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**Online Facial Race and Gender Recognition Based on Convolutional
Neural Network**

Viyan Shukri Mikaeel

**Department of Engineering
MASTER'S THESIS**

supervisors:

Asst. Prof. Dr. Bülent Turan

Asst. Prof. Dr. Maiwan Bahjat Abdulrazaq

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ETHICAL CONTRACT

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Viyan Shukri Mikaeel

JURY ACCEPTANCE AND APPROVAL

The defense examination of the thesis study titled “ONLINE FACIAL RACE AND GENDER RECOGNITION BASED ON CONVOLUTIONAL NEURAL NETWORK” is prepared by VIYAN SHUKRI MIKAEEL was held on 13/06/2024 it has been accepted by jury members as a Master’s Thesis at Tokat Gaziosmanpaşa University, Graduate Education Institute, Department of Computer Engineering

Jury Members

Signature

Üye: Doç. Dr. Bülent Turan (Supervisor)

.....

Üye: Dr. Öğr. Mahir Kaya

.....

Üye: Doç. Dr. Çetin Cem Bükücü

.....

CONFIRMATION

/07/2024

Doç. Dr. Yusuf TEMÜR

Director of Graduate Education Institute

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Özet

Evrişimsel Sinir Ağına Dayalı Çevrimiçi Yüz İrk ve Cinsiyet Tanıma

Viyan Shukri Mikaeel

Yüksek Lisans, Lisansüstü Eğitim Enstitüsü, Bilgisayar Anabilim Dalı

Doç. Dr. Bülent Turan

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Yüz tanıma, adalet, etik, sosyal adalet, yasal bağlılık, teknolojik ilerleme ve kamu güveni üzerindeki geniş etkileri nedeniyle büyük önem taşıyor. Bu alandaki araştırma çabalarını ilerleterek ve daha kesin ve tarafsız sistemler oluşturarak, daha adil ve daha kapsayıcı bir toplumun geliştirilmesine katkıda bulunabiliriz. Derin öğrenme ve bilgisayarla görme teknikleri, çeşitli alanlardaki araştırmacılar ve geliştiriciler tarafından, özellikle önyargı ve temsil sorunlarının ele alınmasında, dikkate değer ve hızlı bir ilerleme göstererek yaygın bir şekilde benimsenmiştir. Bireyleri cinsiyete ve ırka göre ayırt etmek için geliştiriciler genellikle renkleri ve yüz özelliklerini analiz etmeye odaklanır. Bu tez, yüz ırkını ve cinsiyeti tanımlayan iki evrişimli sinir ağı modelini sunmaktadır. Model, dört ırk kategorisini (Afrikalı, Asyalı, Hintli ve Kafkasyalı) ve her iki cinsiyeti kapsayan veri kümeleri üzerinde eğitim ve değerlendirmeden geçti. Bu veri kümelerini "güzel yüz", "SCUT-FBP5500_v2", aynı zamanda AFD veri kümesi olarak da bilinen "cnsifd_faces_bmp", "Indian_actors_faces" ve "img_align_celeba" gibi çeşitli kaynaklardan derledik. Dört ırksal gruba ait birleştirilmiş veri kümeleri, 1.200'ü erkek ve 1.200'ü kadın olmak üzere eşit olarak bölünmüş 2.400 kamuya açık görüntüden oluşuyor. Her ırk kategorisi, her cinsiyetten 300'er adet olmak üzere rastgele seçilmiş 600 örnek içerir. Bu tez, ırk ve cinsiyetlerin sınıflandırılmasına yönelik iki model sunmaktadır. Bunlardan biri çok sınıflı sınıflandırma, ikincisi ise ırk ve cinsiyetin sınıflandırılmasına yönelik İkili sınıflandırmadır. İrk ve cinsiyet analizi. DeneySEL sonuçlar, ikili sınıflandırma yönteminin doğruluk açısından çok sınıflı sınıflandırma performansından daha iyi performans gösterdiğini ortaya koymaktadır. İkili Sınıflandırma modelinde daha iyi performans elde edilmesi nedeniyle. Bu çalışma, dört ırkı sınıflandırmak için İkili Sınıflandırma modelini seçecek ve İkili Sınıflandırma RGCNN modelinin performansını diğer üç önceden Eğitilmiş Modelle karşılaştıracaktır. Bu çalışma, İrk Cinsiyet Evrişim

Sinir Ağının (RGCNN) ikili sınıflandırma performansını CNN önceden eğitilmiş modellerle karşılaştırmaktadır. Deneysel sonuçların analizi şunu ortaya koymaktadır. Irk Cinsiyet Evrişim Sinir Ağı (RGCNN) sonuçları, hem ırk hem de cinsiyet sınıflandırmasında doğruluk açısından diğer modellerden daha iyi performans gösterdiğini ortaya koyuyor. Irksal sınıflandırmada ResNet50 ve InceptionV3 ikinci sırada yer alırken, VGG19 onu takip ediyor. RGCNN modeli özellikle hafif tasarımı ve azaltılmış parametre sayısı ile öne çıkıyor. VGG19 modeli ise ikinci sırada yer alıyor. Parametre sayısı açısından InceptionV3 üçüncü sırada yer alırken, onu en yüksek parametre sayısına sahip ResNet50 takip ediyor. Sistemin 40 kişilik bir örnekleme ırk ve cinsiyet sınıflandırmalarını kapsayan tahmin yetenekleri %98 gibi etkileyici bir doğruluk oranına ulaşıyor.

Anahtar Kelimeler

Yüz Irk ve Cinsiyet Yeniden Bağlantısı, Evrişim sinir ağı, ResNet50, VGG19, InceptionV3

ABSTRACT

Online Facial Race and Gender Recognition Based on Convolutional Neural Network

MIKAEEL, Viyan Shukri Mikaeel

Master's Thesis, Institute of Graduate Studies, Department of Engineering

Doç. Dr. Bülent Turan

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Facial recognition holds significant importance due to its broad implications for fairness, ethics, social justice, legal adherence, technological advancement, and public confidence. By pushing forward research efforts in this domain and crafting more precise and impartial systems, we can contribute to fostering a society that is fairer and more inclusive. Deep learning and computer vision techniques have seen widespread adoption by researchers and developers across various domains, particularly in addressing issues of bias and representation, demonstrating notable and swift progress. To distinguish individuals based on gender and race, developers often focus on analyzing colors and facial features. This thesis presents a two convolutional neural network models that identifies facial race and gender. The models underwent training, validation, testing and evaluation on datasets encompassing four racial categories (African, Asian, Indian, and Caucasian) and both genders. We curated these datasets from various sources, such as "beautiful face," "SCUT-FBP5500_v2," also known as the AFD dataset, "cnsifd_faces_bmp," "Indian_actors_faces," and "img_align_celeba." The combined

datasets for the four racial groups comprise 2,400 publicly identifiable images, evenly divided into 1,200 males and 1,200 females. Each racial category includes 600 randomly selected samples, with 300 from each gender. This thesis present two models for classification of race and genders. one is multi-Class classification and second is Binary classification for classifying race and gender Analysis of race and gender. The experimental outcomes reveals that the binary classification method outperforms the multi class classification performans in the term of accuracy. Due to obtaining better performance in Binary-Classification model. This study will choose Binary-Classification model to classify four races, and compare performance of Binary-Classification RGCNN model with other three pre-Trained Models. This study compares performance of binary classification of Race Gender Convolution Neural Network (RGCNN) to CNN pretrained models. Analysis of the experimental outcomes reveals that the. Race Gender Convolution Neural Network (RGCNN) outcomes reveal outperforms the other models in terms of accuracy in both racial and gender classification. Following in racial classification, ResNet50 and InceptionV3 are in second place, and VGG19 trails behind. Notably, the RGCNN model stands out for its lightweight design and reduced parameter count. On the other hand, the VGG19 model comes in second. In terms of parameter count, InceptionV3 is third, followed by ResNet50, which has the highest parameter count. The system's predictive capabilities, encompassing race and gender classifications across a sample size of 40 individuals, achieve an impressive 98% accuracy rate.

