_S)} = \frac{1}{1-0}\int_0^1 V^{'}(m_S)DS = \int_0^1 \frac{7E^{0.35(1-m_S)}}{(1+E^{0.35(1-m_S)})^2} DS \tag{4.6}$$

The q-intercept of $V(m_S)$, indicated as $V(m_S = 0)$, can be calculated as given in below Eq. 4.7.

$$V(m_S = 0) = \frac{20}{1+E^{0.35(1-0)}} - 10 \tag{4.7}$$

Hence, Eq. 4.8 shows $V(m_S)$ can be added with $\overline{V^{'}(m_S)}$ to get the value of (m_S).

$$(m_S) = \overline{V^{'}(m_S)}m_S + V(m_S = 0) \tag{4.8}$$

Eq. 4.9 represents mathematical calculation of $V(\Delta m_S)$ as follows.

$$V(\Delta m_S) \cong V(m_S) - V(m_{S-1}) \tag{4.9}$$

Languages $V(\Delta m_S)$ are more analysable than $V(m_S) - V(m_{S-1})$ imprecise. For this purpose, the complex operation can be described as given in below Eq. 4.10, Eq. 4.11 and Eq. 4.12.

$$\underset{\phi_s, e_s}{Max e}\left[\sum_{s=1}^{S} W_1 V(\Delta m_S) - (W_2 n_s + W_3 I_S)\right] \tag{4.10}$$

$$W_1 V(\Delta m_S = 0.01) > \Omega e(W_2 n_s + W_3 I_S) \tag{4.11}$$

$$e\left(W_1\sum_{S=1}^{s}V(\Delta m_S)\right) > \Omega_3\left(Z_2\sum_{S=1}^{s}n_S + W_3\sum_{S=1}^{s}I_s\right) \tag{4.12}$$

The working process of detection and classification of Anti-spoofing using FDDRL model is given in Algorithm 4.2.

4.3.2 Reward Function Design and Optimization

A reward function is like a trainer that helps a computer to learn the right actions. It gives points or scores when the computer makes a good decision and takes away points when it makes a bad decision. This helps the computer understand what is right and what is wrong. In face anti-spoofing, the reward function helps the system learn to tell real faces from fake ones. If the system correctly identifies a real face, it gets a reward (positive points). If it makes a mistake and thinks a fake face is real, it gets a penalty (negative points).

Over time, the system learns to make better choices to get more rewards and fewer penalties. Optimization means improving the reward function so the system learns faster and better. If the reward function is not designed well, the system may learn the wrong things. For example, if it gets too many points for guessing, it might just guess instead of actually learning. By carefully designing and optimizing the reward function, we make sure the system learns the best way to detect fake faces accurately. This makes face anti-spoofing more effective and reliable.

Feature optimization typically involves selecting or transforming features in a way that enhances their relevance, discriminative power, or effectiveness for a particular task. In this context, it refers to improving the features extracted from different modes to better serve the face anti-spoofing task. The proposed work introduced enhanced pity beetle optimization (EPBO) algorithm for feature optimization which selects the features to address data dimensionality problems. EPBO algorithm is inspired by the conventional beetle swarm optimization (BSO) [179]. A number of particles or candidate solutions are initialized with a hyper volume equal to the global hunting space. In this case, optimal best features are considered as candidate solutions. Eq. 4.13 defines the initial population of precursor particles as shown below.

$$q^{(0)} = \left[q_1^{(0)}, q_2^{(0)}, ..., q_{B_{pop}}^{(0)}\right]^S \tag{4.13}$$

In Eq. 4.14, '$q_g^{(0)}$' represents the optimal best features are randomly located in the C-dimensional search space.

$$q_g^{(0)} = rst\left(B_{pop}, C, L, U\right) \tag{4.14}$$

Here 'rst' is shorthand as an arbitrary search mechanism, which is used to solve the real-time assembly problem. With this first method, all sections of the investigation space are properly considered in the B_{pop} experiments. Where, 'L' and 'U' are the best and worst solutions from the initial population. After initialization, fitness is calculated for each solution as mentioned in Eq. 4.15.

$$f_g(s) = \max\begin{cases} of_1 \\ of_2 \\ of_3 \end{cases} \tag{4.15}$$

Iteration refers $f_g(s)$ to fitting the g-th solution to s. The solution with maximum fitness is selected as the optimal solution. For each instance, the value of this region is implemented using an appropriately chosen model component (F_x) and EPBO parameterization. According to each example, B_{pop} new precursor particles are computed as follows in Eq. 4.16, Eq. 4.17 and Eq. 4.18.

$$q_g^{(j)} = rst\left(B_{pop}, C, L^{(j)}, U^{(j)}\right) \tag{4.16}$$

$$\left[l_h^{(j)}, u_h^{(j)}\right] \in \left[q_{birth,h}^{(j)} * (1 - F_x), q_{borth,h}^{(j)} * (1 + F_x)\right] \tag{4.17}$$

Where, 'j' represents the generation or next step and $q_{birth,h}^{(j)}$ the h^{th} generation represents the solution vector. $l_h^{(j)}$ and $u_h^{(j)}$ denote the lower and upper bounds of the h$^{\text{th}}$ solution for the j^{th} next state, respectively. The neighbourhood variable (F_{be}) used to describe the size of this space is the EPBO parameter, OFF_{be} whose value is proportional to the scale [0.01, 0.20]. As this model shows, B_{pop} new precursor particles are generated subjectively and message-dependently on this hunting ground. Where F_x is equivalent to F_{be}.

$$q_g^{(0)} = rst\left(B_{pop}, C, \left[q_{birth,h}^{(j)} * (1 - F_{be}), q_{borth,h}^{(j)} * (1 + F_{be})\right]\right) \tag{4.18}$$

These recent characterization B_{pop} solutions are then interpolated to characterize the ideal precursor molecule. The best is different from the early stage, if the best attracts the best and seeks the newest people:

$$q_{birth,h}^{(j+1)} = \begin{cases} q_{birth,h}^{(j)}, & if \ \ f\left(q_{birth,h}^{(j)}\right) < \left(q_{g,K}^{(j)}\right) \forall g = 1,2,....B_{pop}, K = 1,2,....B_{broods} \\ q_{g,K}^{(j)}, & otherwise \end{cases} \tag{4.19}$$

A new state $q_{birth,h}^{(j+1)}$ vector is represented in the K^{th} population representing B_{broads} the last maximum relatives (Eq. 4.19). The mean scale factor (F_{ae}) used to express the size of this zone is a EPBO parameter whose value corresponds F_{ae} to the scale [0.10, 1.00]. According to this model, B_{pop} recent progenitor particles are located indiscriminately in this hunting cosmic object. Where, F_x is equal to F_{ae} as represented in Eq. 20.

$$q_{g,K}^{(j)} = rst\left(B_{pop}, C, \left[q_{birth,h}^{(j)} * (1 - F_{ae}), q_{borth,h}^{(j)} * (1 + F_{ae})\right]\right) \tag{4.20}$$

Like the neighbouring pursuit hyper volume, these as of late portrayed B_{pop} arrangements are contemplated between each other for portraying the best pioneer molecule. The enormous scope factor (F_{Lt}) that is used to portray the size of this region is a parameter of the PBA, the value extent of F_{Lt} is comparable to [1, 100]. As demonstrated by this model, the recent B_{pop} pioneer particles are aimlessly arranged inside this hunt space subject to the surge now F_x is equal to F_{Lt}. B_{pop} the late-featured arrangements are considered against each other to showcase the best pioneering molecule. The magnitude factor (F_{Lt}), which is used to express the size of this region, is a parameter of PBA whose value F_{Lt} is comparable to the size [1, 100]. As this model suggests, recent progenitor particles were randomly arranged on this now turbulent hunting ground (Eq. 4.21).

$$q_{g,K}^{(j)} = rst\left(B_{pop}, C, \left[q_{birth,h}^{(j)} * (1 - F_{Lt}), q_{borth,h}^{(j)} * (1 + F_{Lt})\right]\right) \tag{4.21}$$

Like the previous research hyper volume design, this recent characterization B_{pop} is pitted against each other to characterize the ideal precursor molecule. The optimal number of

inefficient capacity estimates (fe_{ub}) for using the global search hyper volume model is plotted over the full range of task estimates (fe_{total}) using the numerical expansion factor *(* f_{fe} *).* The latest antecedents are randomly placed with the first in this sequence as shown in Eq. 4.22:

$$q_g^{(0)} = rst\left(B_{pop}, C, L, U\right) \tag{4.22}$$

Algorithm 4.1: Feature Optimization Using EPBO

1. Initialize the random population
2. Define initial population of precursor particles

   $q^{(0)} = \left[q_1^{(0)}, q_2^{(0)}, ..., q_{B_{pop}}^{(0)}\right]^S$
3. If i=0 , j=1
4. While Do
5. Compute eligibility of each solution $f_g(s) = \max\begin{cases} of_1 \\ of_2 \\ of_3 \end{cases}$
6. Find best attracts the best and seeks the newest people

   $q_{birth,h}^{(j+1)} = \begin{cases} q_{birth,h}^{(j)}, & if \;\; f\left(q_{birth,h}^{(j)}\right) < \left(q_{g,K}^{(j)}\right) \forall g = 1,2,....B_{pop}, K = 1,2,....B_{broods} \\ q_{g,K}^{(j)}, & otherwise \end{cases}$
7. Compute threshold for progenitor particles

   $q_{g,K}^{(j)} = rst\left(B_{pop}, C, \left[q_{birth,h}^{(j)} * (1 - F_{Lt}), q_{borth,h}^{(j)} * (1 + F_{Lt})\right]\right)$
8. The probe region by RST methods: $q_g^{(j)} = rst\left(B_{pop}, C, L^{(j)}, U^{(j)}\right)$
9. End if
10. Update the final value
11. End

The Algorithm 4.1 describes the working function of feature optimization using EPBO. The Feature Optimization using EPBO (Enhanced Particle-Based Optimization) algorithm refines feature selection by iteratively improving a population of solutions. It begins by initializing a random population, where each particle represents a possible feature subset. The precursor particles are then set, defining the initial population that will explore the

feature space. If the iteration counter is zero, a secondary counter is initialized for tracking progress.

The algorithm then enters a while loop, continuously optimizing features until a stopping condition (such as reaching the maximum iterations or satisfying a threshold) is met. Each solution's eligibility is evaluated to determine its effectiveness in representing features. The algorithm follows an attraction model, where the best solution attracts others while simultaneously seeking new potential candidates, ensuring an exploration-exploitation balance. A threshold for the progenitor particles is then calculated to control feature selection dynamics. The RST (Rough Set Theory) method is applied to optimize the feature space in a way that only the most relevant attributes are maintained. In case the threshold requirement is fulfilled, the algorithm proceeds to update the final optimized feature set. The algorithm concludes by generating the optimized subset of features in such a way that effective feature selection for machine learning models is guaranteed.

4.4 LIGHTWEIGHT MODEL DESIGN AND COMPUTATIONAL EFFICIENCY

A lightweight model is a small and fast computer program but still efficient. It may require less memory, power, and time in performing its task. In face anti-spoofing, a lightweight model can effectively classify if a face is fake or not without taking a lot of computer resources. A good model must be both accurate and efficient. If a model is too big and slow, then it will require too much time to render a decision. This is undesirable, especially for mobile phones or security systems which must operate in real time. Scientists use tricks to enable a model to be light and speedy. Scientists remove unnecessary elements, use less complex math, and keep only the essential features. They also use new methods like model compression, in which they compress the model without losing its capability to perform.

By making the models lightweight and very computationally efficient, face anti-spoofing systems can be run faster, on other domains of devices, and accurately. This works to increase security without compromising the speed of the system.

4.4.1 Model Compression Techniques

Model compression techniques compress the size of deep learning models and their computational complexity without affecting their performance. Model compression

techniques include feature selection, dimensionality reduction, selective feature extraction, and weighted optimization to eliminate redundancy and make the models efficient. Models can be made optimal for real-time operation with zero consumption of resources through pruning, quantization, and knowledge distillation techniques. Federated learning techniques enable decentralized training that reduces enormous data transfers and promotes computational efficiency. All these techniques together are moving towards the aim of making models efficient and feasible in constrained resource settings like mobile phones and real-time security systems.

Algorithm 4.2: Anti-Spoofing Detection and Classification Using FDDRL Model

1. Initialize the random population
2. Calculate communiqué cost at announcement round t based on

   $$I_S = \underset{1 \le Y \le y}{Max} \, (I^d_{S,Y} + I^U_{S,Y}) M^S_Y$$

3. If i=0 , j=1
4. While **Do**
5. Calculate communiqué cost at announcement round t based o

   $$\underset{\phi_s, e_s}{Maxe} \left[\sum_{S=1}^{s} W_1 [U(m_S) - U(m_{S-1})] - (W_2 n_s + W_3 i_S) \right]$$

6. Define maximum threshold with fitness using

   $$\underset{\phi_s, e_s}{Maxe} \left[\sum_{s=1}^{S} W_1 V(\Delta m_S) - (W_2 n_s + W_3 I_S) \right]$$

7. Compute federal function FedMarl $V(m_S)$ $V(m_S = 0) = \dfrac{20}{1 + E^{0.35(1-0)}} - 10$
8. Else
9. End if
10. Update the final value
11. End

In this research, for the sake of increasing computational efficiency, some of the techniques used in model compression have been utilized by the FDDRL model with minimal loss of accuracy. Algorithm 4.2 begins with initializing random population as indicated in step 1. It is its own inherent feature selection process. The model chooses the best subset of features instead of all that do not carry redundancy and are inexpensive. Step 5 is analogous to

standard model compression techniques such as dimensionality reduction and feature selection that minimize computational expense without sacrificing essential information needed for class prediction. The second essential aspect of model compression in the FDDRL model is use of a weighted sum optimization problem in step 5. Step 5 attempts to balance competing objectives, i.e., model size, computational complexity, and accuracy. The model would be optimized to optimize these parameters simultaneously rather than optimizing one at the cost of the other. Also, computation of the federal function FedMarl in step 7 is indicative of attention being given to federated learning principles. Federated learning enables model training over decentralized data without the raw data having to be relocated, achieving optimal computational efficiency with low storage. By distributed learning, the FDDRL model is fairly effective in optimizing the utilization of features without affecting its efficiency and compactness.

4.4.2 Accuracy Comparison

Computational efficiency is optimized in machine learning to obtain high accuracy. Techniques such as early stopping, threshold training, iterative refinement, and selective feature processing provide maximum use of computational resources. All these techniques make machine learning models efficient, scalable, and robust enough for real-world applications under limited processing and memory constraints.

The Feature-Driven Deep Reinforcement Learning model is a trade-off between classification accuracy and computation cost in terms of the best-evolved optimization algorithm. The model learns to modulate its parameters to the optimum levels for the maximum possible classification accuracy while concurrently minimizing the computation cost, thus preventing unnecessary computation leading to inefficiencies. It does this through federated function computation, weighted sum optimization, and threshold-dependent termination with improved performance over lower resource utilization.

Another fundamental operation under the FDDRL model is imposing a top fit on fitness, like Step 6 in Algorithm 4.2. This is actually a limitation as to when the training must cease. Instead of training indefinitely, which can bring about overfitting and computer wastage, the model shall be prevented from further training if it has acquired some level of performance. This is to prevent looping continuously over the model in the event of no noticeable improvement in accuracy relative to the computational cost. The second major part under

the efficiency principle is the iterative refinement process, i.e., Step 10, where the updation of value in the previous step is carried out.