Keywords

Facial Race and Gender Reconnection, Convolution neural network, ResNet50, VGG19, InceptionV3

ABBREVIATIONS

Abbreviations	Meaning
ADAM	Adaptive Moment Estimation
CDBN	Convolutional Deep Belief Networks
CNN	Convolutional Neural Networks

CNSIFC	Centre For Neuroscience Indian Face Dataset
DCNN	Deep Convolutional Neural Networks
DL	Deep Learning
DLA	Deep Learning Algorithms
DLN	Deep Learning Network
DML	Deep Manifold Learning
DNN	Deep Neural Network
Epoch	Especially Period One During Change Happen
FC	Fully Connected
FD&P	Face Detection and Preprocessing
FG-NET	Face And Gesture Recognition Network
FN	False Negative
FP	False Positive
HMM	Hidden Markov Model
IC	Information Collector
IMAN	Information Maximization Adaptation Network
K	Kernal
MLP	Multi-Layer Perceptron
MORPH	Multivariate Observations of Reactions and Physical Health
NN	Neural Network
PF	Privacy Funnel
PPV	Positive Predictive Value
ReLU	Rectified Linear Unit
ResNet	Residual Network
RFW	Racial Faces in The Wild
RGB	Red Green Blue
RGCNN	Race Gender Convolution Neural Network
MCC-CNN	Multi-Class-Classification Convolution Neural Network
RNN	Recurrent Neural Network
ROC	Receiver Operating Characteristic Curve
Tanh	Tangent Hyperbolic
TN	True Negative
TP	True Positive
TPR	True Positive Rate
VGG	Visual Geometry Group
WLD	Weber Local Descriptors

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CHAPTER ONE

1. INTRODUCTION

1.1 Overview

The human task is to be able to express vulnerability in many ways, including writing, posture, sounds, emotions, and physiological indicators. The face houses the most sensory organs in the human body, including the eyes, mouth, nose, and ears. Humans can see, taste, smell, and hear biological signals thanks to these sensors. Moreover, they generate output signals that arrange critical components of human emotional immersion [1]. Natural communication is vital because humans can see reactions through emotions and intentions, as well as communicate their thoughts to others.[2].

We can classify both verbal and nonverbal acts of communication. Verbal actions trace back to spoken words, while non-verbal actions trace back to physical movements and physiological responses [3]. Phone calls, for example, appear to be human-to-human communication and do not require non-verbal cues. [4]. Humans have a very complex facial recognition system. Their brains can distinguish between multiple faces even when their appearances change rapidly. The human brain's ability to recognize faces in a variety of settings has continually amazed researchers, leading to numerous attempts to mimic the human brain system. This concept has led to the development of numerous algorithms for face detection and recognition [5].

Humans express their emotions mostly through their faces, which makes it easier to understand and take into account what they are feeling. Humans differ from each other in the intensity, complexity, and meaning of their facial expressions [6]. The difficulty of automatically identifying an individual's race from his or her visual characteristics is increasing day by day [7]. This provides a useful light for detecting other complex patterns in a variety of applications, such as security system access control and video retrieval system indexing for a multi-agent network of content-based audio-visual archives [8]. The fields of computer vision and deep learning, which are still gradually developing, have made human biometric recognition neutral and continuous [9]. It is increasingly difficult to automatically determine an individual's race based on their gender and visual characteristics. There are many uses, such as content-based audio-visual archive network systems, multi-agent systems, security access control systems, and indexing content-based video retrieval systems [10].

1.2 Problem Statement

In recent years, the massive developments in computer vision and deep learning techniques have paved the way for facial recognition systems, including traditional and automatic ones. Among the various applications of facial recognition, race and gender recognition is of very great importance due to its broad implications across many fields such as security, marketing, and social sciences. However, there are numerous datasets dedicated to facial expression recognition, there are only a few datasets that deal with all races and genders. Trained and tested existing pretrained CNN models on millions of images belonging to thousands of classes. These models compute the weight of a large number of parameters in each epoch, often have difficulty with real-time and online processing, especially in scenarios where rapid decision making is crucial. The automatic

detection of a person's race (African, Asian, Indian Caucasian) based on their facial and gender is becoming an increasingly significant problem.

1.3 Aim of Thesis

1. Collect a new balanced dataset from various datasets for races and genders.
2. Building a new Binary-Class-Classification model The Race Gender Convolution Neural Network (RGCNN) recognizes the facial race and gender for the four races—African, Asian, Caucasian, and Indian—with the fewest parameters to improve performance and time.
3. Create new Multi-Class-Classification CNN model to compare performance of RGCNN Binary-Class-Classification models with
4. Train and test the InceptionV3, ResNet50, and VGG19 models to recognize the facial gender and race of four races: African, Asian, Indian, and Caucasian.
5. On the same datasets, compare the performance Binary-Class-Classification model RGCNN models with the three models.

1.4 Layout of the Thesis

Apart from **Chapter1**, the remainder of the thesis follows this structure:

Chapter 2: Literature review.

Chapter 3: Provides a detailed theoretical background on the facial race gender system.

Chapter 4: Explains the detailed design of the provided scheme.

Chapter 5: Discusses and presents the results of the experiments performed using the proposed algorithms in Chapter 3.

Chapter 6: Shows the conclusion and future work of the provided approach.

CHAPTER TWO

2. LITERATURE REVIEW

2.1 Introduction

In recent years, there has been a notable growth in research efforts within deep learning and computer vision, with a particular emphasis on advancing the capabilities of facial race and gender recognition technologies. The crucial purposes of all works are to develop

the techniques that enhance the performance and accuracy of biometric recognition systems. The literature review presented in this chapter studies the background and research studies related to facial race and gender recognition, including the algorithms and techniques used in each area. Furthermore, this chapter examines the existing studies that have integrated facial race and gender recognition techniques. The following Various studies show that:

Li Z et al.[11] presented an analysis displayed An examination of how well humans and machines performed on the difficult task of classifying Indian faces based on ethnicity. They also established and collected the Centre for Neuroscience Indian Face Dataset (CNSIFC), which consists of 1650 faces labeled with ethnicity (South vs. North Indian). For this binary ethnic classification task, they trained a number of classifiers using CNN-based features, local form features, or spatial intensity features. The classifiers achieved the highest accuracy of 62% using CNN-based features.

Puc A et al.[12] analyzed systematically in depth the performances of two commercially available deep age estimation algorithms using facial image data from the public datasets APPA-REAL and UTKFace. They estimated ages for pertinent demographic subcategories in order to investigate racial and gender prejudice in more detail. The existing datasets that are used to represent gender and ethnicity in the training and testing of age estimation algorithms are not comprehensive enough. They also observed that the tested models performed better on male subjects than on female subjects, although they were unable to identify any overt or ongoing bias against any one race. Particularly for uncontrolled face photographs, test dataset variables such as image quality, position, illumination, occlusion, and so on appear to have a stronger impact on age estimate performance than race. To properly understand the factors influencing age estimation accuracy, more research is necessary. This situation seems to be unique in that there are no distinct quality borders among different demographic groups, which makes it hard to evaluate the effectiveness of the existing models equitably.

Wang M et al.[13], The 4K Racial Faces in the Wild (RFW) dataset was constructed and collected, consisting of pictures representing the four ethnic groupings of African, Asian, Indian, and Caucasian faces. We chose the ethnic group based on data from a list of celebrities. The database consists of pictures from MS-Celeb-1M that were labeled using the Face++ API. The study validated the racial bias of the most advanced facial recognition system using this standard. The authors suggested a deep information

maximization adaptation network that uses Caucasians as the source domain and other races as the target domains in order to address the issue of racial bias. They used to rigorously validate four commercial APIs' and four state-of-the-art (SOTA) algorithms' racial bias. Then, by employing Caucasian as the source domain and other races as target domains, further describe the solution utilizing deep unsupervised domain adaptation and suggest a deep information maximization adaptation network (IMAN) to mitigate this bias. At the cluster level, this unsupervised method learns the discriminative target representations. At the same time, it aligns the global distribution to lower the racial disparity at the domain level. We suggest a new mutual information loss to further improve network output discrimination in the absence of label information. Long-term tests on the RFW, GBU, and IJB-A databases show that IMAN learns features well that work well in a wide range of racial and database settings.

Narang N, Bourlai T [14], proposed a deep network for recognizing visible and multi-distance infrared images for Asian or Caucasian racial groupings, as well as male and female groups. After training and testing on images related to a modest 203 classes, the model performs well and achieves a 95% success rate in classifying races.

Muhammad G et al.[15] proposed a method for recognizing race from face images using Weber local descriptors (WLD). Initially, the algorithm extracts the WLD histogram from photos of normalized faces. Next, the algorithm selects the optimal bins using the Kruskal-Wallis feature selection technique. They perform testing using chi-square, Euclidean, and city block minimum distance classifiers. The FERET database utilized in the studies represents the five main racial groupings: Asian, African, American Black, Hispanic, Middle Eastern, and White. According to experimental data, the proposed system employing a city block distance classifier, WLD histogram, and feature selection obtains the following accuracy rates: Asian: 97.74%, Black: 96.89%, Hispanic: 92.06%, Middle: 98.33%, and White: 99.53%. Comparing these accuracies to principal component analyses, they are noticeably greater.

Roomi SM et al.[16] proposed a method that can easily be incorporated into any facial recognition system to recognize humans into three major races: Caucasoid, Negroid, and Mongoloid. To properly classify the races, the suggested classification technique first extracts the unique principal facial feature, skin color model, and other secondary aspects like the supplied face's lip and forehead. Comprehensive simulations using photos from Yale, FERET, and other sources demonstrate how well the suggested approach performs.

Ahmed MA [17] demonstrated a CNN model for identifying race from low-resolution (40 * 40) grayscale photos. Photographic films for various applications or real-life scenarios could potentially incorporate the generated model. We further validate the model's efficacy by testing it on various datasets and comparing it with pre-trained models. By using high-resolution colored photos as input, we anticipate further progress. Using the recently created BUPT Equalized Face dataset, which contains over 1.3 million photos in an unrestricted setting, we trained our deep convolution network (R-Net) to reach 97% state-of-the-art accuracy. We assess the validity of this model using other datasets, such as UTK and CFD. They also used R-Net to test the optimized VGG19 model for race estimation. Experimental data demonstrate the robustness of this model for application in uncontrolled contexts. Grad-CAM, also known as gradient-weighted class activation mapping, ultimately visualizes the deep learning model.

Kaur D et al.[18] The reported retrospective analysis used 12-lead ECGs from 326,518 patient encounters referred to Stanford Hospital for standard clinical indications between 2008 and 2018. Within five years, we trained convolutional neural networks as the main model to predict incident heart failure. We assessed biases on the testing set (160 312 ECGs) using the area under the receiver operating characteristic curve, stratified by the protected variables of age, sex, race, and ethnicity. We observed 59,817 occurrences of incident heart failure within five years of the ECG collection. As the original model grew older, its performance decreased. Overall, we found no discernible variations between the racial groupings. However, compared to all other ethnic groups in this age group, the primary model performed noticeably worse in black patients aged 0 to 40, with the greatest disparities observed in young black women. Adding race, ethnicity, sex, and age to the model architecture, training separate models for each racial group, or providing a data set with an equal representation of different races did not improve the differences in model performance. Using probability thresholds tailored for age, sex, and race resulted in significant gains in F1 scores.

Zhang H et al.[19] Huiying Zhang et al. proposed deep manifold learning (DML), a synthesis of deep learning and manifold learning. Deep learning in DML extracted high-dimensional facial features, while manifold learning selected age-related features for facial age recognition. Lastly, we used the Face and Gesture Recognition Network (FG-NET) and Multivariate Observations of Reactions and Physical Health (MORPH) datasets to validate the DML. The findings showed that FG-NET's mean absolute error

(MAE) is 2.48 and MORPH's is 1.60. Furthermore, DML's accuracy has significantly increased when compared to the most advanced facial age recognition techniques.

Razeghi B [20] et al. They have incorporated the privacy funnel model to bridge the gap between information-theoretic privacy and representation learning, all while maintaining privacy in deep learning. They use an end-to-end training framework to propose a method for privacy-preserving representation learning based on the information-theoretic Privacy Funnel (PF) model. We analyse the trade-off between utility and obfuscation in detail. We quantify both using logarithmic loss, also known as self-information loss. This study adds to what we know about how to protect data for both discriminative and generative models, which makes the connection between information-theoretic privacy and representation learning stronger. The model they applied to the most advanced facial recognition programs highlights the need to strike a balance between utility and information obfuscation. The approach enhances data safety in discriminative and generative environments, and its replicable software package facilitates its easy adoption and further exploration. It is capable of performing tasks like creation, reconstruction, and classification from raw face images to both derived and refined embeddings.

Ruda Hassan BA [21] and Ali Dawood FA [x3] The three key phases of the new model they presented for face gender classification are as follows: The first involves using the Viola-Jones algorithm, which consists of four steps, to detect facial images. 1) Integral Image; 2) Adaboost Learning; 3) Haar-like features; and 4) Cascade Classifier. The second phase employs four pre-processing steps: cropping, scaling, transforming the image from RGB to LAB colour space, and employing HE and CLAHE to enhance the photos. The final step employs transfer learning, a powerful deep learning technique, to classify faces based on gender using the Alex-Net architecture. We assessed the effectiveness of the suggested gender categorization model using three datasets: the 1,200-face image-rich LFW dataset. The Faces94 dataset had 400 facial photos, and the family dataset had 400. On the LFW dataset, transfer learning using the Alex-Net model yielded an accuracy of 98.77%. In addition, the model achieved 100% accuracy on the Faces94 and family datasets. As a result, the suggested system highlights how important it is to use pre-processing methods and transfer learning with the Alex-Net model. These techniques help produce gender classification results that are more accurate. We

compared the results obtained by image contrast enhancement methods such as HE and CLAHE. When compared to HE, CLAHE's face classification accuracy was the highest.

Çavşı Zaim H, et al.[22] They proposed a deliberate comparison between quantum convolutional neural network algorithms and their classical counterparts, convolutional neural network algorithms, through specific applications conducted under identical conditions. The Database of Faces includes a collection of face photos taken at the lab between April 1992 and April 1994. Each image is 92 by 112 pixels in size, with 256 grey levels per pixel. There are forty directories containing the images. Results show that the Quantum Convolutional Neural Network achieved a 92% performance accuracy rate, whereas the Convolutional Neural Network achieved a 90% performance accuracy rate. The Quantum Convolutional Neural Network takes 128.85 seconds to process, while the Convolutional Neural Network takes 832.30 seconds.

Kumar BA [23] and Misra NK [yu] they examined and contrasted ten (10) distinct MFAGI strategies, including conventional approaches like MobileNet, MobileNetV2, ResNet101, DenseNet169, DenseNet201, EfficientNetB0, ResNet152V2, InceptionV3, Xception, and our own method. We employed ten models to categories individuals with masked faces into sixteen (16) classes. We created a unique approach known as the "CMNV2" model by combining the modified MobileNetV2 (MNV2) model with the convolutional architecture of rapid feature embedding (CAFFE). This study introduces a novel CMNV2 model by creating a pre-trained model with eight (8) layers, achieving the goals of model performance and classification accuracy for MFAGI of people's faces. We have developed a novel approach to image feature extraction using deep learning (DL) and transfer learning, which outperforms the nine (9) conventional approaches for masked face classification (MFC), masked face age identification (MFAI), and masked face gender identification (MFGI). We created, trained, and assessed a Python model using 12,160 masked face photos. This study shows that integrating deep neural network (DNN) development with transfer learning can lead to an effective CMNV2 technique. This proposed CMNV2 model outperformed the other nine conventional masked identification techniques with 96.54% accuracy and a 3.46% error rate, while requiring fewer parameters and less computing time. Additionally, it demonstrates that our suggested CMNV2 approach outperforms the other nine models in terms of accuracy and is capable of recognising the age and gender of masked individuals in both still and moving photos.

All things considered, the study's findings suggest that deep learning techniques can enhance the precision and velocity of masked face identification and categorization.

Tahyudin GG et al. [24] They proposed a method for determining an individual's gender based on facial image analysis, and they also investigated the extent to which a facial image-based model can discriminate between male and female genders. Furthermore, the study delves into the often-overlooked aspects of data complexity and variance caused by ethnic and age-group disparities. We conducted both same-dataset and cross-dataset evaluations, with the latter taking the UTKFace dataset into account after training on the AFAD dataset. The image of size pixel with eight patches has the maximum validation accuracy, according to the experiments and analysis in the same-dataset assessment. By contrast, the image of size pixels with patches exhibits the best testing accuracy. Additionally, the cross-dataset evaluation's experiments and analysis demonstrate that the model performs best for picture-sized pixels with patches, with the accuracy, precision, recall, and F1-score values being, respectively. Moreover, the misclassification analysis demonstrates that the model performs best when determining the gender of individuals aged 21 to 70. We can use the results of this study as a foundation for further research on the effectiveness of gender classifier models that take into account various physical characteristics.

Vo T et al. [25] suggested make up face detection and preprocessing (FD&P), RR, and information collector (IC) modules, effective Race Recognition Framework (RRF). The study suggests two separate models for the RR module. The first model, known as the RR-CNN model, is RR employing a deep convolutional neural network (CNN). The second model, RR-VGG, is a fine-tuning RR model that is based on the well-known trained object recognition model, VGG. To assess the effectiveness of the suggested framework and compare the accuracy of RR-CNN and RR-VGG, the authors conduct an experiment on the VNFaces dataset, specifically composed of photos from Vietnamese people's Facebook profiles. According to the experimental results, the RR-VGG model with enriched input photos produces the best accuracy for the VNFaces dataset, yielding 88.87%, while the independent, lightweight RR-CNN model produces an accuracy of 88.64%. The extension experiments show that the suggested models can solve problems involving different racial datasets, such as Brazilian, Chinese, or Japanese, with over 90% accuracy. We advise using the fine-tuned RR-VGG model for the majority of cases, as it produces the best results.