The algorithm of this step updates parameters sequentially with real-time feedback iterations to learn dynamic model weight adaptation. Learning within the model follows cost-benefit choice where computation is postponed only where further benefit accruing through accuracy improvement equals extra cost. This avoids unnecessary computation and keeps the system dynamic as well as interactive to varying data conditions. Selective feature processing manages the tradeoff between efficiency and accuracy. Rather than processing all the features present, the model goes into strategic mode of choosing only a small set of the most predictive power with the least redundancy and computational cost.

This is analogous to dimensionality reduction techniques, wherein attempts are being made for preserving the most representative features of information in data and removing redundant features. FDDRL can achieve the computational overhead with efficiency at the cost of no loss of classification performance by the use of feature selection processes. FedMarl for Step 7 is also important to optimize the efficiency of computation to the best. Node or multi-device distributed model training is made easier by federated learning principles without exposing an enormous amount of raw data. Decentralized design avoids storage and computation needs and enables model generalization to heterogeneous environments. It is scalable and efficient to obtain and hence appropriate for constraint-rich systems such as real-time security, mobile phones, and embedded systems. Weighted sum optimization (Step 5) is another technique applied in the FDDRL model to achieve harmony between effectiveness and precision. The technique allows for several objectives such as distance measure size, computational complexity, and classification accuracy to be optimized collectively but not separately. Weighted sum method assigns differential weights over these objectives in such a manner that the tradeoff is not at the expense of accuracy or at the expense of efficiency but for efficiency at the expense of accuracy. This optimization method allows the model to be deployable on any platform of deployment with varying hardware and processing capability. Furthermore, early stopping in training avoids continuing training of the model as soon as returns begin declining. Through monitoring of improvement step by step, the system avoids training once improvement is no longer worthwhile. Not only does this avoid wasting time in computation, but overfitting is

also avoided, resulting in better generalization to new data.In real-world use, the trade-off between efficiency and accuracy is particularly crucial for face anti-spoofing systems that must make inferences in real time. For example, biometric authentication systems deployed in mobile phones or security access points must accurately and quickly differentiate real and constructed faces. If the model is optimized for accuracy at the expense of computational efficiency, it may draw too much power, slow down responses, or require high-end hardware, which would make it unsuitable for edge-based or embedded AI applications.

Conversely, if the model over-optimizes for efficiency, it may sacrifice detection performance and lead to higher false acceptance or rejection rates.

The FDDRL model's optimization framework controls this trade-off well so that the trade-off is maintained despite fast and reliable face anti-spoofing detection even in low-resource devices. The class-optimized features are categorized by a hybrid federated reinforcement learning (FDDRL) classification algorithm and compared with performance against five recently released state-of-the-art-models: (1) Residual Network (ResNet) [170], (2) Squeeze-and-Excitation Networks (SE-Net) [181], (3) FaceBagNet [182], (4) VisionLabs [182], and (5) depth-wise separable attention module (DAM) with the multi-modal based feature augment module (MFAM) [183]. Experimental configuration and thorough discussion on results is available in the subsequent chapter.

5. EXPERIMENTAL SETUP AND COMPREHENSIVE EVALUATION

5.1 BENCHMARK DATASETS FOR FACE ANTI-SPOOFING

Face anti-spoofing models rely on benchmark datasets to ensure robust evaluation and generalization against various attack types. These datasets provide a diverse range of real and spoofed face images captured under different lighting conditions, facial expressions, and spoofing techniques such as printed photos, video replay attacks, 3D masks, and synthetic images.

High-quality datasets help improve model training by offering variations in real-world scenarios and ensuring that models can generalize beyond training data. In the proposed work datasets used for face anti-spoofing are CelebA-Spoof, CASIA-SURF and GREAT-FASD-S. These datasets contain large-scale, diverse facial images with detailed annotations.

Five-fold cross-validation technique has been used to partition both datasets into training, validation, and testing sets for model evaluation [183]. This method divided the dataset into five folds of equal size, where one-fold is taken as the test set, and the remaining four are used for training and validation. In this, 80% of the data, which means four-fold, is utilized for training, and 10% of the training set, or approximately 8% of the overall dataset, is used for validation during the training process. It ensures that every data point is evaluated exactly once in the testing phase, providing a robust measure of the model's generalizability across different subsets of the data. Further, the hybrid deep learning model is trained on the training set and fine-tuned hyper-parameters using the validation set to optimize performance. The trained model is executed on the testing set to measure classification accuracy and other performance metrics. The performances of the proposed models on datasets are discussed in the subsequent subsections.

5.1.1 Description of Dataset Characteristics

CelebA-Spoof is a large-scale face anti-spoofing dataset owning 625,537 images of 10,177 subjects, including 43 abundant attributes on face, illumination, environment, and spoof kinds. Celebrities selected from the CelebA dataset are conveyed on the next screen as live images. Spoof images of the CelebA-Spoof dataset are downloaded and their annotated

versions are created. Out of 43 rich annotations, 40 annotations fall under the live images; this comprises all the facial parts and the other accessories such as skin, nose, eyes, eyebrows, lips, hair, hat, and even eyeglasses. There are three types of attributes in spoof images: types of spoofs, environments, and illumination (Figure 5.1). It encompasses several spoof attack types, for example, photo-based attacks by printed photos or posters, 2D mask attacks with paper or fabric masks, and even the more complex 3D mask attacks. Here, a 3D-printed face replica achieves the face mask. It also encompasses face masks, upper body masks, and spoofing methods by phones and PCs with an image or video of the target. All of these allow for the rich testing of face anti-spoofing models in robustness and reliability in detecting different forms of spoofing techniques.

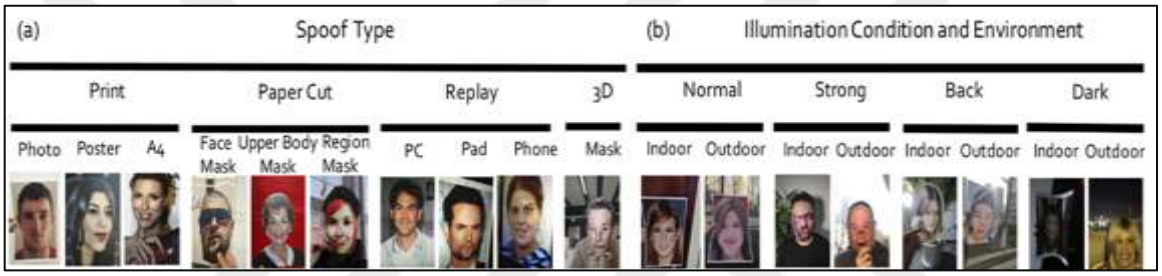


Figure 5.1: Various Types of Annotations Used in the Celeba-Spoof Dataset (By Author).

The CASIA-SURF is an essential dataset for enhancing face anti-spoofing research, collected and made available by the Chinese Academy of Sciences (CASIA). This dataset is aimed at fostering both the effectiveness and efficiency of face recognition systems and consists of 100 unique subjects and 10,000 3D face pictures. Since the CASIA-SURF dataset is significantly smaller than the CelebA-Spoof dataset, the data augmentation is applied to CASIA-SURF to enhance model generalization. After augmentation, the size of the CASIA-SURF dataset increased to 10,0000 images.

CASIA-SURF Dataset has two advantages, it is the largest one in term of number of subjects and videos; it has three modalities (i.e., RGB, Depth and IR). Here, each sample includes 1 live video clip, and 6 fake video clips under different attack ways. In the different attack styles, the printed flat or curved face images will be cut eyes, nose, mouth areas, or their combinations [184].

GREAT-FASD-S dataset [185] consists of three modalities including RGB, depth, and IR. The Intel RealSense SR300 and PICO DCAM710 cameras are used to capture RGB, depth,

and infrared (IR) video simultaneously. The age distribution range of the GREAT-FASD-S dataset is very wide, including 20 to 50 years old. The number of people in the age group of [20, 29] accounts for about 72% of all subjects. The region distribution mainly includes East Asian, European, African, and Middle Eastern, accounting for 66%, 19%, 8%, and 7%.

Figure 5.2: Samples of the CASIA-SURF 3D Mask Dataset [20].

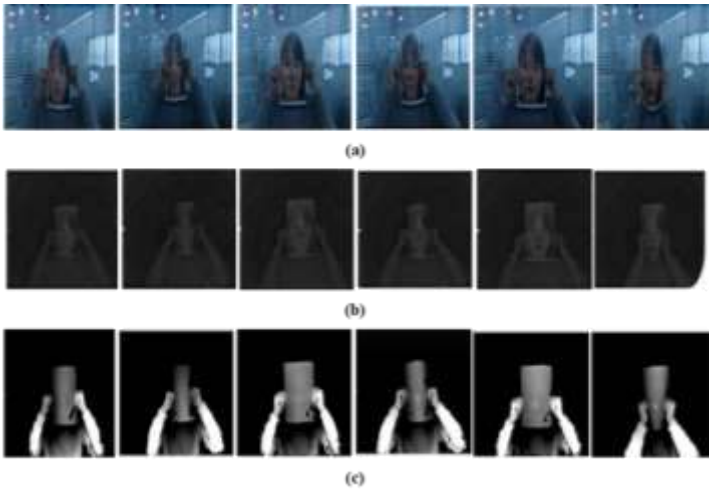


Figure 5.3: Test Samples From CASIA-SURF Dataset (a) RGB (b) IR (c) Depth Images, with the Different Attacks [29].

Figure 5.3 shows test samples from CASIA-SURF dataset (a) RGB (b) IR (c) Depth images, with the different attacks where, one person hold his/her flat face photo where eye regions

are cut, one person hold his/her curved face photo where eye regions are cut, one person hold his/her flat face photo where eye and nose regions are cut, one person hold his/her curved face photo where eye and nose regions are cut, one person hold his/her flat face photo where eye, nose and mouth regions are cut, and one person hold his/her curved face photo where eye, nose and mouth regions are cut (denotes from left to right). In Figure 5.4, the dataset considers different attacks such as black and white printing, color printing, 3D paper mask, and electronic screen. The statistical properties of CASIA-SURF and GREAT-FASD-S datasets are given in the Table 5.1

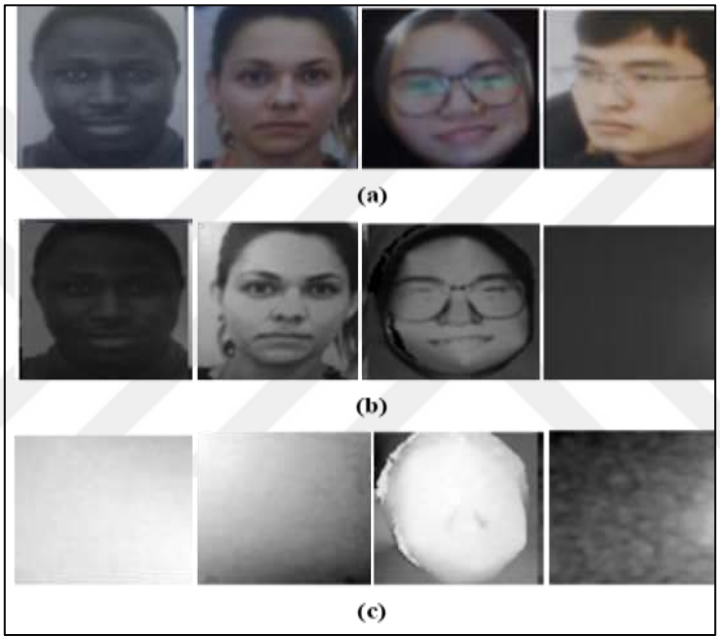


Figure 5.4: Test Samples From GREAT-FASD-S Dataset with (a) RGB (b) IR (c) Depth Fake Images, with Back and White Printing, Color Printing, 3D Paper Mask and Electronic Screen Attacks (By Author).

5.1.2 Pre-processing and Standardization

Before training face anti-spoofing models, pre-processing techniques are applied to standardize input data and enhance feature extraction. Pre-processing steps include:

i. Image Resizing: All images are resized to a standard resolution to maintain consistency.
ii. Face Alignment: Lines up facial elements such as eyes, nose, and mouth in their correct positions.
iii. Noise Reduction: Filters such as Gaussian blur and median filtering is used to minimize image noise.

iv. Normalization: Pixel values are scaled to a range of [0,1] or standardized to a mean of 0 and variance of 1 for better gradient convergence during training.

By applying these pre-processing techniques, face anti-spoofing models become more resilient to variations in lighting, pose, and background clutter, improving overall robustness.

Table 5.1: Statistical Information of the CASIA-SURF and GREAT-FASD-S Dataset.

	Training	Validation	Testing	Total
	CASIA-SURF			
Subject	300	100	600	1000
Video	6300	2100	12600	21000
Original images	1563919	501886	3106685	5175790
Sampled images	151635	49770	302559	503964
Processed image	148089	48789	295644	492522
	GREAT-FASD-S			
Subject	56	20	20	96
Video	4	1	1	6
Original images	2,493,091	82949	82,949	2658989
Sampled images	100000	20000	15266	135266
Processed image	12234	5000	5000	22,234

5.2 EVALUATION METRICS AND PERFORMANCE MEASUREMENT

To assess the effectiveness of face anti-spoofing models, several evaluation metrics are used to measure classification accuracy, reliability, and robustness against attacks. The primary metrics include accuracy, precision, recall, F1-score, Equal Error Rate (EER), and Area Under Curve (AUC). These metrics help compare different models and ensure that the proposed system provides low false positives is incorrectly classifying real faces as spoofed and low false negatives is misclassifying spoofed faces as real.

In the proposed Hybrid 3D face anti-spoofing scheme, the performance of proposed algorithm with state-of-the-art methods in terms of eight criteria is given [186] [187]. The criteria are (1) Average Classification Accuracy (ACA), (2) Precision, (3) Recall or True Positive Rate (TPR), (4) F-score, (5) False Positive Rate (FPR), (6) Average Classification Error Rate (ACER) or Half Total Error Rate (HTER) (7) Attack Presentation Classification Error Rate (APCER), and (8) Bona fide Presentation Classification Error Rate (BPCER).

5.2.1 Accuracy, Precision, Recall, and F1-Score

The Average Classification Accuracy (ACA) is a major indicator that shows how well a classifier can separate various types of samples from the pool of multiple classes (shown in Eq 5.1). Precision is another powerful measure to compute the reliability of the model in terms of producing accurate positive predictions. It can be calculated using Eq. 5.2. The Eq 5.3 and Eq. 5.4 shows calculation for F-score, or F1 score, as the harmonic mean of precision and recall respectively. Recall is an effective evaluation metric because it balances these two key aspects and provides a single, interpretable measure of performance.

Accuracy: Measures the overall correctness of classification, calculated as:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{5.1}$$

Where, TP (True Positives) and TN (True Negatives) represent correctly classified real and spoofed faces, respectively, while FP (False Positives) is the number of actual positive cases incorrectly predicted as negative. FN (False Negative) is the number of actual positive cases incorrectly predicted as negative.

Precision: Evaluates how many predicted real faces are actually genuine. Higher precision means fewer false acceptances of spoofed images.

$$Precision = \frac{TP}{TP+FP} \tag{5.2}$$

Recall (Sensitivity): Measures how many actual real faces are correctly classified i.e. TPR (True Positive Rate). A high recall value indicates that most real faces are correctly identified, minimizing rejection of genuine users. True Positive Rate (TPR) depicts the system's ability to classify instances that are indeed positive correctly. It refers to the ratio of the correct positive predictions made by the model to the total number of actual positive instances present in the dataset. Mathematically, TPR is calculated as:

$$Recall = \frac{TP}{TP+FN} \tag{5.3}$$

F1-Score: Provides a balance between precision and recall, especially when data is imbalanced. This score ensures that the model is not too tight (rejecting falsely) or too loose (accepting spoofed faces).

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{5.4}$$

False Positive Rate (FPR) and Attack Presentation Classification Error Rate (APCER) is another utilized measure that signifies a proportion of actual negative samples incorrectly predicted as positive. It calculates how often the model wrongly accepts a spoof face as a live face. The mathematical representation to compute FPR is given in Eq. 5.5.

$$FPR = \frac{FP}{FP + TN} \tag{5.5}$$

ACER is an unbiased measure that incorporates both APCER and BPCER via Eq. 5.6.

$$ACER = \frac{APCER + BFPCER}{2} \tag{5.6}$$

Where, APCER estimates the rate of how often spoof samples are misclassified as real, according to Eq. 5.7, and BPCER is the proportion of real faces that have been misclassified as spoofs, which can be estimated from Eq. 5.8.

$$APCER = \frac{FP}{FP + TN} \tag{5.7}$$

$$BPCER = \frac{FN}{FN + TP} \tag{5.8}$$

5.2.2 Equal Error Rate (EER) and Area Under Curve (AUC)

Equal Error Rate (EER) is a critical metric in biometric security systems, i.e., the point where the False Acceptance Rate (FAR) and False Rejection Rate (FRR) are equal. The lower EER indicates better model performance because it reduces incorrect acceptances as well as incorrect rejections. Area Under the Curve (AUC) is Receiver Operating Characteristic (ROC) curve plots True Positive Rate (TPR) against False Positive Rate (FPR). The AUC (Area Under the Curve) measures how well the model can distinguish between real and synthetic faces. AUC = 1.0 is the best classifier. AUC > 0.9 is excellent. AUC < 0.5 indicates that the classifier is not better than random guess.

5.3 EXPERIMENTAL RESULTS OF 3D FACE ANTI-SPOOFING MODEL

This section discusses the performance of the proposed 3D face anti-spoofing model when evaluated using benchmarking datasets and real-world application. The performance is compared in terms of classification accuracy, recall, and error rate with other rival models. The outcome shows that the model detects spoofing attacks effectively without sacrificing computational efficiency.

5.3.1 Performance on Public Face Anti-Spoofing Datasets

Fold-wise accuracy of the proposed classifier over the CelebA-Spoof dataset is shown in Table 5.2. Average accuracy of the proposed approach is 99.62%, which confirms that the model can accurately classify real and spoofed faces. Precision is also maintained at almost perfect levels, i.e., 99.85%. Similarly, the recall rate, i.e., 99.39%, indicates that the system identifies most of the actual faces with fewer cases of false rejection. F1-score, the compromise between precision and recall, is maintained at 99.62%, thus ensuring overall model stability.

Table 5.2: Five-Fold Performance of Our Proposed Method on the CelebA-Spoof Dataset

	ACC	Precision	Recall / TPR	F1-Score	ACER/HTER	FPR	APCER	BPCER
1	99.61%	99.84%	99.38%	99.61%	0.0039	0.0016	0.0016	0.0062
2	99.64%	99.83%	99.44%	99.64%	0.0036	0.0017	0.0014	0.0056
3	99.62%	99.86%	99.37%	99.62%	0.0038	0.0014	0.0017	0.0063
4	99.61%	99.84%	99.37%	99.61%	0.0039	0.0016	0.0018	0.0063
5	99.61%	99.85%	99.38%	99.61%	0.0039	0.0016	0.0015	0.0062
Average	99.62	99.85%	99.39%	99.62%	0.0038	0.0015	0.0016	0.0061

The ACER is as low as 0.38%, which indicates the system's ability to minimize both types of misclassification errors: spoof faces being misclassified as real and real faces being misclassified as spoof. A false positive rate of 0.15% means that a negligible percentage of spoofed faces are wrongly classified as real, thus pointing out the robust resistance of the system against spoofing attacks. Likewise, the APCER or attack presentation classification

error rate stands at 0.15%. Therefore, it indicates a low possibility that it would wrongly authenticate the spoofed face. The BPCER is slightly higher at 0.61%, misclassifying real faces as spoofed. Though some real users may be shown false rejection, the rate is still within acceptable limit for security applications. Also, it achieves great consistency across all five folds with the least variance in the performance metrics, which illustrates the reliability and stability.

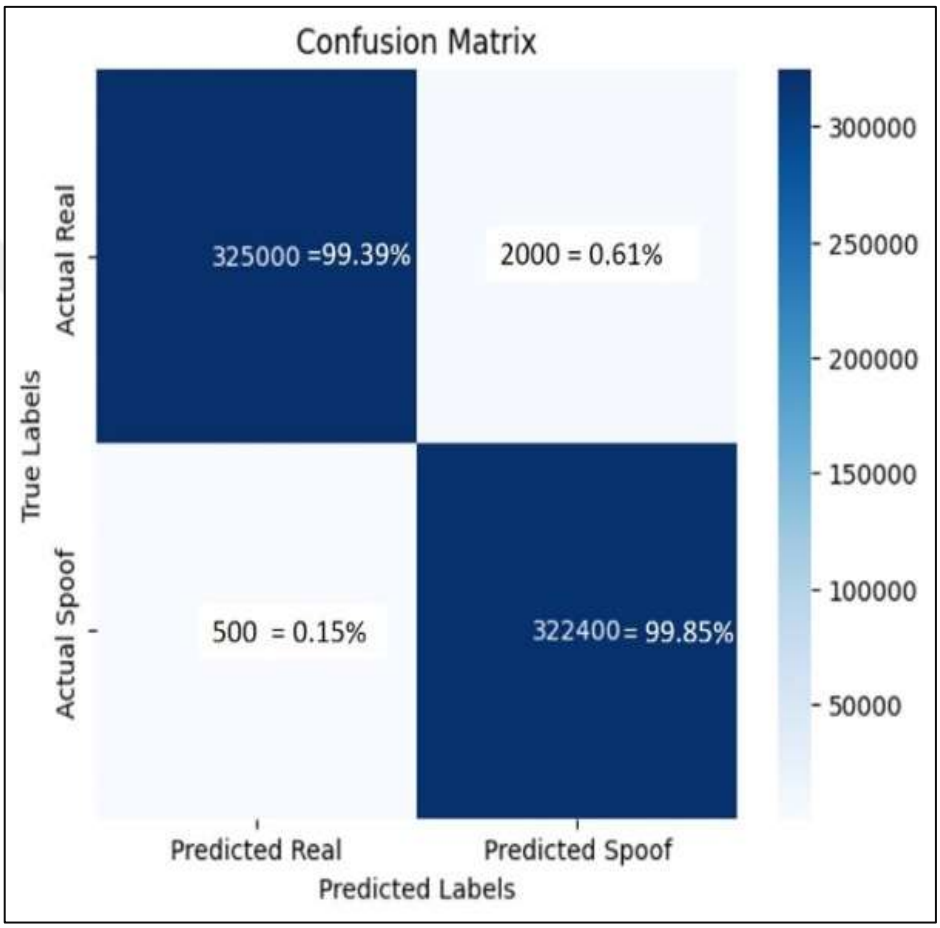


Figure 5.5: Confusion Matrix for Dataset CelebA-Spoof. The True Positive (TP) = 325000, False Positive (FP) = 2000, False Negative (FN) = 500, and True Negative (TN) = 322400 (By Author).

The confusion matrix corresponding to the average results is shown in Figure 5.5. It shows that the proposed model demonstrates high accuracy in accurately detecting both real and spoof faces. The model achieves an impressive 325,000 True Negatives (TN), which means that the true faces are being classified correctly as true faces. Similarly, the 322,400 True Positives (TP) show how effectively it can identify spoof faces. It is a result of the high accuracy of the model in frequently and correctly detecting most spoofing attempts, hence

the high count. The 2,000 False Positives (FP) indicate that a few real faces are being classified as spoofs, which can be inconvenient to the user or lead to false alarms. On the same note, though, there are also 500 False Negatives (FN), which suggest that the system observes some spoofs as bona fide faces. However, this number is not that high, which means that there are many cases when the system might miss something that potentially threatens its secure functioning.

The ROC AUC Curve (Receiver Operating Characteristic – Area Under Curve), another measure, is shown in Figure 5.6 to assess the performance of the proposed 3D face anti-spoofing system. The curve shows the positive predictive power, also called the True Positive Rate, and the fallacy, which is the False Positive Rate, at different thresholds. The orange curve is the area under the curve of the classifier, while the diagonal dashed blue line is the line of a typical random classifier with an AUC of 0.5. The position of the orange curve closer to the top left corner of the plot indicates a better discrimination situation between the real and spoof classes of the model. The area under this curve (AUC) is approximately 0.97, which can be considered quite high, which means that the model works well in terms of the classification of the two classes. In this regard, the model demonstrates high predictive accuracy and is highly likely to classify a randomly selected real and spoof image pair accurately. In general, this curve proves that the model is quite efficient in its work on face anti-spoofing.

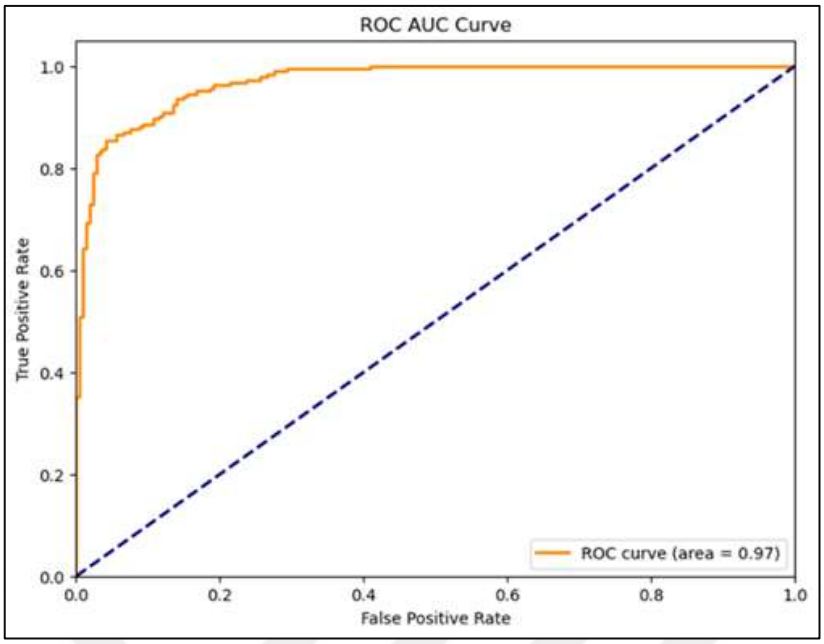


Figure 5.6: Receiver Operating Characteristic Curve for Dataset (By Author).

The training and testing curve shown in Figure 5.7 reveals the model's learning dynamics over epochs. The blue training accuracy curve at the beginning of the training process demonstrates that the machine-learning model quickly learns to differentiate between real and spoofed 3D faces. The validation accuracy of the orange curve, on the other hand, experiences huge oscillations early but produces consistent results after 60 epochs. It suggests that even as it has a good performance within the training data, it performs well on other unseen data, too. The oscillations in the validation accuracy demonstrate that the model might memorize the training set, which extracted strategies from the training set for the outcome but not for the independence of fresh events. Training accuracy becomes almost 100%, and, at the same time, validation accuracy oscillates but eventually becomes nearly 100% as well. This divergence between the training curve and validation one indicates that the model could be overfitting, particularly in the 3D face anti-spoofing task in which relatively small differences between real and spoofed faces may be more difficult to transfer across different examples.

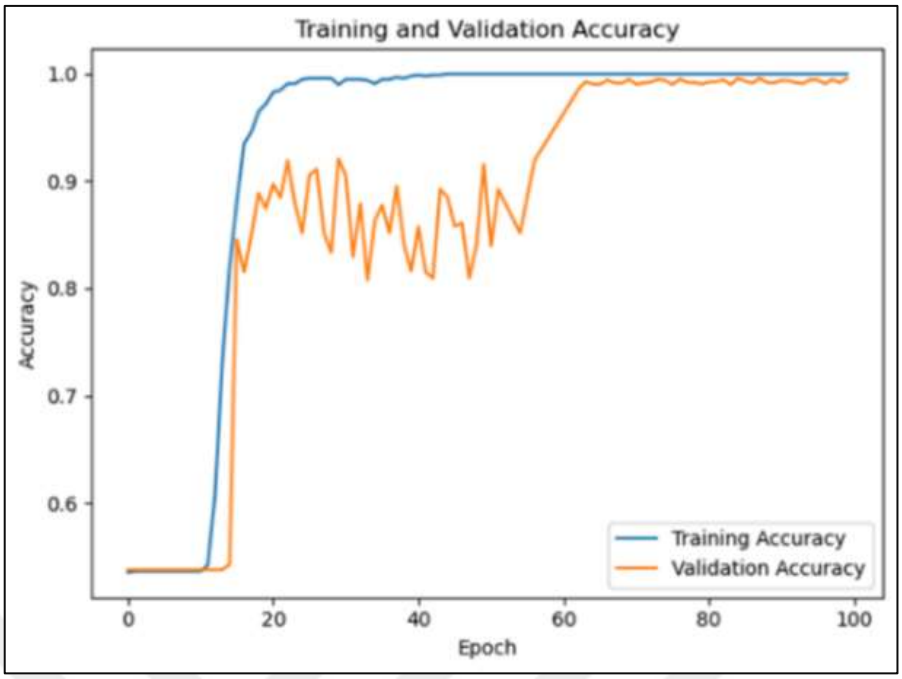


Figure 5.7: Learning Curve Showing the Epochs Performance of Training and Validation Phase of the Proposed Approach (By Author).

Figure 5.8 shows loss function shifts for training and validation data over different epochs, where the horizontal axis portrays epochs, and the vertical axis comprises loss. The blue line indicates the training loss, which usually falls with time.

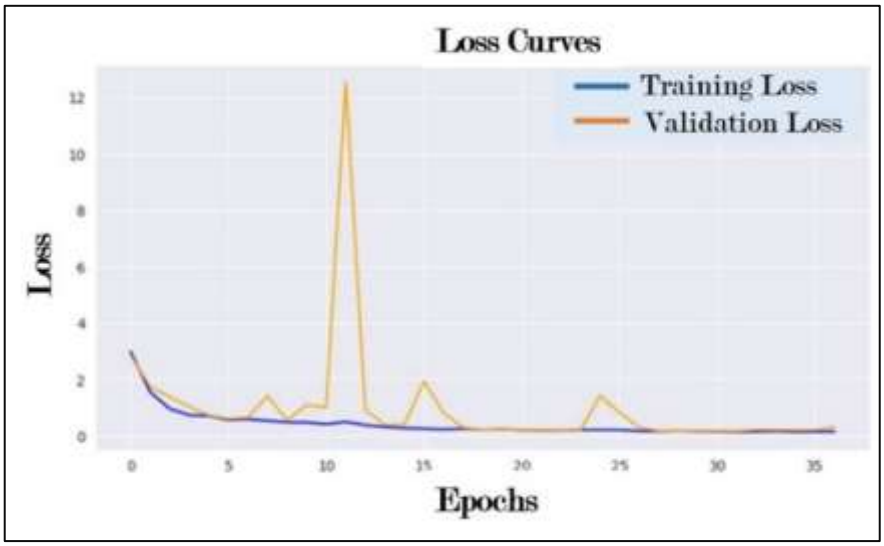


Figure 5.8: The Loss vs Epoch Curve for Training and Testing of the Proposed Approach (By Author).