Khan K et al. [26] proposed a method for classifying races by leveraging a previous framework for facial segmentation. We built a face segmentation model using a deep convolutional neural network (DCNN). We labelled the facial photos according to seven different classes—nose, skin, hair, eyes, brows, back, and mouth—to train the DCNN. The first phase's DCNN model produced the segmentation results. The probabilistic classification approach generates probability maps (PMs) for each semantic class. Out of seven distinct facial traits that aid in racial classification, the author examined five that stand out. After extracting features from the PMs of five different classes, the DCNN trains a new model. They evaluated the suggested race classification method's performance using four common face datasets, and their findings outperformed those of earlier research.

Coe J and Atay M [26] They examined how race affected facial recognition using two different kinds of algorithms. They address four issues surrounding facial recognition and provide an overview of the field. They examined the system's architecture, development, and design and provided a thorough evaluation plan for every type of algorithm, dataset, and software. They provide analysis for the deep learning and machine learning algorithms, as well as a full explanation of the experiment's outcomes. In order to determine which algorithms best reduce racial bias, the study's findings contrasted two different types of algorithms and evaluated their accuracy, metrics, miss rates, and performances. Using racially balanced and imbalanced datasets, they assessed racial bias in five machine learning algorithms and three deep learning algorithms. After conducting an experimental investigation, they assessed and compared the accuracy and miss rates of all tested algorithms, and they concluded that SVC is the best machine learning algorithm and VGG19 is the best deep learning algorithm. They come to the conclusion that all deep learning algorithms performed better than their machine learning equivalents, with VGG19 being the algorithm that reduces bias the most.

CHAPTER THREE

3. BACKGROUND THEORY

3.1 Introduction

The identification of human races and genders is a crucial area of study in the field of machine learning, especially in the current era where digitalization has a direct impact on

practically everything. [27]. Despite fifty years of technological progress in several areas, including object identification and discriminating techniques [28].], analysing human races and genders continues to be a key categorization problem in the realm of machine learning. However, because of its significance and possible uses, this topic has drawn the interest of numerous academics, including computer scientists and experts in the classification of race and gender [29]. The ability to identify human races and genders has many benefits, including facilitating users' understanding of the characteristics common to each race and gender [30]. This not only saves consumers time, but also reduces the effort required to speed up feature-related tasks, a crucial aspect of image recognition procedures, highlighting its importance in the artificial intelligence field[31].

This chapter deals with the theoretical framework for facial race and gender recognition using different CNN models. It also deals with the models' layers and parameters. The performance evaluation confusion matrix and its types following activation function analysis, along with their types.

3.2 Convolutional Neural Networks

The human visual system inspired one deep learning algorithm, CNN [32]. Its ability to autonomously detect relevant features without human intervention is a primary advancement over previous approaches. CNN also draws inspiration from the human visual system [33]. CNNs can support tasks like natural language processing, image categorization, and identification because of their design, which makes computer perception more in line with human cognition [34]. As a subtype of deep neural networks (DNNs), CNNs typically encompass key layers including convolutional, activation (employing nonlinear functions), and various types of layers[35]. The structure of the visual cortex inspires the interconnected layers that compose CNNs, which perform specific operations on incoming data.[37]. CNNs can't work without convolutional layers, which use learnable filters or kernels to scan and extract spatial features. This generates feature maps that show local patterns and features. By lowering spatial dimensions while maintaining crucial information, pooling layers improve CNNs even more. Typically, max pooling selects the maximum value within a specified window. Finally, fully linked layers aggregate the retrieved characteristics for final predictions by connecting each neuron in one layer to every other neuron in the next layer [39]. CNNs frequently use backpropagation to train with labelled data. In this method, the network learns to map

inputs to corresponding labels by updating parameters like filter weights and biases based on prediction error until it achieves performance that is satisfactory [40]. All things considered, CNN is one of the most well-known and widely applied methods in deep learning. The tiers of CNN are as follows:

3.2.1 Convolutional Layer

The convolutional layer, which carries out the "convolution" function that gives a CNN its name, is an essential component of a CNN. Additionally, the convolutional kernel plays a crucial role in many computer vision technologies and significantly impacts CNN's functionality [41]. This process involves subjecting a picture to a series of convolutional filters, also known as kernels. To accomplish this, we must use a tiny matrix known as the kernel, or filter. Its values are consistent with the picture [42]. Each filter performs the convolution on the input image by aligning to a distinct matrix. This convolution produces feature maps [43].

3.2.2 Activation Layer

The activation layer, also called the nonlinear layer, comes after a convolutional layer. The main goal of this layer is to add nonlinearity to a computational system that is primarily linear [44]. The application of the rectified linear unit (ReLU) activation layer, in conjunction with a convolutional layer, serves as a practical illustration of this idea [45]. achieved this by converting all input values into positive integers, as ReLU yields an output of 0 for negative inputs. Moreover, ReLU provides a main benefit in terms of computing performance over other activation functions, which reduces computational overhead [46]. As a result, ReLU in CNNs leads to faster and more straightforward operations in the current environment. as shown in equation (3.1) [47] the ReLU mathematical statement as follows:

$$f(k) = \max(0, k) \quad (3.1)$$

This function implies that for positive values of k , the output denoted by $f(k)$ is always constant, but for negative values of k , it is zero.

3.2.3 2. Pooling Layer

CNN architectures frequently place subsampling or pooling layers between convolution layers [48]. The convolutional layer processes each generated feature map

independently. The purpose of pooling operations is to reduce the spatial dimensions of the feature map by limiting the number of retrieved features and preventing overfitting [49]. The maximum pooling approach and the average pooling method are two popular pooling techniques [50]. Figure [51] shows the pooling layer with a 2x2 filter.

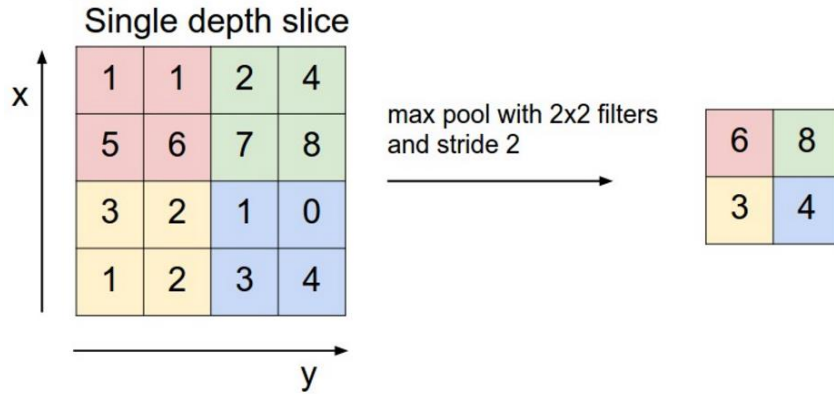


Figure: 3.1 The pooling layer with 2x2 filter

3.2.4 Fully Connected Layer

Using fully connected (FC) layers can be particularly helpful, even if convolutional and pooling layers provide insight into the more complex characteristics of source images [52]. The integration of an FC layer provides an economical way to obtain these features in non-linear configurations [53]. This FC layer makes it easier to label images that come in from the input layer by putting together data from the pooling and convolution layers to make a possible classification score [54]. Subsequently, the output layer receives the two-dimensional output of the FC layer and uses SoftMax activation or a sigmoid function to predict the input class labels [55].

3.3 Pre-trained learning

Pre-trained learning can train CNNs to improve their performance on novel tasks. A pretrained CNN model serves as the foundation for pre-trained learning with CNNs. The pre-trained model has already gained the ability to extract general features helpful for a variety of computer vision applications from a large dataset, such as ImageNet. These features can then serve as the foundation for building a new CNN model trained on a smaller, task-specific dataset [56]. Feature extraction and fine-tuning are two frequently used pre-trained learning techniques with CNNs. Feature extraction, which uses the pre-trained CNN model as a fixed feature extractor, trains a new classifier layer on top of the retrieved features. This method may be useful when the new dataset is small and

comparable to the pre-trained dataset. Fine-tuning involves retraining the previously trained CNN model on the new dataset, usually using a lower learning rate and fewer training epochs. When the fresh dataset is bigger and more varied than the pre-trained dataset, fine-tuning might be especially helpful [57]. Numerous applications, including natural language processing, autonomous driving, and medical imaging, have made extensive use of pre-trained learning with CNNs. Researchers and developers can now use pre-trained CNN models like DenseNet, VGG, InceptionNet, and ResNet for their jobs because they are publicly available [58].