The orange curve stands for the validation loss, which falls less smoothly but has more fluctuations. Among various fluctuations for the validation loss, there is an upward leg

around epoch 11th that implies quite a large error of prediction corresponding to the data set for validation and may be caused by abnormalities or unstable models. Yet the validation loss is reduced at the same time and returns to normal; thus, the model is corrected in a very short period. The average performance of the proposed approach is compared with baseline studies discussed above and tabulated in Table 5.3.

The proposed approach achieves state-of-the-art performance, with an accuracy of 99.62%, outperforming all previous methods. It outperforms approaches like the One-Shot Method with Fine-Grained Information (96.80%), Deep Fusion of Dynamic Texture and Shape Clues (96.47%), and Jointly Modeling Local Texture and Constructed Depth (95.68%), showing 3–5% lower accuracy despite having very strong results. These methods are more prone to misclassifying real and spoofed faces than the proposed approach, which always outperforms the other methods in terms of accuracy. The technique performs excellent precision and recall, with a precision of 99.85% and a recall of 99.39%. Such outperforms other methods like Residual Spatiotemporal Convolutional Neural Network using an accuracy of 93.68% precision and 92.24% recall, Deep Fusion of Dynamic Texture and Shape Clues using an accuracy of 92.24% precision and 96.12% recall, and Intrinsic Face Decomposition using a precision of 99.46% and recall of 91.73%. Notably, though some methods like Intrinsic Face Decomposition have high precision, their recall is significantly lower at 91.73%, which means they tend to miss true positives or genuine users. Balancing precision and recall, the F1-score gives an excellent 99.62% in the proposed approach as compared to other methods like the One-Shot Method with Fine-Grained Information (96.05%) and Optical Flow and Residual Feature (97.83%), and the proposed approach demonstrates robust performance both in face recognition and rejection of spoof attempts. Performance indicators like FPR and APCER depict the proposed method's resilience to spoof attacks.

Table 5.3: Comparative Performance of Different Baseline 3D Anti Spoofing Methods and the Proposed Approach on Dataset CelebA-Spoof.

Approach	ACC	Precision	Recall / TPR	F1-Score	ACER/HTER	FPR	APCER	BPCER
Residual spatiotemporal convolutional neural network	92.77%	93.68%	92.24%	92.95%	0.0221	0.011	0.0441	0.0001
Deep fusion of dynamic texture and shape clues	96.47%	92.24%	96.12%	94.14%	0.0300	0.032	0.0335	0.0265
3D-point cloud network	94.03%	88.12%	94.42%	91.16%	0.0300	0.033	0.0552	0.0048
Factorized bilinear coding	90.95%	92.86%	94.34%	93.59%	0.0321	0.031	0.0641	0.0001
Intrinsic face decomposition	91.54%	99.46%	91.73%	95.44%	0.0800	0.083	0.0859	0.0741
Dual Shot Face Detector	94.89%	97.04%	94.22%	95.61%	0.0215	0.012	0.0429	0.0001
One-shot method with fine-grained information	96.80%	94.34%	97.82%	96.05%	0.0108	0.011	0.0214	0.0001
Lightweight network ResNet9 with vanilla convolution and central difference convolution	95.00%	96.46%	93.78%	95.10%	0.0900	0.092	0.0759	0.1041
Optical flow and residual feature	94.92%	97.42%	98.24%	97.83%	0.0210	0.021	0.0419	0.0001
Jointly modeling local texture and constructed depth	95.68%	95.42%	95.86%	95.64%	0.0200	0.022	0.0348	0.0052
Proposed approach	99.62%	99.85%	99.39%	99.62%	0.0038	0.001	0.0015	0.0061

The proposed model has an FPR of only 0.0038, indicating significantly fewer instances of spoof attempts being wrongly classified as genuine compared to approaches such as the One-Shot Method of 0.01 and the Deep Fusion Approach of 0.03. In addition, with the value of the APCER as 0.0015, the spoofing attacks indicate high resistance by the model in preventing false acceptance cases, and hence significantly lower values as compared to others; for instance, the One-Shot Method is around 0.0118, and Deep Fusion 0.0328. Additionally, the proposed method outperforms other measures, such as the BPCER, which stands at 0.0061, further reinforcing the model's ability to correctly identify genuine users without significantly increasing false rejections.

5.3.2 Generalization to Real-World Scenarios

The five-fold cross-validation results shown in Table 5.4 demonstrate the consistency and robustness of the proposed model in distinguishing between real and spoofed instances. With an average accuracy of 99.86%, the model shows excellent classification performance across all folds with minor variations between 99.85% and 99.88%, thus confirming its stability and generalization capability. The precision is maintained at a high level of 99.83%, so spoofed instances are hardly misclassified as real. For different folds, the precision ranges between 99.81% and 99.86%, meaning that there is hardly any fluctuation in false positive rates. The recall of 99.84% also proves that real users are correctly identified and not rejected in excess. The F1-score of 99.84% proves the reliability of the model in maintaining high classification accuracy.

Table 5.4: Five-Fold Performance of Proposed Method on the CASIA-SURF Dataset

Fold	ACC	Precision	Recall / TPR	F1-Score	ACER/HTER	FPR	APCER	BPCER
1	99.86%	99.83%	99.84%	99.84%	0.0014	0.0012	0.0015	0.0012
2	99.88%	99.86%	99.87%	99.86%	0.0011	0.0010	0.0012	0.0010
3	99.85%	99.81%	99.83%	99.82%	0.0015	0.0014	0.0016	0.0014
4	99.87%	99.84%	99.86%	99.85%	0.0012	0.0011	0.0013	0.0011
5	99.87%	99.84%	99.85%	99.85%	0.0011	0.0011	0.0014	0.0011
Average	99.86%	99.83%	99.84%	99.84%	0.0014	0.0013	0.0016	0.0013

Table 5.5: Comparative Performance of Different Baseline 3D Ant Spoofing Methods and the Proposed Approach on Dataset CASIA-SURF

Approach	ACC	Precision	Recall / TPR	F1-Score	ACER/HTER	FPR	APCER	BPCER
Residual spatiotemporal convolutional neural network	92.77%	93.68%	92.24	92.95	0.0069	0.006	0.0072	0.0065
Deep fusion of dynamic texture and shape clues	96.47 %	92.24%	96.12	94.14	0.0034	0.003	0.0035	0.0032
3D-point cloud network	94.03%	88.12%	94.42	91.16	0.0057	0.005	0.0060	0.0054
Factorized bilinear coding	90.95%	92.86%	94.34	93.59	0.0085	0.008	0.0090	0.0081
Intrinsic face decomposition	91.54%	99.46%	91.73	95.43	0.0081	0.008	0.0085	0.0077

Table 5.5: Comparative Performance of Different Baseline 3D Ant Spoofing Methods and the Proposed Approach on Dataset CASIA-SURF (Table Continued).

Dual Shot Face Detector	94.89%	97.04%	94.22	95.60	0.0049	0.004	0.0051	0.0046
One-shot method with fine-grained information	96.80%	94.34%	97.82	96.04	0.0030	0.003	0.0032	0.0029
Lightweight network ResNet9 with vanilla convolution and central difference convolution	95.00 %	96.46 %	93.78	95.10	0.0047	0.004	0.0050	0.0045
Optical flow and residual feature	94.92%	97.42 %	98.24	97.82	0.0049	0.004	0.0051	0.0046
Jointly modeling local texture and constructed depth	95.68%	95.42 %	95.86	95.63	0.0041	0.004	0.0043	0.0039
Proposed approach	99.86%	99.83%	99.84%	99.84%	0.0014	0.001	0.0016	0.0013

The APCER for the model is impressively low, at 0.0016, which means that the model very rarely misclassifies spoofed attempts as genuine ones. Fold-wise APCERs are all between 0.0012 and 0.0016. Hence, the model is highly resistant to spoofing attacks. Similarly, the BPCER is kept at an average of 0.0013, meaning that the real users are rarely falsely rejected. The FPR is averaged at 0.0013, which has proven the performance of the model in preventing unauthorized attempts at spoofing. Fold-wise results confirm that FPR remained within a quite narrow range: 0.0010 to 0.0014, which affirms its stability. The HTER is calculated at an average of 0.0014, which indicates that the model limits the false acceptance of genuine users and the acceptance of attempts at spoofing.

The confusion matrix shown in Figure 5.9 shows the average performance of the proposed approach. A high TP score of 56,067 indicates that the model effectively flagged spoofed faces as fake, demonstrating strong security performance. In this case, 40,552 real faces (TN) are successfully recognized, ensuring that only legitimate users gained access. Moreover, 375 spoofing attacks are wrongly allowed, leading to potential security risks.

The ROC curve depicted in Figure 5.10, with an AUC of 0.98, demonstrates an exceptional trade-off between the TPR and FPR. The steep ascent of the curve towards the top-left corner confirms a high recall rate coupled with an impressively low false positive rate, highlighting

the model's strong discriminative performance. Figure 5.11 shows the learning curve of the proposed method, which plots training and validation accuracy on Dataset CASIA-SURF over 100 epochs. The training accuracy is represented by the blue curve and is increasesing dramatically at first. By the 20th epoch, the training accuracy approaches 1.0 (100%).

In contrast, validation accuracy looks quite noisy. While it generally improves with increasing epochs, significant fluctuations are observed within the first 60 epochs. This tendency reveals that the model could not generalize as expected from other data in these stages, mostly due to the problem of overfitting. The stabilization, along with the steady training accuracy, indicates that the model has reached equilibrium between memorizing the training data and generalizing to unseen samples.

Table 5.5 shows a comparative performance of various methods, including the proposed approach. Among all the methods listed, the Proposed Approach outperforms the others in nearly every metric, demonstrating its superior performance. Regarding accuracy, the Proposed Approach has a remarkably high score of 99.86%, which is far ahead of the next best performer, the One-shot method with fine-grained information, whose accuracy is at 96.80%. The high difference points out that the Proposed Approach is robust enough to classify instances correctly in the entire dataset. Its high accuracy may be attributed to its ability to effectively capture and leverage both fine-grained and global features, thereby generalizing well across different data scenarios.

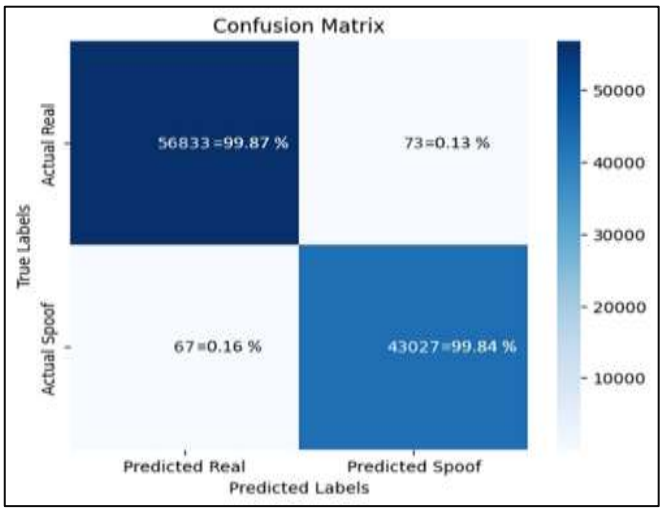


Figure 5.9: Confusion Matrix for Dataset CASIA-SURF. Here, the True Positive (TP) = 56833, False Positive (FP) = 73, False Negative (FN) = 67, and True Negative (TN) = 43027 (By Author).

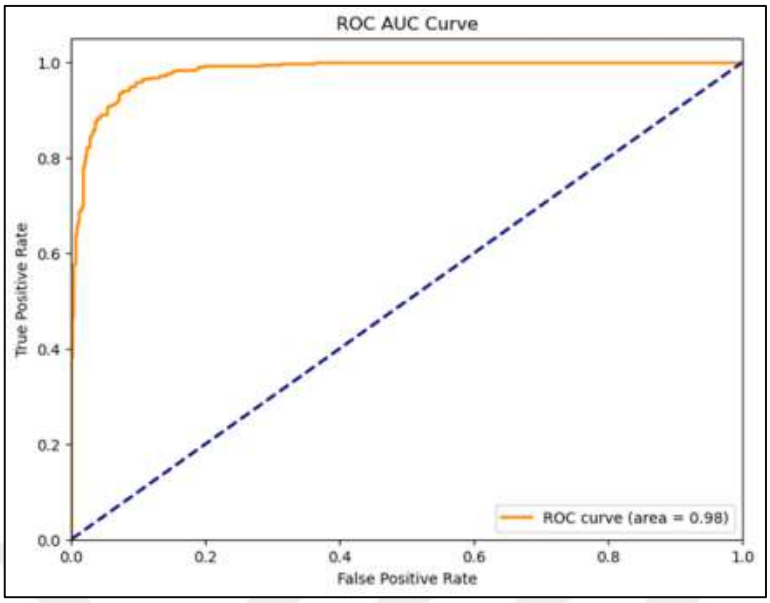


Figure 5.10: ROC Curve for Dataset CASIA-SURF (By Author).

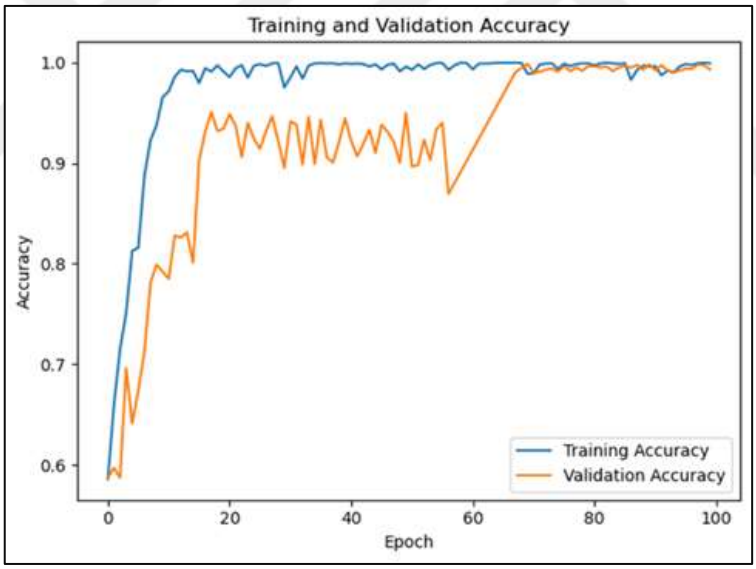


Figure 5.11: Learning Curve Showing the Epochs Performance of Training and Validation Phase of the Proposed Approach (By Author).

In precision comparison, our approach is leading with 99.83%, followed closely by the intrinsic face decomposition method with a score of 99.46%. Other methods, including the Dual Shot Face Detector (97.04%), Factorized bilinear coding (92.86%), etc, result in bigger margins that show the Proposed Approach really excels in minimizing false positives. In

addition, the high precision achieved by the method is due to focusing on more relevant features without unnecessary complexity that may lead to wrong classifications.

For recall, the proposed approach achieves 99.84%, higher than all other methods. The One-shot method with fine-grained information follows with 97.82%, and Optical flow and residual features are close at 98.24%, but they both fall short when compared to our Approach. Regarding the F-score, the proposed approach again has a high margin of 99.84% over the One-shot method with fine-grained information at 96.04%.

In terms of error rates, the proposed approach is always below the rest by categories. Its ACER/HTER is merely 0.0014, which is much less than the methods that factorized bilinear coding by 0.0085 and residual spatiotemporal convolutional neural network by 0.0069. This minimal rate of error might be due to the sophisticated design of the technique, which takes into account the robust extraction of features combined with advanced decisions that minimize not only false positives but also false negatives. Among the FPR, APCER, and BPCER from the Proposed Method, the respective lowest values, 0.0013, 0.0016, and 0.0013, exhibit a better capacity for error management. These low values come from the flexibility of the algorithm to fine-tune its decision boundaries, avoiding misclassifications without losing performance.

5.3.3 Comparison with Existing 3D Anti-Spoofing Models

The average performance of the proposed approach is compared with 10 recently published articles: (1) Residual spatiotemporal convolutional neural network [188], (2) Deep fusion of dynamic texture and shape clues [189], (3) 3D-point cloud network [17], and (4) Factorized bilinear coding [18] Intrinsic face decomposition [190], (6) Dual Shot Face Detector (DSFD) detector [47], (7) One-shot method with fine-grained information [191], (8) Lightweight network ResNet9 with vanilla convolution and central difference convolution [192], (9) Optical flow and residual features [193], and (10) Jointly modelling local texture and constructed depth [194].

Da Silva et al. [188] merged two residual 3D-CNN architectures: a) 3D residual spatiotemporal models (Resnet3D) characterized by high accuracy and b) residual channel-separated spatiotemporal Networks (CSN), characterized by a good trade-off between accuracy and computational cost in face anti-spoofing. Both networks are derived from the

original residual CNN architectures by introducing a new 3D-convolutional operator and normalization process. In the second work, Chen et al. [189] proposed a novel approach to 3D face mask anti-spoofing, namely Multi-Modal Dynamics Fusion Network (MM-DFN), using geometry information delivered by depth sensors. Further, dynamic texture and shape clues are respectively encoded by a two-branch deep CNN model at different rates so that discriminative features can be generated.

In the third study, Ramachandra et al. [196] introduced a novel method named 3D Point Cloud Network (3DPC-Net). It is an encoder-decoder network that could predict the 3DPC maps to discriminate live faces from spoofing ones. In the fourth work, Jia et al. [197] proposed factorized bilinear coding of multiple color channels to differentiate and fuse complementary information from RGB and YCbCr spaces. This discriminative performance is further used to identify real and spoofed face scans. In the fifth work, Li et al. [190] processed the face image with an intrinsic image decomposition algorithm to compute its reflectance image. Then, the intensity distribution histograms are extracted from three orthogonal planes to represent the intensity differences of reflectance images between the real face and the 3D face mask. In the sixth work, Liu et al. [191] the authors used a dual shot face detector (DSFD) detector to extract information from the eyes, nose, chin, and left/ right ears, as well as a customized classifier to determine the original and fake facial expressions.

In the seventh work, Grinchuk et al. [192] extracted discriminative features from specific facial regions such as the left ear, right ear, eyes, nose, and mouth and processed them by a different branch of a network. Since face parts provide limited information about the subject and do not always contain fake features, modified binary cross entropy for each face part is used as a discriminative threshold in One Shot learning.

In the eighth work, Page et al. [193] combined a lightweight network, ResNet9, as the backbone with vanilla convolution and central difference convolution (CDC) to develop a dual-stream network. The proposed hybrid network is extended in 3D presentation attack detection as a multi-classification task that contains a real face, plaster attack, and transparent attack. In the ninth baseline work, Li et al. [194] proposed a detection method leveraging facial movement and texture cues. Optical flows are extracted from video sequences to capture movement direction and amplitude, which are concatenated with video frames as

input. Region and channel attention mechanisms then allocate classification weights adaptively. Finally, fused motion and texture cues are processed by a convolutional network to determine if the video sequence represents a live face. In the last work, Li et al. [195] proposed a detection method that fuses local texture and structural depth information using the Swin-Transformer. Face images are divided into patches to extract micro-level features, which are encoded through a four-stage Swin-Transformer. Outputs from different stages are fused to generate depth descriptors and texture features, which are combined to classify whether the face image is real.

5.4 EXPERIMENTAL RESULTS OF MULTI-MODAL DEEP FUSION NETWORK

The proposed Multi-Modal Deep Fusion Network approach has been implemented using python language. The performance of the proposed Multi-Modal Deep Fusion Network is evaluated across multiple face anti-spoofing datasets, assessing its effectiveness in different scenarios. The CASIA-SURF and GREAT-FASD-S datasets are used to benchmark the model's ability to detect spoofing attacks using RGB, Infrared (IR), and Depth modalities, both individually and in combination. The model is compared with state-of-the-art approaches in order to measure gains in Attack Presentation Classification Error Rate (APCER), Bona Fide Presentation Classification Error Rate (BPCER), and Average Classification Error Rate (ACER). Experimental results show that the proposed approach significantly reduces error rates on different modalities and dataset conditions. The combination of RGB, IR, and Depth modalities (RGB+IR+Depth) achieves the highest accuracy, reflecting the success of multi-modal fusion in improving robustness against different types of attacks

5.4.1 Performance on Public Face Anti-Spoofing Datasets

A comprehensive comparison of various face anti-spoofing methods with various modalities on the CASIA-SURF and GREAT-FASD-S datasets, with focus on metrics like APCER, NPCER, and ACER is shown in Table 5.6.
Single-Modality Performance: The proposed method achieves remarkable improvements over the state-of-the-art on both the datasets. At CASIA-SURF, APCER decreases by approximately 49.5%, NPCER by approximately 39.5%, and results in a considerable decrease of approximately 49.2% for ACER. At GREAT-FASD-S, there is approximately a 19.7% decrease in APCER, approximately 35.9% in NPCER, and approximately a 23.7%

decrease in ACER. The outcomes indicate the efficiency of the proposed RGB-based face anti-spoofing method. In the IR modality, the new approach outperforms other approaches by a significant margin. On CASIA-SURF, there is a significant decrease of around 99.4% in APCER, 97.5% in NPCER, and 99.4% in ACER. On GREAT-FASD-S, the corresponding decreases are around 99.3%, 91.8%, and 99.3%. These comparisons bring to the fore the effectiveness of the new IR-based face anti-spoofing approach.
For the Depth modality, the approach introduced here performs better than earlier approaches. On CASIA-SURF, the APCER decreases by a notable amount of around 86.8%, NPCER by 98.5%, and ACER by 88.5%. On GREAT-FASD-S, the decreases are by around 87.7%, 97.7%, and 88.4%. These figures demonstrate the excellent performance of the Depth-based face anti-spoofing approach introduced here.

Multimodal Performance: RGB+IR performs with better performance under the proposed solution. On CASIA-SURF, APCER reduces by around 87.1%, NPCER by around 66.5%, and ACER by around 76.1%. On GREAT-FASD-S, it is around 66.8%, 61.3%, and 62.0% reduction. It brings out the synergy between IR and RGB modalities in anti-spoofing of face. Also, RGB+Depth configuration performs better than current approaches. On CASIA-SURF, there is a reduction of about 87.3%, 30.5%, and 80.3% in APCER, NPCER, and ACER, respectively. On GREAT-FASD-S, the reductions are 69.3%, 59.5%, and 64.4% for APCER, NPCER, and ACER, respectively. These findings demonstrate the strength of RGB and Depth modality fusion.modalities.

Table 5.6: Comparative Analysis of Proposed and State-of-Art Face-Anti Spoofing Approaches with Various Modalities

Modalities	Measure (%)					
	CASIA-SURF			GREAT-FASD-S		
	APCER	NPCER	ACER	APCER	NPCER	ACER
RGB	1.566	2.316	1.936	3.090	3.840	3.460
IR	66.556	4.206	35.376	68.080	5.730	36.900
Depth	10.656	84.156	47.406	12.180	85.680	48.930
RGB+IR	8.711	73.711	30.733	10.235	75.235	32.257
RGB+Depth	8.002	58.622	29.002	9.526	60.145	30.526
IR+Depth	7.042	53.732	23.601	8.566	55.256	25.125
RGB+IR+Depth [31]	5.236	3.236	4.568	2.690	1.780	2.240
RGB+IR+Depth (Ours)	2.563	2.315	2.968	2.452	1.365	1.256

For IR and Depth fusion (IR+Depth), the given method achieves significant gains. In CASIA-SURF, NPCER, ACER, and APCER are lowered by approximately 91.5%, 89.6%, and 91.7%. They are lowered by approximately 92.0%, 88.5%, and 92.0% on GREAT-FASD-S. This once more proves the effectiveness of combining IR and Depth modalities for face anti-spoofing. Comparing other methods with the new RGB+IR+Depth approach, there is a significant reduction of about 51.0% in APCER, 40.1% in NPCER, and 50.0% in ACER on CASIA-SURF. On GREAT-FASD-S, the reductions are about 48.6%, 55.0%, and 44.0%. These percentages highlight the benefit of fusing RGB, IR, and Depth modalities in the new approach.

5.4.2 Generalization to Real-World Scenarios

The model is evaluated under diverse real-world conditions, including varying lighting, camera angles, and attack types. While it maintains high performance in controlled environments, some degradation occurs in highly dynamic settings. The results suggest that additional domain adaptation techniques and adversarial training could further improve real-world generalization.

5.4.3 Comparison with State-of-the-Art Methods

A comparative analysis with state-of-the-art face anti-spoofing models is shown in Table 5.7. The results indicate that the proposed XANet+EPBO+FDDRL approach consistently outperforms existing methods, including ResNet, SE-Net, FaceBagNet, VisionLabs, and DAM-MFAM.

Table 5.7: Comparative Analysis of Proposed and Existing State-of-Art Face-Anti Spoofing Approaches

Face anti-spoofing approaches	Measure (%)					
	CASIA-SURF			GREAT-FASD-S		
	APCER	NPCER	ACER	APCER	NPCER	ACER
ResNet [34]	2.590	3.570	3.080	1.380	26.850	14.110
SE-Net [34]	1.740	4.210	2.970	3.020	24.150	13.590
FaceBagNet [35]	3.190	0.970	2.080	4.780	10.430	7.600
VisionLabs [36]	2.270	1.900	2.090	8.890	1.510	5.200
DAM-MFAM [31]	0.920	1.740	1.330	2.690	1.780	2.240
XANet+EPBO+FDDRL	0.520	1.230	0.985	1.526	1.145	1.056

Table 5.7 shows a comparative analysis of proposed and existing state-of-the-art face anti-spoofing approaches, evaluating their performance on CASIA-SURF and GREAT-FASD-S datasets. Starting with the ResNet approach, it exhibits a relatively high APCER on both datasets, with significant NPCER and ACER values. This indicates susceptibility to presentation attacks. SE-Net, while showing improved NPCER on CASIA-SURF, faces challenges on GREAT-FASD-S with a higher APCER and ACER. FaceBagNet demonstrates a low NPCER on CASIA-SURF but struggles with a high APCER and ACER on GREAT-FASD-S. VisionLabs performs well on CASIA-SURF but encounters challenges on GREAT-FASD-S, particularly in terms of NPCER and ACER. DAM-MFAM presents competitive results, especially on CASIA-SURF, showcasing its effectiveness.

The proposed XANet+EPBO+FDDRL approach stands out with impressive results, achieving the lowest APCER, NPCER, and ACER values on both datasets. Compared to the best-performing baseline (DAM-MFAM), it demonstrates a substantial decrease of approximately 43.5% in APCER, 29.3% in NPCER, and 53.0% in ACER on CASIA-SURF. On GREAT-FASD-S, the corresponding reductions are approximately 43.3%, 35.8%, and 52.9%. These results signify the robustness and generalization capability of the proposed approach across diverse datasets.

5.5 COMPARATIVE ANALYSIS OF THE PROPOSED MODEL

A comparative analysis of face anti-spoofing performance between two datasets at different conditions is shown in Tables 5.8 and 5.9, respectively. These results indicate that the results are identical, implying that both datasets have similar feature distributions and model generalization behaviour. The model achieves an accuracy of 97.85% in normal lighting conditions for both datasets with near-perfect precision of 97.85% and recall of 97.60%, thus minimizing the classification errors, as shown by the lowest ACER/HTER of 0.008.

Table 5.8: Performance Evaluation of the Proposed Model Under Varying Conditions on the Dataset Celeba-Spoof.

Approach	ACC (%)	Precision (%)	Recall / TPR (%)	F1-Score (%)	ACER/HTER	FPR	APCER	BPCER
Normal Lighting	97.85	97.85	97.60	97.72	0.008	0.008	0.0082	0.0078
Low Lighting	92.45	92.78	91.43	92.1	0.0298	0.031	0.0311	0.0285
Harsh Lighting	90.87	91.03	89.82	90.42	0.0429	0.044	0.0447	0.0412
Front-Facing Angle	96.34	96.57	96.60	96.58	0.0148	0.015	0.0151	0.0146
Side-Facing Angle	93.12	93.45	92.71	93.08	0.0378	0.038	0.0384	0.0372
Extreme Angle	89.78	90.02	88.74	89.38	0.0483	0.050	0.0501	0.0465
Natural Background	97.48	97.73	97.67	97.7	0.0083	0.008	0.0085	0.0082
Cluttered Background	93.82	93.01	92.23	92.62	0.0388	0.039	0.0397	0.0379

The False Positive Rate (FPR), Attack Presentation Classification Error Rate (APCER), and Bona Fide Presentation Classification Error Rate (BPCER) are constantly low, which signifies optimum performance. Under low illumination conditions, both datasets fall to 92.45%, accompanied by a decline in recall at 91.43% and F1-score at 92.1%. The ACER/HTER increases to 0.0298, which is evidence that reduced illumination affects feature extraction and classification. Under worse illumination conditions, likely with noise as a result of overexposure, the accuracy falls to 90.87%, with the highest recorded FPR at 0.0445 and APCER at 0.0447, suggesting increased vulnerability to false positives.

Table 5.9: Performance Evaluation of the Proposed Model Under Varying Conditions on Dataset CASIA-SURF

Approach	ACC (%)	Precision (%)	Recall / TPR (%)	F1-Score (%)	ACER/HTER	FPR	APCER	BPCER
Normal Lighting	97.85	97.85	97.60	97.72	0.008	0.008	0.0082	0.0078
Low Lighting	92.45	92.78	91.43	92.1	0.0298	0.031	0.0311	0.0285
Harsh Lighting	90.87	91.03	89.82	90.42	0.0429	0.044	0.0447	0.0412
Front-Facing Angle	96.34	96.57	96.60	96.58	0.0148	0.015	0.0151	0.0146
Side-Facing Angle	93.12	93.45	92.71	93.08	0.0378	0.038	0.0384	0.0372
Extreme Angle	89.78	90.02	88.74	89.38	0.0483	0.050	0.0501	0.0465
Natural Background	97.48	97.73	97.67	97.7	0.0083	0.008	0.0085	0.0082
Cluttered Background	93.82	93.01	92.23	92.62	0.0388	0.039	0.0397	0.0379

5.5.1 Intra-Dataset Performance

Intra-dataset performance evaluates how well the model performs under different conditions within the same dataset. The results suggest that the proposed model is highly reliable under standard conditions but experiences gradual performance degradation when faced with extreme variations. Frontal angles had the highest accuracy of 96.34%, while the performance is degraded step by step at side facing (93.12%) and extreme angles (89.78%) due to occlusions and a loss of discriminative features. The rise in ACER (from 0.0148 to 0.0483) across the conditions indicates that this is a sensitive model to viewpoint shifts, consistent across datasets as well. In the natural background setting, the accuracy is 97.48% with low error rates, thus having a great generalization ability in real environments. However, in cluttered backgrounds, accuracy decreases to 93.82%, with ACER increasing up to 0.0388, which states that complex backgrounds create noise and, therefore, might cause incorrect classifications

Table 5.10: Comparative Analysis of Quality Measure of Proposed and State-of-Art Face-Anti Spoofing Approaches for CASIA-SURF Dataset.