3.4 VGG19

In 2014 [59], Oxford University proposed the VGG network as a deep learning network model. This well-liked convolutional neural network model performs exceptionally well in target identification and picture classification tasks [60]. Its benefits include simplicity and practicability. Figure 3.2 displays the VGG network structure. VGG makes the network deeper than a regular convolution neural network [61], by using more than one convolutional layer and nonlinear activation layers, that is, more than one convolutional layer. The structure can more effectively extract image features. One of the VGG networks has 19 layers, called VGG19. With five stages of convolution layers, five pooling layers, and three fully connected layers, the VGG19 employs a 3×3 filter to collect picture detail information. The VGG19 network enhances its ability to extract picture feature vectors by increasing the convolution kernel's depth from 64 to 512. A pooling layer will come after each convolutional layer stage [62].

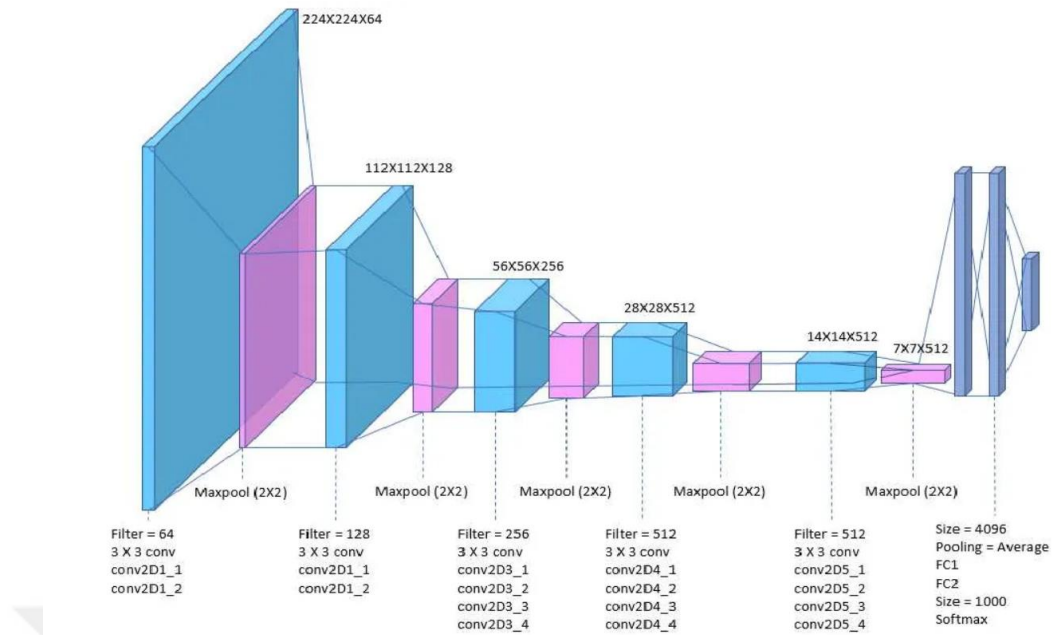


Figure:3.2 The VGG19 Architecture

Every pooling layer is the same size, measuring 2 by 2. We use Rectified Linear Units (ReLUs) as the activation function, and MaxPooling is used to down sample the pooling layer. The three fully connected layers have 4096, 4096, and 1000 nodes in total [63]. The final layer of the network consists of a SoftMax regression classifier, which uses probability to classify the 224 x 224 input images [64].

3.5 InceptionV3

3.6 InceptionV3, a development of the Inception architecture, is a sophisticated CNN for image categorization applications. It draws attention to itself with its inception modules. The network combines parallel convolutional operations with different filter sizes (1x1, 3x3, and 5x5) to make it easier to extract features at multiple scales for hierarchical pattern recognition [65]. With 48 layers in all, it is a deep neural network. Convolutional layers, pooling layers, fully connected layers, and auxiliary classifiers are all combined in these layers, as studied by Adnan et al. [66]. Auxiliary classifiers handle the vanishing gradient issue during training; factorization approaches maximize computational resources; and batch normalization stabilizes training. InceptionV3 is a potent tool for picture categorization thanks to the careful instrumentation of these architectural components, which strikes a compromise between identifying subtle features and processing speed [67].

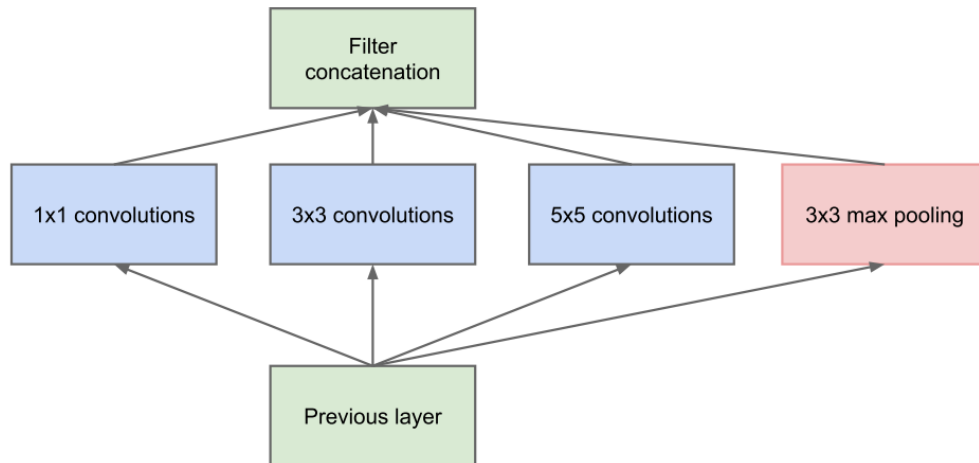


Figure:3.3 The InceptionV3 Architecture

The final inception module employs global average pooling, stacking these inception modules on top of one another. This led to a deeper analysis that included up to 22 layers, improving accuracy. However, this model encountered the deterioration issue commonly observed during deep neural network training [68].

3.7 ResNet50

In 2015, the Residual Network (ResNet) model family unveiled a CNN architecture known as ResNet50 [69]. Its proficiency in deep learning tasks—specifically, picture identification and classification—is well known [70]. Specifically, ResNet50 refers to a 50-layer version of ResNet. The model consists of several convolutional blocks, each containing multiple convolutional layers and identity shortcuts [71]. These shortcuts enable the model to represent [72]. ResNet50 has proven its impressive performance in a variety of computer vision applications, including object detection, picture segmentation, and image classification [73]. It won the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) in 2015 and performed better than several previous architectures [74].

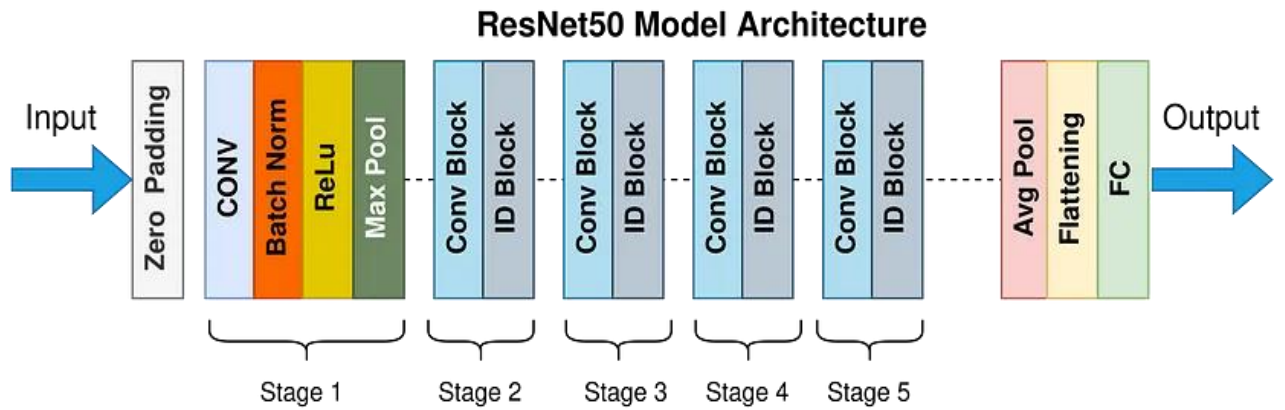


Figure:3.4 The ResNet50 Architecture

3.8 RGCNN Models

This new model, called RGCNN, recognizes four racial and gender identities: African, Asian, Caucasian, and Indian. It does so with the fewest possible parameters. Figure 3.5 summarizes the architecture of the RGCNN model.

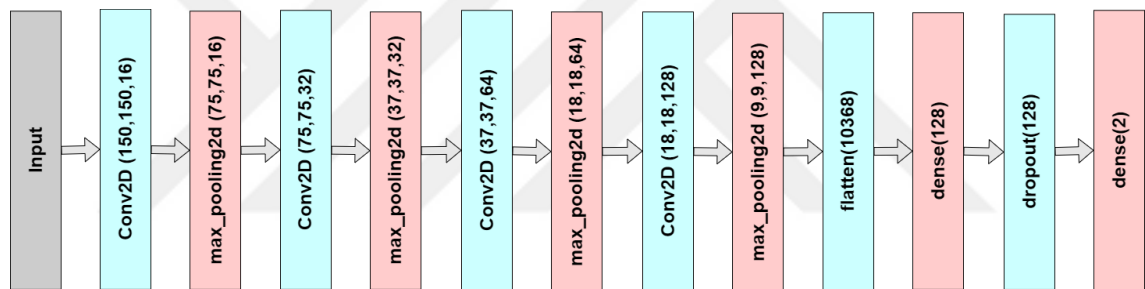


Figure:3.5 The RGCNN Architecture

The table presents a summary of the RGCNN model in Python.

Table 3.1: The summarized python RGCNN model

Model: "sequential_3"

Layer (type)	Output Shape	Param #
=====		
conv2d_12 (Conv2D)	(None, 150, 150, 16)	784
max_pooling2d_12 (MaxPooling (None, 75, 75, 16))		0
conv2d_13 (Conv2D)	(None, 75, 75, 32)	8224
max_pooling2d_13 (MaxPooling (None, 37, 37, 32))		0
conv2d_14 (Conv2D)	(None, 37, 37, 64)	32832
max_pooling2d_14 (MaxPooling (None, 18, 18, 64))		0
conv2d_15 (Conv2D)	(None, 18, 18, 128)	131200

max_pooling2d_15 (MaxPooling (None, 9, 9, 128))		0
flatten_3 (Flatten)	(None, 10368)	0
dense_6 (Dense)	(None, 128)	1327232
dropout_3 (Dropout)	(None, 128)	0
dense_7 (Dense)	(None, 1)	129
=====		
Total params: 1,500,401		
Trainable params: 1,500,401		
Non-trainable params: 0		

3.9 Confusion Matrix

When it comes to predictive analysis in machine learning, the confusion matrix is a crucial instrument. Machine learning models based on classification use it to evaluate their performance. The confusion matrix, especially in binary classification scenarios, functions as a condensed tabulation that shows the precise and incorrect predictions that a classifier has made [75]. Working with multi-class classification tasks creates an $N \times N$ matrix, where N represents the number of different target classes [76]. This is due to the growing confusion matrix. We can determine the accuracy of the model by visualizing the diagonal values, which represent the successfully classified cases. Confusion matrices, as their name suggests, give a thorough way to assess a classification model's effectiveness across a range of classes [77].

Table 3.2: The binary confusion matrix for actual and predicted model

		Actual Values	
		Positive	Negative
Predicted Values	Positive	TP	FP
	Negative	FN	TN

The confusion matrix takes the form of a square matrix. The rows and columns represent various class or category representations. Typically, in this matrix, the rows show the values that the model predicted, while the columns show the actual values (ground truth). However, we can also interpret it in the opposite manner, where the columns display the expected values and the rows reflect the actual values. This configuration makes it possible to clearly see how well the model performs in terms of instances across various classes that are correctly and wrongly classified [78].

True Positive (TP): This describes situations in which the model accurately classifies positive instances as such. For example, in a medical diagnosis situation, TP might indicate instances in which the model accurately classified patients as having a specific ailment.

False Positive (FP): This occurs when the model incorrectly interprets negative examples as positive ones. Otherwise, the model predicts a favorable outcome when a negative one occurs. This type of problem is also known as a Type 1 error. For instance, a mistaken categorization of a valid email as spam results in false positives (FP) in spam email detection.

False Negative (FN): This happens when the model incorrectly identifies positive instances as negative. In other words, the model predicts a negative outcome when it is actually positive. FN is also known as a Type 2 error. For example, in a medical diagnosis, FN would occur when the model fails to identify patients with a certain condition.

True Negative (TN): This happens when the model mistakenly classifies positive examples as negative ones. Otherwise, the model forecasts a negative result when a positive one occurs. Another name for FN is a Type 2 mistake. For example, FN can appear in a medical diagnosis if the model is unable to identify people with a specific ailment.

3.8.1 Accuracy

Accuracy is the number of accurate predictions your model makes across the entire test dataset determines. A useful baseline metric for assessing the model's performance is accuracy as shown in equation (3.2). In unbalanced datasets, accuracy degrades as a statistic [79].

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (3.2)$$

3.8.2 Misclassification

In a confusion matrix, misclassification describes situations in which the model assigns the incorrect class label to individual data points. Off-diagonal cells of the confusion matrix can contain false positives (erroneously guessing a positive class) and false negatives (erroneously anticipating a negative class). Misclassification sheds light on the classifier's shortcomings and areas for performance enhancement as shown in equation (3.3) [80].

$$\text{Misclassification} = \frac{FP+FN}{TP+TN+FP+FN} \quad (3.3)$$

3.8.3 Recall

Recall is the proportion of real positive cases that our model was able to accurately predict. When a false negative outweighs a false positive, recall is a meaningful statistic. If the recall is higher, we will identify most positive instances (TP+FN) as positive (TP). As a result, FP readings will rise, and overall accuracy will fall. If your memory is poor, you have a large number of FN (which should have been positive but is labeled as negative). This means that if you find a positive case, you can be more confident that it is a true positive as shown in equation (3.4) [81].

$$\text{Recall} = \frac{TP}{TP+FN} \quad (3.4)$$

3.8.4 Precision

Precision tells us how many of the correctly predicted case actually turned out to be positive. This would determine whether our model is reliable or not. Precision is a useful metric in case where False Positives is a higher concern than False Negative as shown in equation (3.5) [82].

$$\text{Precision} = \frac{TP}{TP+FP} \quad (3.5)$$

3.8.5 F1-Score

When we try to increase the precision of model, the recall grows down and vice-versa. F1-Score is a harmonic mean of Precision and Recall and so it gives a combined idea

about these two metrics. It is maximum when precision is equal to recall.

The interpretability of the F1-Score is poor, it means that we don't know what our classifier is maximizing- precision or recall. So, we use it in combination with other evaluation metrics which gives us a complete picture of the result as shown in equation (3.6) [83].

$$F1 - Score = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (3.6)$$

3.8.6 False Positive rate

False positive rate is a measure for how many results get predicted as positive out of all the negative cases as shown in equation (3.7).

$$FPR = \frac{FP}{TN + FP} \quad (3.7)$$

3.10 Activation Function

An activation function in the context of neural networks is a mathematical operation applied to the output of a neuron, which determines whether the neuron should be activated or not based on the input it receives. This function introduces non-linearity into the network, enabling it to learn complex patterns and relationships within the data. Activation functions transform the input signals into output signals that are then passed on to the next layer of the network. Common activation functions include the followings[84]:

3.9.1 Sigmoid

In neural networks, the sigmoid function is commonly used as an activation function in the output layer for binary classification problems. It squashes the raw output of the neural network into a probability score, indicating the likelihood of the input belonging to the positive class. Sigmoid functions are mathematical functions that map input values to a range between 0 and 1, making them particularly useful in binary classification problems. The sigmoid function is defined as in equation (3.8):

$$f(x) = \frac{1}{1 + e^{-x}} \quad (3.8)$$

Sigmoid function is continuously differentiable and a smooth S-shaped function. The derivative of the function is in equation (3.9).:

$$f'(x) = \frac{e^{-x}}{(1+e^{-x})^2} \quad (3.9)$$

It is also not symmetric about zero which means that the signs of all output values of neurons will be same. This matter can be enhanced by scaling the sigmoid function[85].

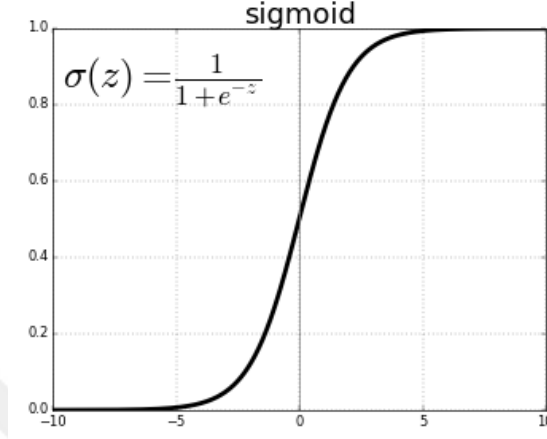


Figure 3.6: The sigmoid function

3.9.2 The ReLU (Rectified Linear Unit)

ReLU is a popular non-linear activation function extensively used in neural networks. One of its main advantages is that it introduces sparsity by only activating neurons for positive input values, while deactivating them for negative inputs. Mathematically, ReLU can be defined as in equation (3.10):

$$f(x) = \max(0, x) \quad (3.10)$$

This equation implies that the output of the ReLU function is equal to the input value (x) if (x) is positive, and zero otherwise. This property encourages the network to learn more efficient representations and helps mitigate the vanishing gradient problem[86].