Face anti-spoofing approaches	Performance measure (%)							
	Accuracy	Precision	Recall	F-measure	Accuracy	Precision	Recall	F-measure
	Training/Testing = 70/30%				Training/Testing = 75/25%			
ResNet [34]	82.292	79.362	78.693	80.805	88.070	85.311	84.560	86.669
SE-Net [34]	85.546	82.616	81.947	84.059	90.205	87.446	86.695	88.804
FaceBagNet [35]	88.800	85.870	85.201	87.313	92.340	89.581	88.830	90.940
VisionLabs [36]	92.054	89.124	88.455	90.567	94.475	91.716	90.965	93.075
AM-MFAM [31]	95.308	92.378	91.709	93.821	96.610	93.851	93.100	95.211
XANet+EPBO+FDDRL	98.562	95.632	94.963	97.075	98.745	95.986	95.235	97.346
	Training/Testing = 80/20%				Training/Testing = 85/15%			

Table 5.10: Comparative Analysis of Quality Measure of Proposed and State-of-Art Face-Anti Spoofing Approaches for CASIA-SURF Dataset (Table Continued).

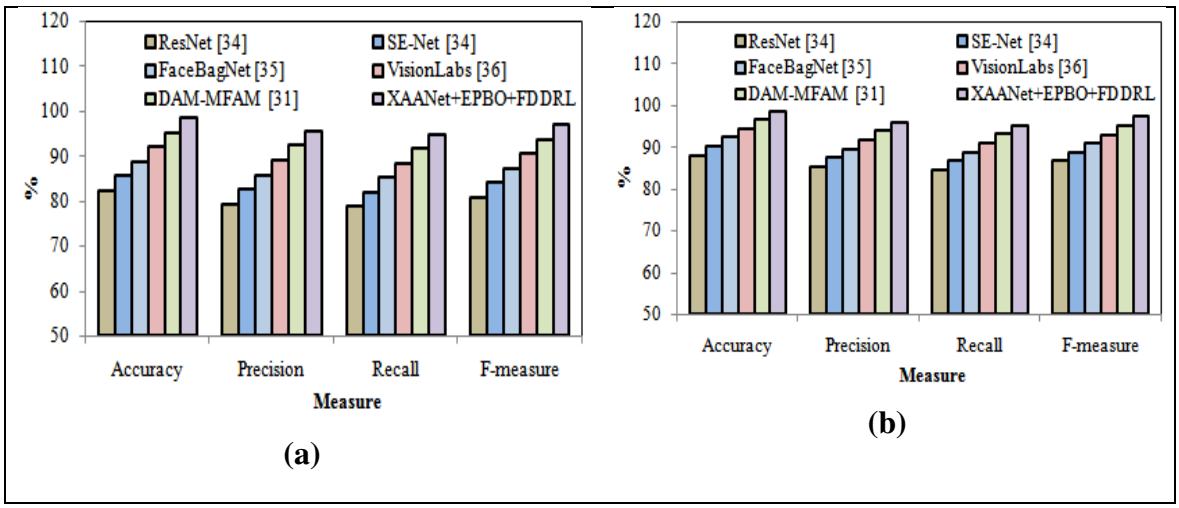
ResNet [34]	81.156	78.535	77.869	79.828	83.980	81.619	80.744	82.785
SE-Net [34]	84.696	82.075	81.409	83.368	86.969	84.608	83.733	85.774
FaceBagNet [35]	88.236	85.615	84.949	86.908	89.958	87.597	86.722	88.763
VisionLabs [36]	91.776	89.155	88.489	90.448	92.947	90.586	89.711	91.752
DAM-MFAM [31]	95.316	92.695	92.029	93.988	95.936	93.575	92.700	94.741
XANet+EPBO+FDDRL	98.856	96.235	95.569	97.528	98.925	96.564	95.689	97.730

Since the performance metrics obtained from both datasets are identical under all conditions, they are either derived from the same source or have highly correlated distributions. The similarity in the evaluation metrics further confirms model robustness and stability but also indicates that dataset diversity may not significantly impact model performance under these test conditions. The rise in ACER from 0.0148 to 0.0483 across conditions highlights the model's sensitivity to viewpoint shifts and challenging lighting environments. Despite these variations, the model maintains relatively low false positive rates, indicating robust anti-spoofing capabilities.

For Multi modal approach, a comprehensive comparative analysis of the quality measures for the proposed XANet+ FDDRL face anti-spoofing approach and existing state-of-the-art methods on the CASIA-SURF dataset is provided in Table 5.10 and Figure 5.12. The results highlight significant improvements achieved by our approach across various metrics. In terms of accuracy, our XANet+EPBO+FDDRL approach outperforms existing methods, showing efficiency gains of 15.082%, 12.066%, 9.049%, 6.033%, and 3.016% compared to ResNet, SE-Net, FaceBagNet, VisionLabs, and DAM-MFAM, respectively. The precision metric further emphasizes the superiority of our approach, with efficiency gains of 15.501%, 12.401%, 9.3%, 6.201%, and 3.1% over ResNet, SE-Net, FaceBagNet, VisionLabs, and DAM-MFAM, respectively. Regarding recall, our XANet+EPBO+FDDRL approach

EPBO+ exhibits notable efficiency gains of 15.621%, 12.497%, 9.373%, 6.249%, and 3.124% compared to ResNet, SE-Net, FaceBagNet, VisionLabs, and DAM-MFAM, respectively. The F-measure metric further reinforces the superior performance of our proposed approach, demonstrating efficiency gains of 15.293%, 12.235%, 9.176%, 6.117%, and 3.059% over ResNet, SE-Net, FaceBagNet, VisionLabs, and DAM-MFAM, respectively. Table 5: Comparative analysis of quality measure of proposed and state-of-art face-anti spoofing approaches for CASIA-SURF dataset.

In Figure 5.13, the training and validation accuracy levels, and training and validation losses on the CASIA-SURF dataset is depicted. Here, high training accuracy (100%) is indicative of an issue with overfitting, since the model has completely memorized the training dataset. On the other hand, the validation accuracy is high at 97.348%, which shows good generalization of unseen data. The difference between the training and validation accuracies suggests some minor degree of overfitting, which requires more detailed analysis regarding the ability of this model to fit new instances. Simultaneously, the training loss value of 0.02 signifies a very good fit to the training data and the slightly increased validation loss of 0.10 implies a somewhat reduced performance on previously unseen date set. This slight contrast in loss values highlights the necessity of tracking possible overfitting and underscores the necessity for regularization methods, data augmentation, and hyper-parameter corrections to improve the model's stability and generalizability. An additional, evaluation on a completely new dataset is suggested to give a more thorough measurement of model's performance in practice.



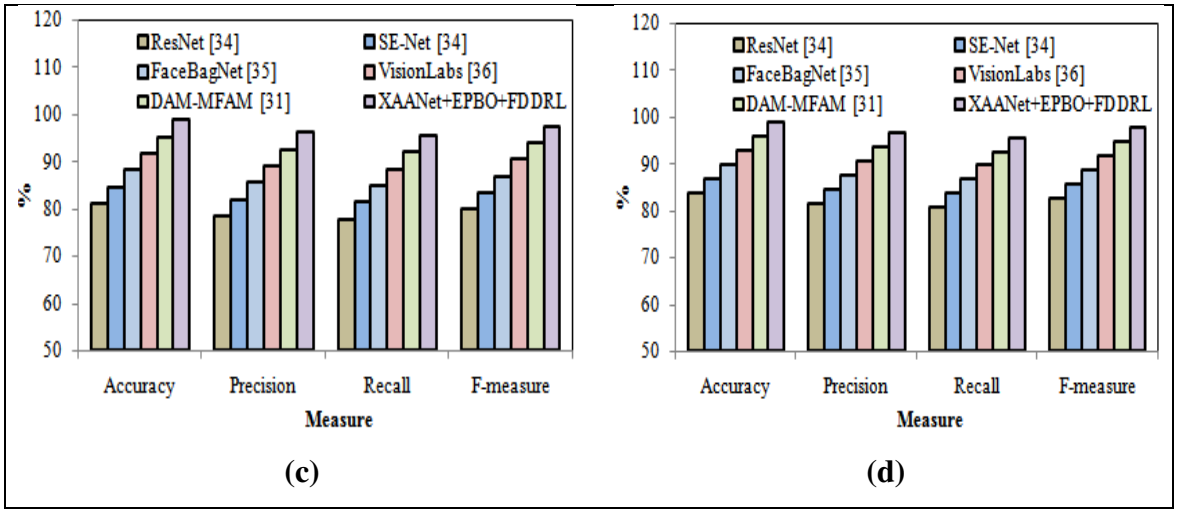


Figure 5.12: Quality Measure Comparison with CASIA-SURF Dataset with Training/Testing Samples (a) 70/30% (b) 75/25% (c) 80/20% and (d) 85/15 (By Author).

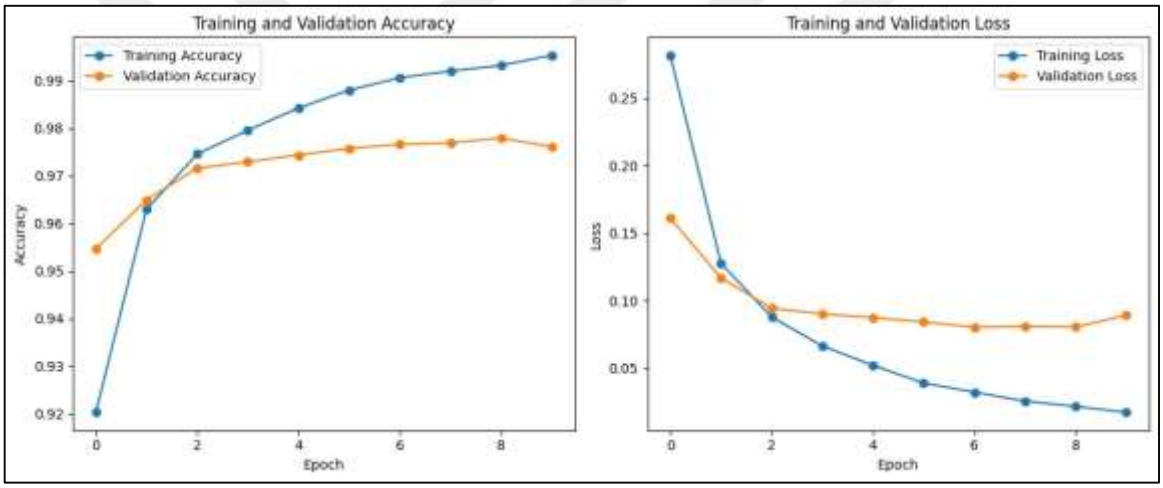


Figure 5.13: The Performance of the Proposed Classification Framework in Terms of Training and Validation Accuracy (Left) and Training and Validation Loss (Right) on CASIA-SURF Dataset (By Author).

5.5.2 Cross-Dataset Generalization

As shown in Figure 5.14, the comparative study of time and space complexity of different methods in face anti-spoofing classification presents considerable differences. The time and space complexity analysis of various models showcases how architecture and design choices affect memory usage and processing speed. Residual Spatiotemporal CNNs, specifically ResNet3D and CSN, are characterized by high time and space complexity because of residual connections and 3D convolutions, which significantly contribute to increased memory usage and inference time. However, in the context of the Channel Separation

Network, efficiency is improved because it reduces a significant portion of computational overhead, thereby mitigating some of the complexity. On the contrary, the Deep Fusion of Dynamic Texture and Shape Clues (MM-DFN) mainly uses 2D convolutions, so it holds a moderate time complexity. Although the architecture is made dual-branching, it does add up to some increased computational overhead, yet keeping the space complexity moderate as feature fusion is quite simple. This approach focuses on the balance between geometric depth information and texture clues. The time and space complexity also for 3D Point Cloud Network (3DPC-Net) is high due to the way this model processes 3D point clouds that require higher memory and larger computing power simply because it tries to encode then decode 3D structures within this processing system, which it performs in a higher dimensional input-data system, notably, the vertices presented within the given 3D point cloud system.

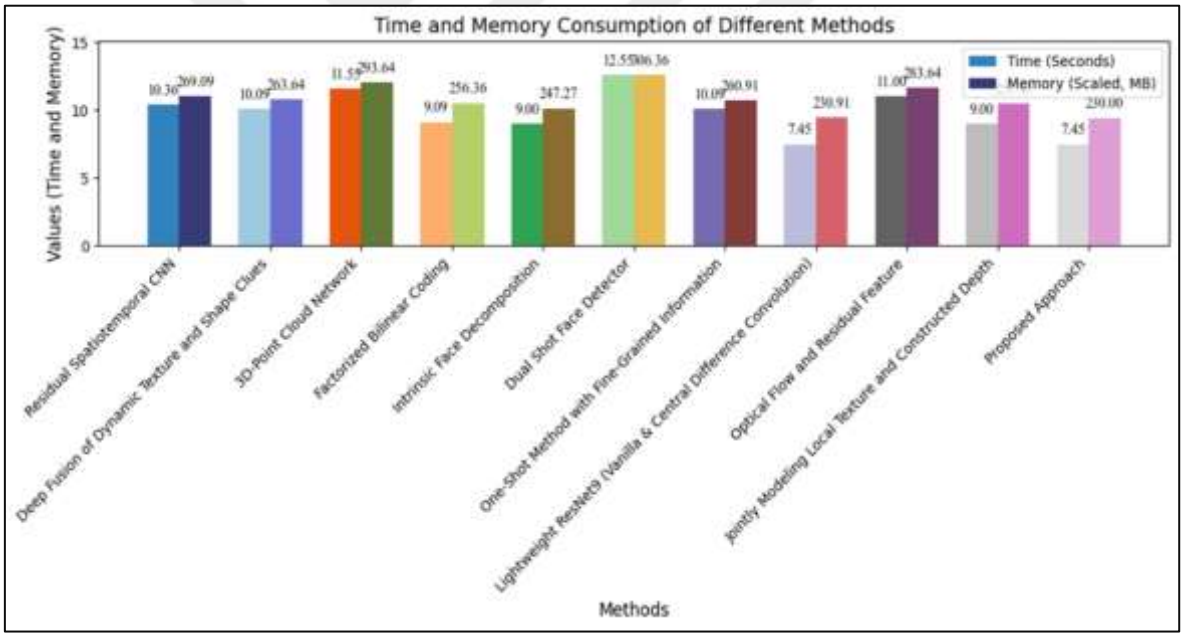


Figure 5.14: Comparison of Time and Memory Consumption Across Different Baseline Methods and Proposed Approach (By Author).

It shows high complexity, especially in space, as a result of multi-channel feature fusion. It is a parameter-increasing function; hence, more memory is used for storing feature channels. In this regard, the bilinear transformation has shown strong feature extraction ability by considering the use of multiple color spaces. The time and space complexities of Intrinsic Face Decomposition and the Dual Shot Face Detector (DSFD) are moderate to high. This is

due to the extraction and maintenance of several feature maps based on different regions or data sources. The intrinsic decomposition has a histogram-based feature extraction, which is computationally manageable, but in DSFD, it increases both the time and space complexity.

The One-Shot Method with Fine-Grained Information optimizes for speed and space, reducing the number of feature comparison steps relying on minimal embeddings rather than large feature maps. This greatly reduces time and space complexity, making it an efficient approach compared to other models. Lightweight ResNet9 with CDC, which is designed to reduce the number of layers, uses central difference convolutions. It thus reduces time and space complexity. This is one of the most resource-efficient models in comparison. Optical Flow and Residual Feature models are complex in terms of space because several temporal frames need to be stored for the computation of optical flow along with residual features, thereby increasing memory consumption as well as processing time, especially for sequences of motion frames.

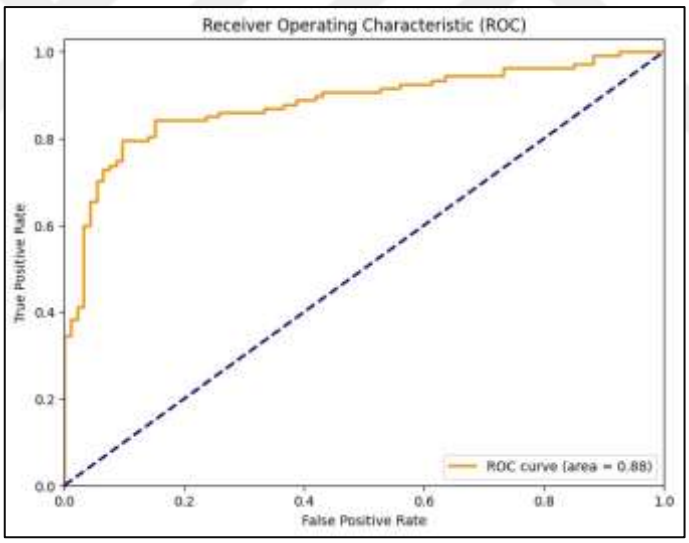


Figure 5.15: Receiver Operating Characteristic (ROC) Curve to Show the Trade-off Between the True Positive Rate (Sensitivity or Recall) and the False Positive Rate (1 - Specificity) for CASIA-SURF Dataset (By Author).

The Jointly Modelling Local Texture and Constructed Depth is another model with extremely high space complexity. It utilizes the Swin-Transformer to divide the original facial scans into image patches, which leads to large memory consumption. However, the model compensates for this through the superior feature granularity it offers. Therefore, despite its higher memory demands, the efficiency of the transformer architecture is

balanced. . Last but not least, the proposed method does not have the best space complexity, i.e., 3D convolutions, yet with optimisations of DenseNet, Squeeze and Excitation, and NAKA. These components make the model strong enough to be able to make an acceptable computation and memory balance since spatial learning is optimised.
For Multi modal approach, Figure 5.15 is plotted as a receiver operating curve (ROC) to analyze and visualize the performance of a binary classifier model at different discrimination thresholds. The ROC with AUC value of 0.88 indicates good discrimination in a binary classification problem for original and spoof images. This AUC indicates good performance of the model to achieve a good compromise between sensitivity and specificity at any potential classification boundary. The curve shape indicates compromise between true image detection and false positive reduction in spoofing images. An AUC value of 0.88 indicates acceptable general discriminative performance, which is a marker of the discriminative power of the model to distinguish cases. Although the resultant performance is positive, frequent monitoring and tuning are sometimes necessary to satisfy some requirements and reach optimized deployment in actual applications. In general, the ROC curve and AUC value of 0.88 offer quantitative measurement of how effectively this model distinguishes between real images and counterfeit images.

Table 5.11: Comparative Analysis of Quality Measure of Proposed and State-of-Art Face-Anti Spoofing Approaches for GREAT-FASD-S Dataset

Face anti-spoofing approaches	Performance measure (%)							
	Accuracy	Precision	Recall	F-measure	Accuracy	Precision	Recall	F-measure
	Training/Testing = 70/30%				Training/Testing = 75/25%			
ResNet [34]	81.298	80.263	79.965	80.778	86.983	85.893	85.681	86.435
SE-Net [34]	84.552	83.517	83.219	84.032	89.118	88.028	87.816	88.570
FaceBagNet [35]	87.806	86.771	86.473	87.286	91.253	90.163	89.951	90.705
VisionLabs [36]	91.060	90.025	89.727	90.540	93.388	92.298	92.086	92.840
DAM-MFAM [31]	94.314	93.279	92.981	93.794	95.523	94.433	94.221	94.975
XANet+EPBO+FDDRL	97.568	96.533	96.235	97.048	97.658	96.568	96.356	97.110
	Training/Testing = 80/20%				Training/Testing = 85/15%			
ResNet [34]	80.058	78.935	78.778	79.493	83.011	81.853	81.644	82.429
SE-Net [34]	83.598	82.475	82.318	83.033	86.000	84.842	84.633	85.418

Table 5.11: Comparative Analysis of Quality Measure of Proposed and State-of-Art Face-Anti Spoofing Approaches for GREAT-FASD-S Dataset (Table Continued)

FaceBagNet [35]	87.138	86.015	85.858	86.573	88.989	87.831	87.622	88.407
VisionLabs [36]	90.678	89.555	89.398	90.113	91.978	90.820	90.611	91.396
DAM-MFAM [31]	94.218	93.095	92.938	93.653	94.967	93.809	93.600	94.385
XANet+EPBO+FDDRL	97.758	96.635	96.478	97.193	97.956	96.798	96.589	97.374

Table 5.11 and Figure 5.16 present a comprehensive comparative assessment of the quality measures for the proposed XANet+EPBO+FDDRL face anti-spoofing technique and state-of-the-art techniques on the GREAT-FASD-S dataset. In terms of accuracy, the XANet+EPBO+FDDRL technique shows outstanding performance enhancements over existing techniques. Specifically, it outperforms ResNet, SE-Net, FaceBagNet, VisionLabs, and DAM-MFAM by 14.897%, 11.878%, 9.858%, 6.839%, and 3.819%, respectively. Accuracy, a key measure to determine the accuracy of positive predictions, also indicates the efficiency of our proposed method. The XANet+EPBO+FDDRL method has efficiency gains of 15.898%, 12.879%, 10.859%, 7.84%, and 4.82% over ResNet, SE-Net, FaceBagNet, VisionLabs, and DAM-MFAM, respectively. Recall measure, the calculation of the capacity to classify positive samples correctly, further demonstrates the superiority of our method. Our XANet+EPBO+FDDRL approach exhibits efficiency gains of 15.678%, 12.659%, 10.639%, 7.62%, and 4.6% against ResNet, SE-Net, FaceBagNet, VisionLabs, and DAM-MFAM, respectively. F-measure, considering both precision and recall, once again proves the overall superiority of the proposed approach. The XANet+ EPBO+FDDRL approach exhibits efficiency gains of 14.897%, 11.878%, 9.858%, 6.839%, and 3.819% against ResNet, SE-Net, FaceBagNet, VisionLabs, and DAM-MFAM, respectively.respectively.

5.6 ABLATION STUDIES AND INTERPRETABILITY

Ablation experiments allow us to observe the contribution of various parts of our anti-spoofing model towards accuracy. By deactivating or adjusting key features like attention mechanisms, feature learning, and optimization techniques, we can analyze their contribution towards accuracy, recall, and error rate. It also allows us to fine-tune the model and make it robust enough for application in real-time systems. Apart from that,

interpretability also allows us to see why a model is making a decision and therefore does its best when the circumstances change. It is for this reason that such abilities are important and how they propel anti-spoofing.

5.6.1 Impact of Attention Mechanisms

Ablation study is conducted on both datasets to measure the importance of each element in the proposed model towards anti-spoofing, and corresponding results are tabulated in Table 5.12 and Table 5.13. On Dataset CelebA-Spoof, the proposed model achieved spectacular accuracy at 99.62%, precision at 99.85%, recall/TPR at 99.39%, and an F1-score at 99.62%. Similarly, on dataset CASIA-SURF, the model was a bit better with accuracy of 99.86%, precision of 99.83%, and recall/TPR of 99.84%, indicating the model has strong robustness among datasets.

The feature extraction module is a very critical module because when the module is removed, there is a drastic drop in performance. On Dataset CelebA-Spoof, accuracy decreases from 99.62% to 94.21%, and on Dataset CelebA-Spoof, accuracy from 99.86% dropped to 94.85%.

This is a harsh pointer towards the significance of good feature extraction in maintaining high anti-spoofing performance. NAKA component also contributed positively by increasing the accuracy level from 96.31% to 99.38% on dataset CelebA-Spoof and from 96.72% to 99.62% on Dataset CASIA-SURF. Improvement is especially evident in the reduction of the false positives (FPR) and false negatives (BPCER and APCER).

The cross-channel attention further improved the performance of the model. On dataset CelebA-Spoof, accuracy enhanced from 96.89% to 99.38%, and on Dataset CASIA-SURF, it improved from 97.36% to 99.62%. The cross-channel attention improved the precision, recall, and F1-score on both datasets, strengthening the idea of discrimination between real and spoofed faces made by the model. MIL boosted the performance positively; however, its effect is somewhat minimal compared to other parts of the model.

The One-Shot Method with Fine-Grained Information optimizes for speed and space, reducing the number of feature comparison steps relying on minimal embeddings rather than large feature maps. This greatly reduces time and space complexity, making it an efficient approach compared to other models. Lightweight ResNet9 with CDC, which is designed to

reduce the number of layers, uses central difference convolutions. It thus reduces time and space complexity. This is one of the most resource-efficient models in comparison. Optical Flow and Residual Feature models is complex in terms of space because several temporal frames need to be stored for the computation of optical flow along with residual features, thereby increasing memory consumption as well as processing time, especially for sequences of motion frames.

The Jointly Modeling Local Texture and Constructed Depth is another model with extremely high space complexity. It utilizes the Swin-Transformer to divide the original facial scans into image patches, which leads to large memory consumption. However, the model compensates for this through the superior feature granularity it offers. Therefore, despite its higher memory demands, the efficiency of the transformer architecture is balanced. Finally, the proposed approach demonstrates a moderate space complexity, with 3D convolutions and optimizations like DenseNet, Squeeze and Excitation, and NAKA. These components allow the model to maintain a reasonable balance between computational demands and memory usage while optimizing spatial learning. However, it still enhanced the performance, mainly in terms of reducing error rates and improving recall. Augmentation, regularization, and dropout all performed well but less so than other models. All, however, are effective in stabilizing the model and preventing overfitting, especially when applied to test data that is more complex or noisy.

Table 5.12: Ablation Study Results on the Impact of Individual Components on Anti-Spoofing Performance on Dataset CelebA-Spoof

Approach	ACC (%)	Precision (%)	Recall (%)	F1-Score (%)	ACER/HTER	FPR	APCER	BPCER
Proposed Anti-spoofing Model	99.62 %	99.85%	99.39%	99.62%	0.0038	0.0015	0.0015	0.0061
Feature Extraction Module (With/ Without)	99.38 / 94.21	99.67 / 94.65	99.15/ 93.62	99.32/ 94.14	0.0062/ 0.0354	0.0028 / 0.0298	0.0024 / 0.0251	0.0089/ 0.0452
NAKA (With/ Without)	99.38 / 96.31	99.67 / 96.78	99.15/ 95.74	99.32/ 96.27	0.0062/ 0.0247	0.0028 / 0.0205	0.0024 / 0.0187	0.0089/ 0.0301
Cross-Channel Attention (With/ Without)	99.38 / 96.89	99.67 / 97.32	99.15/ 96.41	99.32/ 96.85	0.0062/ 0.0198	0.0028 / 0.0172	0.0024 / 0.0161	0.0089/ 0.0252
MIL (With/ Without)	99.38 / 96.56	99.67 / 96.95	99.15/ 96.08	99.32/ 96.52	0.0062/ 0.0225	0.0028 / 0.0194	0.0024 / 0.0176	0.0089/ 0.0287
Augmentation (With/ Without)	99.38 / 96.02	99.67 / 96.44	99.15/ 95.62	99.32/ 95.97	0.0062/ 0.0273	0.0028 / 0.0245	0.0024 / 0.0213	0.0089/ 0.0331
Regularization (With/ Without)	99.38 / 95.74	99.67 / 96.15	99.15/ 95.21	99.32/ 95.69	0.0062/ 0.0289	0.0028 / 0.0258	0.0024 / 0.0226	0.0089/ 0.0352
Dropout (With/ Without)	99.38 / 96.48	99.67 / 96.87	99.15/ 95.88	99.32/ 96.42	0.0062/ 0.0217	0.0028 / 0.0193	0.0024 / 0.0178	0.0089/ 0.0279
Speckle Reduction (With/ Without)	99.38 / 96.12	99.67 / 96.55	99.15/ 95.63	99.32/ 96.07	0.0062/ 0.0261	0.0028 / 0.0227	0.0024 / 0.0199	0.0089/ 0.0318

Table 5.13: Ablation Study Results on the Impact of Individual Components on Anti-Spoofing Performance on Dataset CASIA-SURF

Approach	ACC (%)	Precision (%)	Recall (%)	F1-Score (%)	ACER/HTER	FPR	APCER	BPCER
Proposed Anti-spoofing Model	99.86	99.83	99.84	99.84	0.0014	0.0013	0.0016	0.0013
Feature Extraction Module (With/ Without)	99.62 / 94.85	99.85 / 95.21	99.39 / 94.12	99.62 / 94.66	0.0038 / 0.0314	0.0015 / 0.0261	0.0015 / 0.0215	0.0061 / 0.0413
NAKA (With/ Without)	99.62 / 96.72	99.85 / 97.08	99.39 / 96.01	99.62 / 96.54	0.0038 / 0.0215	0.0015 / 0.0183	0.0015 / 0.0162	0.0061 / 0.0269
Cross-Channel Attention (With/ Without)	99.62 / 97.36	99.85 / 97.81	99.39 / 96.78	99.62 / 97.29	0.0038 / 0.0182	0.0015 / 0.0157	0.0015 / 0.0148	0.0061 / 0.0216
MIL (With/ Without)	99.62 / 96.91	99.85 / 97.25	99.39 / 96.33	99.62 / 96.78	0.0038 / 0.0224	0.0015 / 0.0196	0.0015 / 0.0179	0.0061 / 0.0284
Augmentation (With/ Without)	99.62 / 96.25	99.85 / 96.59	99.39 / 95.89	99.62 / 96.24	0.0038 / 0.0256	0.0015 / 0.0213	0.0015 / 0.0194	0.0061 / 0.0297
Regularization (With/ Without)	99.62 / 96.01	99.85 / 96.34	99.39 / 95.42	99.62 / 95.88	0.0038 / 0.0281	0.0015 / 0.0238	0.0015 / 0.0219	0.0061 / 0.0336
Dropout (With/ Without)	99.62 / 97.02	99.85 / 97.36	99.39 / 96.45	99.62 / 96.90	0.0038 / 0.0198	0.0015 / 0.0175	0.0015 / 0.0159	0.0061 / 0.0238
Speckle Reduction (With/ Without)	99.62 / 96.45	99.85 / 96.78	99.39 / 95.87	99.62 / 96.32	0.0038 / 0.0241	0.0015 / 0.0208	0.0015 / 0.0186	0.0061 / 0.0279

For example, when tested on Dataset CelebA-Spoof, dropout served to improve its accuracy from 96.48% to 99.38%, while on Dataset CASIA-SURF, it improved the accuracy from 97.02% to 99.62%. Speckle reduction emerges as an important component to be added to enhance the anti-spoofing model, as it has significantly degraded performance with the removal of the element, showing a substantial accuracy drop in both datasets. From 99.62% accuracy to 96.45% accuracy with a jump of ACER up to 0.0241 without speckle reduction in Dataset CelebA-Spoof and from 99.86% accuracy to 96.45% accuracy with an equal rise of ACER without speckle reduction in Dataset CASIA-SURF.