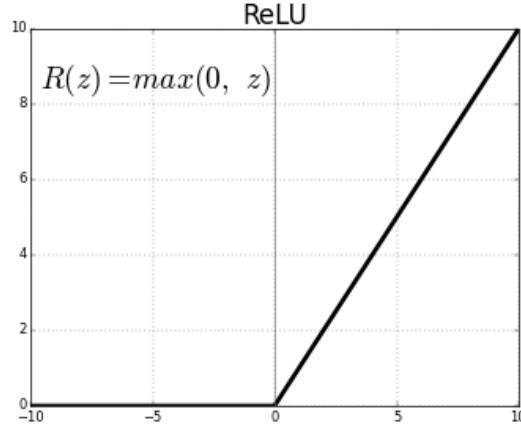


Figure 3.7: The ReLU Activation Function plot

ReLU proves more effective than alternative functions as it doesn't activate all neurons simultaneously; instead, only a specific subset of neurons is activated at any given time. However, in certain instances, the gradient may equal zero, causing weights and biases to remain unchanged during the backpropagation process in neural network training[87].

3.9.3 SoftMax

The SoftMax activation function is essentially a fusion of multiple sigmoid functions. Unlike the sigmoid function, which is commonly employed for binary classification due to its output range of 0 to 1, SoftMax extends its utility to multiclass classification tasks. For each data point across all individual classes, the SoftMax function computes the probability. In the context of constructing a network or model for multiclass classification, the output layer of the network will consist of a number of neurons equivalent to the total number of classes in the target variable. This architectural arrangement enables the SoftMax function to generate probabilities for each class, facilitating the classification of multiple classes concurrently in equation (3.11) [88].

$$\sigma(z)_j = \frac{e_j^z}{\sum_{k=1}^K e_k^z} \text{ for } j = 1, \dots, k \quad (3.11)$$

CHAPTER FOUR

4 Results and Discussions

4.1 Introduction

The chapter focuses on developing a facial race and gender recognition system. The system consists of several stages: dataset collection and data preprocessing to segment face images. This chapter discusses each stage in detail and introduces the proposed deep neural networks (RGCNN) and hyperparameter tuning.

4.2 The datasets

In the proposed model, the dataset includes images of individuals displaying all the mentioned races. In this study, we utilized the dataset from various sources:

1. Samples of Asian face images were collected from three data sets: the first dataset, Pretty Face, contains 3318 images. The number of samples selected from this dataset is 497; the second dataset is SCUT-FBP5500_v2.1, which consists of 5500 images as well as randomly selected (1005) images. The third dataset is referred to as the AFD dataset. We arrange the images in 135 directories, with each directory name representing the actor's present facial image. The total number of images for each actor is not exactly equal. There are 598 images of randomly selected samples. This translates to a total of 2100 randomly selected Asian face-race samples, as illustrated in Table 4.1.

Table 4.1: The Asian Face Race Samples

Race	Datasets name	Dataset samples	Selected samples	Link of Datasets
Asian face	pretty-face	3318	497	https://www.kaggle.com/datasets/yewtsi-ng/pretty-face
	SCUT-FBP5500_v2.1	5500	1005	https://github.com/HCIILAB/SCUT-FBP5500-Database-Release
	CASIA-FaceV5	135 directories	598	https://github.com/X-zhangyang/Asian-Face-Image-Dataset-AFD-dataset
total			2100	

The Asian face race random samples that are collected from the tree datasets shown in Figure 4.1

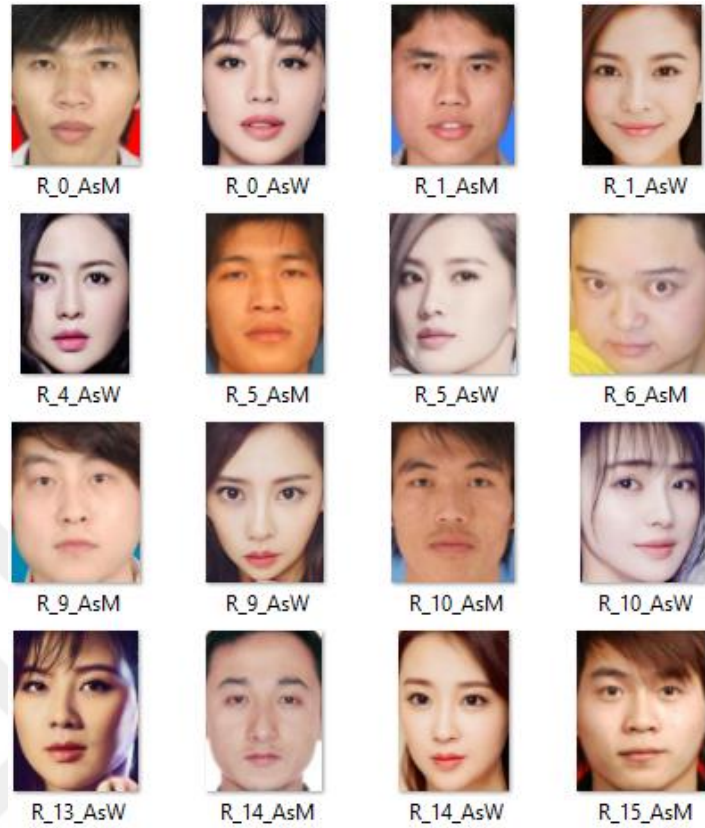


Figure 4.1: The Asian Face Race Samples

- The collected images of Indian faces came from two datasets. The first dataset, `cnsifd_faces_bmp`, consists of 1647 images. We selected 804 samples from this dataset, and we call the second dataset `Indian_actors_faces`. We arrange the images in 135 directories, with each directory name representing the actor's facial image within it. The total number of images for each actor is not exactly equal. The total number of randomly selected samples is 906. Table 4.2 shows that there is a total of 1710 randomly selected Indian face-race samples.

Table 4.2: The Indian Face Race Samples

Race	Datasets name	Dataset samples	Selected samples	Link of Datasets
India face	<code>cnsifd_faces_bmp</code>	1647	804	https://github.com/harish2006/IISCIFD
	<code>Indian_actors_faces</code>	135 directories	906	https://www.kaggle.com/datasets/nagasai524/indian-actor-faces-for-face-recognition
total			1710	

The Indian face race random samples that are collected from the two datasets shown in Figure 4.2

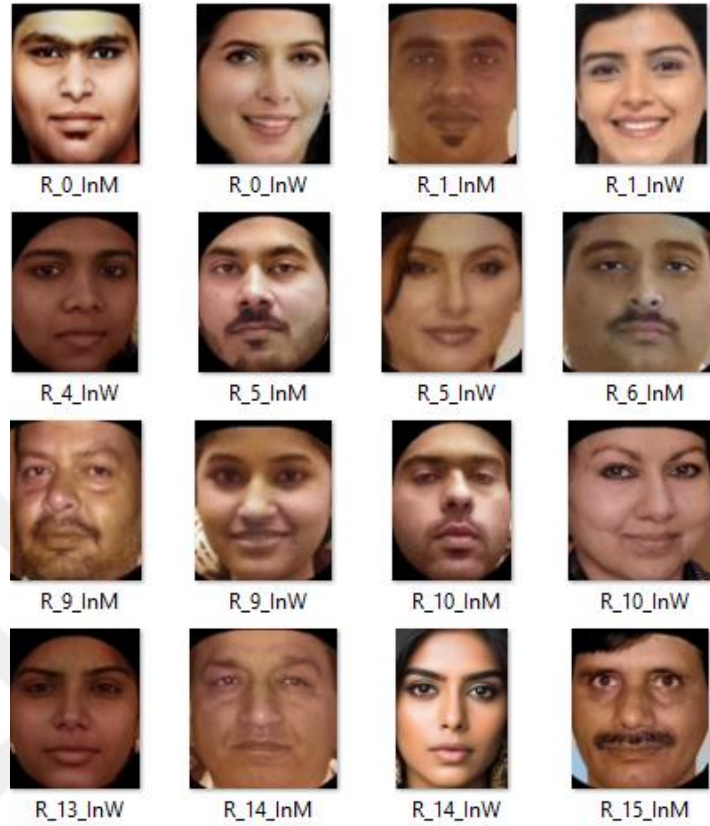


Figure 4.2: The Indian Face Race Samples

3. The Caucasian faces are samples collected from the `img_align_celeba` dataset, which consists of 202599 images. The total number of samples selected randomly from this dataset is 1785 images, as illustrated in Table 4.3.