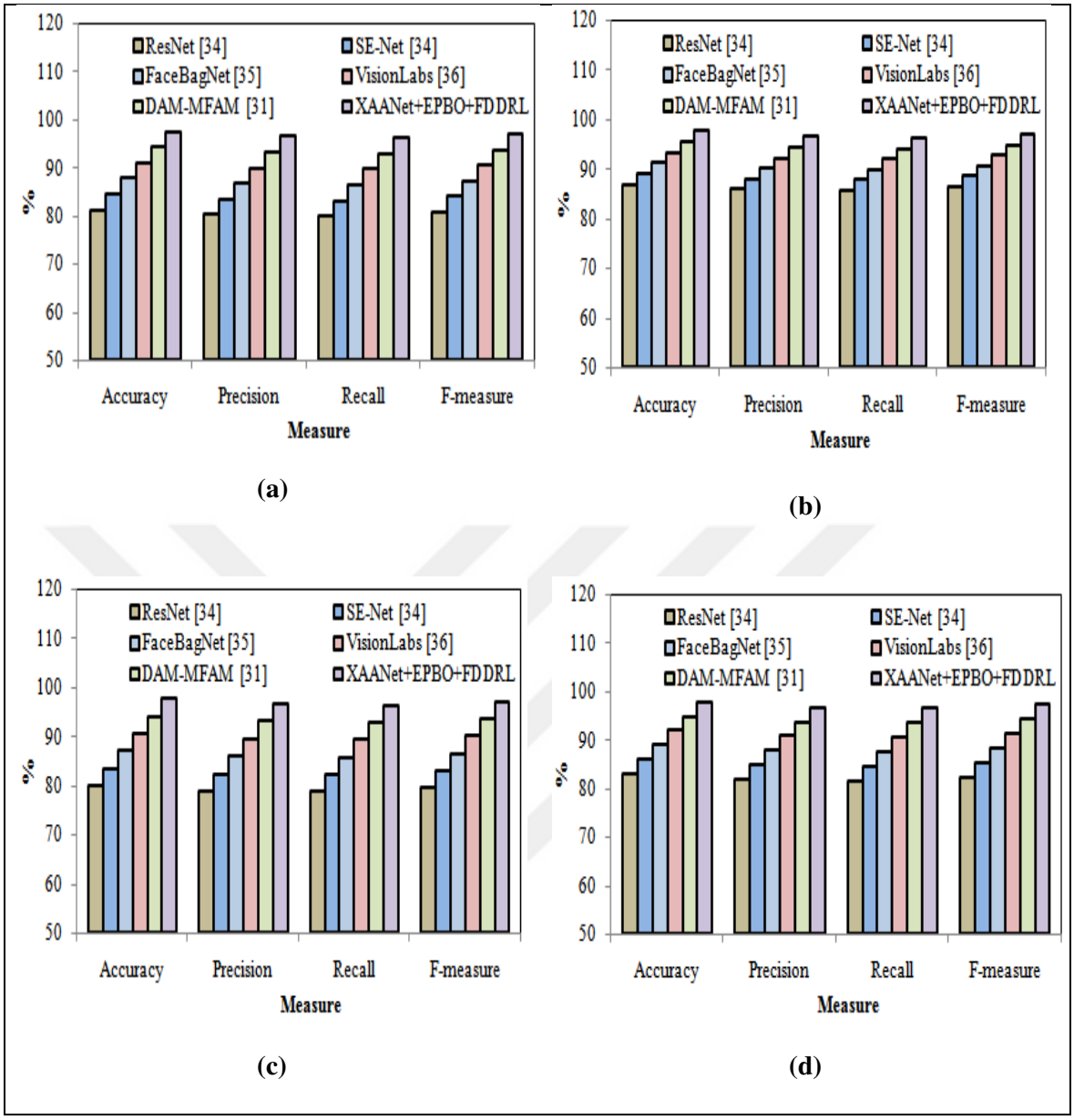


Figure 5.16: Quality Measure Comparison with GREAT-FASD-S Dataset with Training/Testing Samples (a) 70/30% (b) 75/25% (c) 80/20% and (d) 85/15% (By Author).

Many spoofing methods use silicon masks, paper printouts, and digital screen replays. These necessarily involve non-physiological artefacts of artificial surface patterns, excessive smoothness, or unnatural reflectance that can lead the model astray by masking critical features important for classification. Without effective speckle reduction, these artificially created artefacts cannot be suppressed effectively, making it harder for the model to tell a real face from a good spoofing attempt. It helps the model preserve important micro-textural information, which is otherwise hidden in spoofed images.

5.6.2 Effect of Model Optimization Strategies

In Figure 5.17, the training and validation accuracy levels, and training and validation losses are shown for the GREAT-FASD-S dataset is shown. Similar to CASIA-SURF, the training accuracy is very high (99.97%) showing overfitting issue during learning process. However, the validation accuracy of 97.73% shows the satisfactory performance of the proposed classification model. The loss during training and validation (0.02 and 0.09 respectively) is minimum and shows the requirement of some advance regularization methods to overcome the overfitting issue.

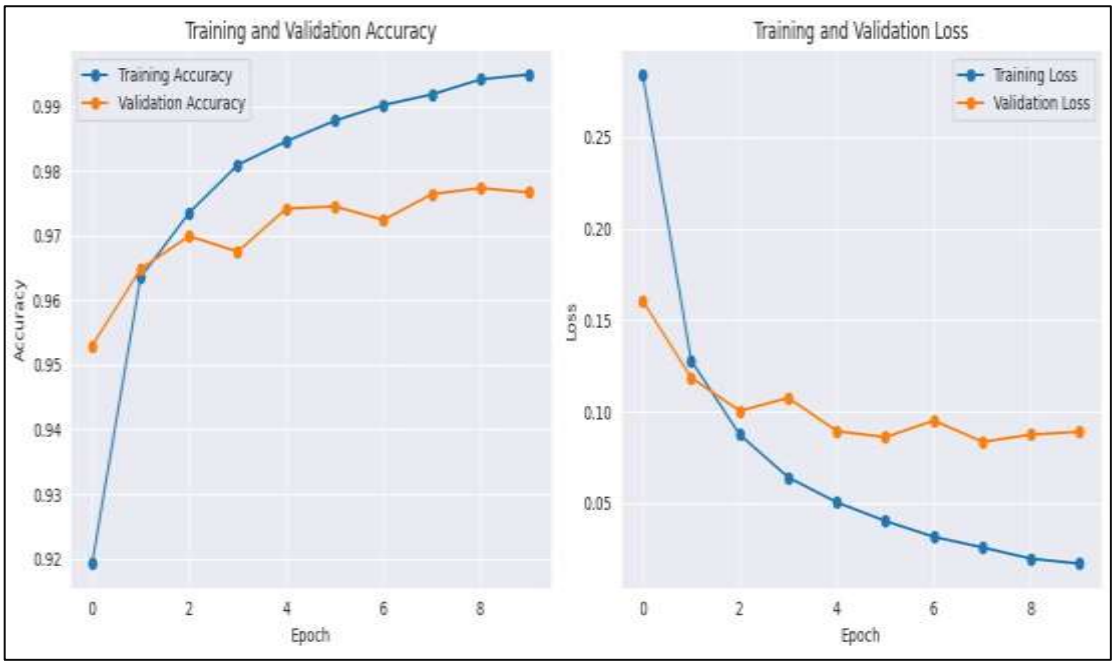


Figure 5.17: The Performance of the Proposed Classification Framework in Terms of Training and Validation Accuracy (Left) and Training and Validation Loss (Right) on GREAT-FASD-S Dataset (By Author).

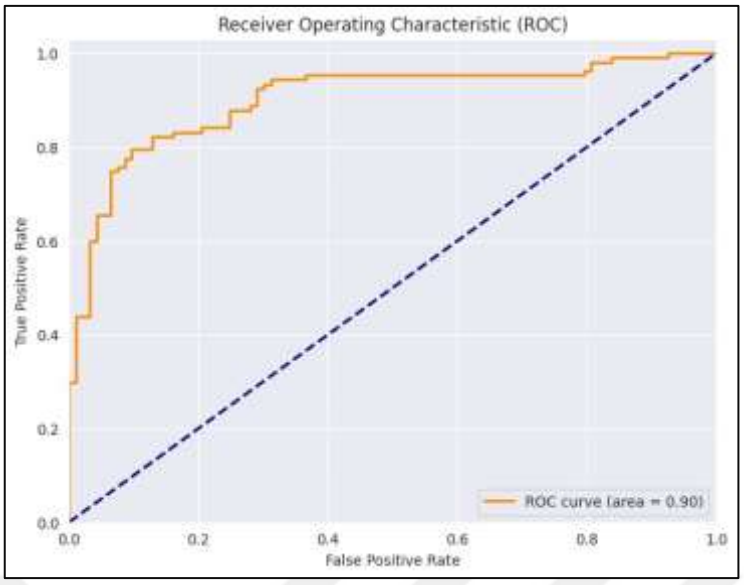


Figure 5.18: Receiver Operating Characteristic (ROC) Curve to Show the Trade-off between the True Positive Rate (Sensitivity or Recall) and False Positive Rate (1 - Specificity) for GREAT-FASD-S Dataset (By Author).

The ROC curve for GREAT-FASD-S dataset is visualized in the Figure 5.18, showing a high AUC score of 0.90 which is better than the AUC realized on CASIA-SURF dataset. In the figure, each point on the curve represents a different classification threshold, and the AUC score determines overall performance of the model across these thresholds. This enables the practitioners to set a threshold that is in sync with their preferred balance between sensitivity and specificity, considering what each application needs. Based on the comparative performance, an AUC of 0.90 can be considered favourably as this implies robust discriminatory power. But the importance of this score depends on a particular situation when applying it; for example, applications that are considered critical such as security systems may require an even higher AUC. Accepting the positive AUC, there is still ground for improvement.

This chapter discussed a comprehensive evaluation of the proposed face anti-spoofing models using benchmark datasets and standard performance metrics. It analyses the effectiveness of the 3D Face Anti-Spoofing Model and the Multi-Modal Deep Fusion Network, comparing their performance across various datasets and real-world scenarios. The results highlight improvements in accuracy, generalization, and robustness against spoofing attacks. A comparative analysis with existing methods demonstrates the superiority of the proposed models. Thereafter, ablation studies examine the impact of key components like

attention mechanisms and optimization strategies. The findings contribute to enhancing face anti-spoofing technology for practical applications. The next chapter will conclude the research by summarizing key findings, discussing contributions, addressing limitations, and outlining future research directions for advancing face anti-spoofing technology.

6. CONCLUSION AND FUTURE WORK

6.1 SUMMARY OF KEY FINDINGS

This research develops a high-accuracy, real-time face anti-spoofing system. 3D Face Anti-Spoofing Model with Dense Squeeze and Excitation Networks and Neighbourhood-Aware Kernel Adaptation (NAKA) enhances feature extraction. Multiple Instance Learning (MIL) improves spoof detection, while a lightweight multi-modal deep fusion network with axial attention (XA-Net) extracts deep features from RGB, depth, and texture data [198-201].

A bidirectional fusion technique optimizes feature combination, and the Enhanced Pity Beetle Optimization (EPBO) algorithm refines feature selection. A hybrid Federated Deep Reinforcement Learning (FDDRL) approach ensures adaptability against new spoofing attacks, while Deep Reinforcement Learning (DRL) dynamically adjusts model parameters. The system is optimized for real-time, low-power applications like smartphones and biometric security. An explainable AI framework increases transparency and user trust. Testing on multiple datasets (CASIA-SURF, CelebA-Spoof, GREAT-FASD-S) confirms high accuracy and robustness, advancing face recognition security.

6.2 CONTRIBUTIONS OF THE THESIS

This thesis contributes to face anti-spoofing by developing a 3D Face Anti-Spoofing Model using Dense Squeeze and Excitation Networks with a Neighbourhood-Aware Kernel Adaptation (NAKA) strategy for better feature extraction. Multiple Instance Learning (MIL) enhances spoof detection by identifying inconsistencies in facial regions.

A Light-weight Multi-Modal Deep Fusion Network is introduced, which combines axial attention (XA-Net) with a bidirectional fusion technique to merge RGB, depth, and texture features. The Enhanced Pity Beetle Optimization (EPBO) technique improves feature selection, whereas a hybrid Federated Deep Reinforcement Learning (FDDRL) strategy incorporates adaptive learning against evolving attacks. Deep Reinforcement Learning (DRL) adaptively adjusts parameters for improved resilience. The network is real-time optimized and can be made biometric security and mobile computing adaptable. An explainable model makes it more transparent with reasoning based on which class it classifies instances into. CASIA-SURF, CelebA-Spoof, and GREAT-FASD-S datasets are

employed to demonstrate robustness using this model. The research greatly improves face recognition security through the employment of multi-modal learning, adaptive techniques, and real-time optimization.

6.3 LIMITATIONS AND CHALLENGES FACED

It is beset with advanced spoofing attacks that spoof depth and texture information. It is computationally costly, and real-time deployment on low-power hardware is challenging. Sensitivity to design choices and bias in the dataset affects its generalization towards novel attacks.

Over-fitting remains a key issue, reducing generalization to new spoofing techniques. High computational cost makes the real-time deployment challenging. Feature selection and reinforcement learning require extensive tuning, impacting efficiency. Regularization and adaptive training are needed to enhance robustness.

6.4 FUTURE RESEARCH DIRECTIONS

Further improvements are needed to enhance generalization, real-time performance, and adaptability to evolving spoofing techniques. Future research will focus on refining learning strategies, optimizing computational efficiency, and improving robustness in diverse real-world conditions.

i. Exploring Unsupervised and Self-Supervised Learning Approaches: For future improvements, unsupervised and self-supervised learning techniques can be explored to enhance model robustness and reduce dependency on large labelled datasets. In 3D Spoofing, integrating contrastive learning or autoencoders may improve feature learning from unlabelled data, addressing overfitting issues and improving generalization to unseen spoofing attacks. In Multi-Modal Approaches, self-supervised learning could enable the model to learn richer representations from multi-modal data, making it more adaptable to new attack types [202-208].

ii. Real-Time Face Anti-Spoofing for Edge Devices: To enhance real-time performance, optimizing the models for edge devices like smartphones and IoT-based biometric security systems is crucial. For 3D Spoofing, lightweight architectures such as MobileNet or quantization techniques can be applied to reduce computational load while maintaining

accuracy. In Multi-Modal Approaches, dynamic feature selection methods can be refined further, allowing the system to intelligently choose the most relevant features for spoof detection in real-time, reducing memory usage and processing time [209-214].

iii. Improving Generalization for Diverse Attack Scenario: Addressing generalization issues remains a key challenge. In 3D Spoofing, techniques like L1/L2 regularization, dropout layers, transfer learning, and adversarial training can be integrated to mitigate overfitting and improve performance on unseen attacks. In Multi-Modal Approaches, metaheuristic algorithms such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Ant Colony Optimization (ACO) can be explored for optimizing feature selection and model parameters. Additionally, advanced deep learning techniques like temporal knowledge graphs and Transformers could be leveraged to improve detection of sophisticated attacks, making the system more robust and adaptive to evolving threats.

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