Table 4.3: The Caucasian Face Race Samples

Race	Datasets name	Dataset samples	Selected samples	Link of Datasets
Caucasian face	<code>img_align_celeba</code>	202,599	1785	http://mmlab.ie.cuhk.edu.hk/projects/CelebA.html
total			1785	

The Caucasian face race random samples that are collected from the two datasets shown in Figure 4.3

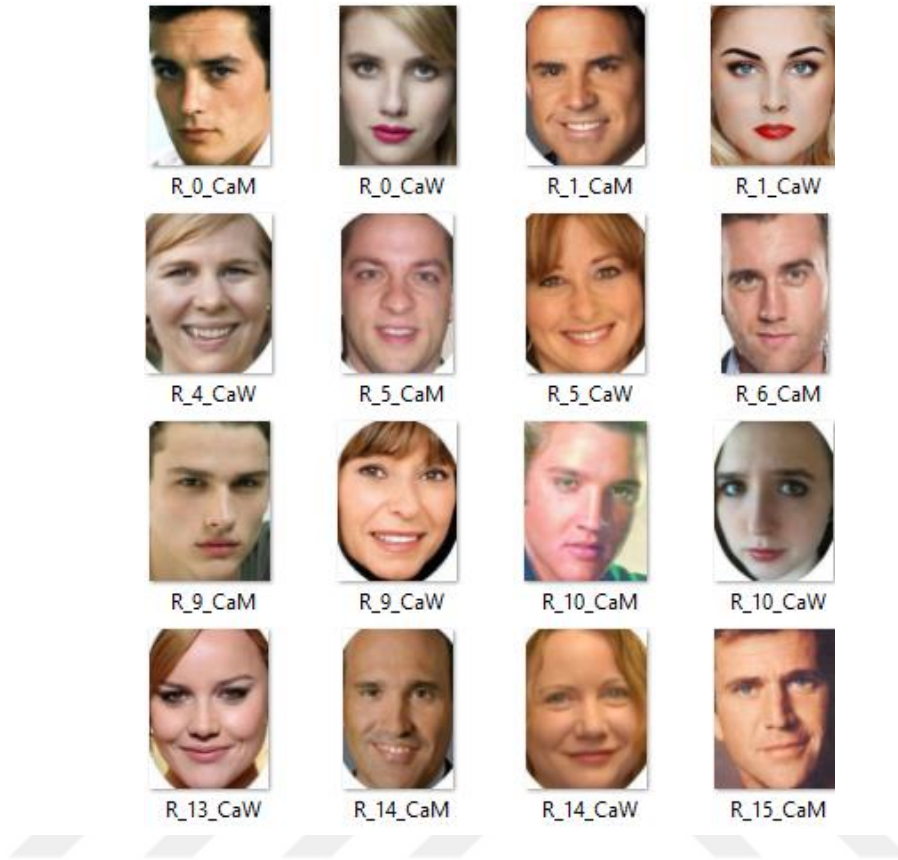


Figure 4.3: The Caucasian Face Race Samples

4. The collected African faces image samples, consisting of 38546 images, were from the CASIA-Face-Africa dataset. The total number of samples selected randomly from this dataset is 1286 images, as illustrated in Table 4.4.
- 5.

Table 4.4: The African Face Race Samples

Race	Datasets name	Dataset samples	Selected samples	Link of Datasets
African face	CASIA-Face-Africa	38,546	1286	https://paperswithcode.com/dataset/casia-face-africa
Total			1286	

The African face race random samples that are collected from the two datasets shown in Figure 4.4

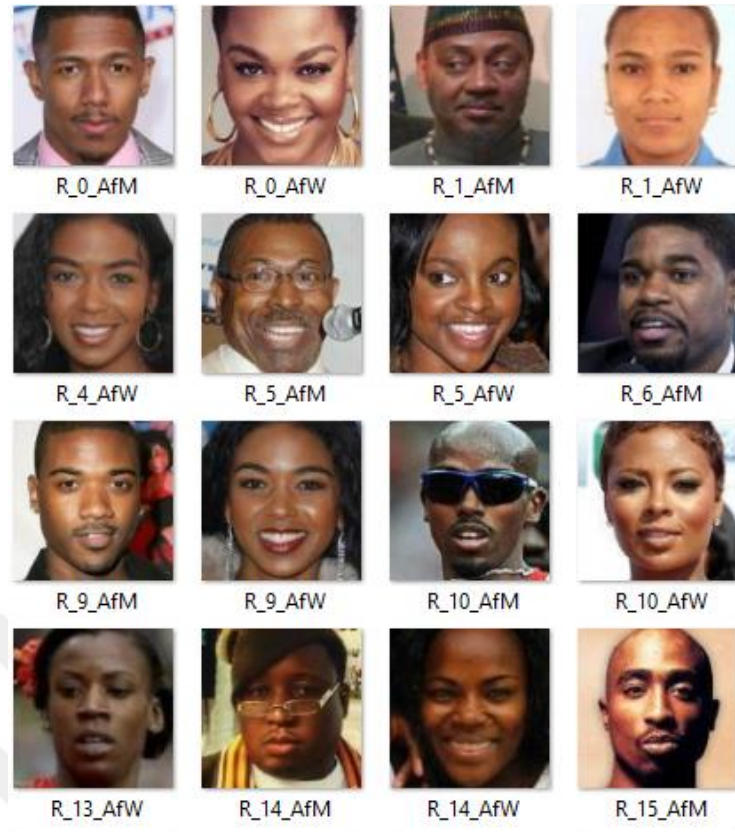


Figure 4.4: The Caucasian Face Race Samples

4.3 Preprocessing of the dataset:

In the four race datasets, the total number of overall selected images is 6881. separated between males and females. The number of female images is 3200, and the number of male images is 3681. From each race, we randomly selected 300 females and 300 males, as illustrated in Table 4.5. The sum of 300 images from each race and gender will be 1200 female and 1200 male images, as illustrated in Table 4.6.

Table (4.5): The race datasets samples used in this study

Race	Sample dataset	Selected Dataset
Asia	2100	600
Africain	1286	600
Caucasian	1785	600
India	1710	600

Table (4.6): The gender datasets samples used in this study

Gender	Sample dataset	Selected Dataset
Female	3200	1200
Male	3681	1200

Preprocessing the dataset is a common initial step in the workflow of deep learning. We prepared the collected dataset using methods that CNN models can use for training, validation, and testing. The first step is resizing the images to 150x150 pixels. The author carried out the racial image encoding process by first assigning the race name (R) to the first character, then the image sequence number of the image, followed by (As) for Asian images, (Af) for African images, (Ca) for Caucasian images, and (In) for Indian images. Finally, we assigned the first character's gender name (M) for male images and (F) for female images. The second step involves normalization, where we convert the image into a matrix and adjust the pixel value range using the. min-max normalization. The third step is splitting the two data sets into a training and validation dataset (70%) and a testing dataset (30%). The final step is data augmentation. This method applies various types of transformation techniques to real images, thereby generating modified versions of the same image with alterations such as flipping, rotation, shifting, and zooming.

4.4 Training and testing the CNN race models

The race model consist of the folowing steps:

Step1: Preprocessing the dataset (African, Asian, Indian Caucasian).

Step2: Split the dataset to (70%)for (tarining and validation) and (30%) for testing.

Step3: Tarin and test the modles (InceptionV3, ResNet50, VGG19, RGCNN).

Step4: Evaluate and save the modles.

The RGCNN_ model summary are:

Table (4.7): The summary of RGCNN model

Model: "sequential_8"

Layer (type)	Output Shape	Param #
conv2d_12 (Conv2D)	(None, 150, 150, 16)	784
max_pooling2d_12 (MaxPooling)	(None, 75, 75, 16)	0
conv2d_13 (Conv2D)	(None, 75, 75, 32)	8224
max_pooling2d_13 (MaxPooling)	(None, 37, 37, 32)	0
conv2d_14 (Conv2D)	(None, 37, 37, 64)	32832
max_pooling2d_14 (MaxPooling)	(None, 18, 18, 64)	0
conv2d_15 (Conv2D)	(None, 18, 18, 128)	131200
max_pooling2d_15 (MaxPooling)	(None, 9, 9, 128)	0
flatten_3 (Flatten)	(None, 10368)	0
dense_6 (Dense)	(None, 128)	1327232
dropout_3 (Dropout)	(None, 128)	0
dense_7 (Dense)	(None, 1)	129
Total params: 1,500,401		
Trainable params: 1,500,401		
Non-trainable params: 0		

In this study, two methods are utilized to train and test all races dataset the one-versus-all approach and multiclass classification approach. Multiclass classification approach will be used to train and test all race on the other hand one-versus-all approach will be used to train and test all races models individually. The Binary-Classification models (RGCNN, ResNet50, VGG19, and InceptionV3) will train and test individually on each race dataset. And Multi-Class-Classification RGCNN model will be used for multi class classification to classify all four races at once. The collection includes images of 300 men and 300 women, for a total of 600 images per race (African, Asian, Indian, and Caucasian). First, the RGCNN- binary classification model training and testing methodology will be as follows: use the African (600) image samples as one and the 1800 images samples from the (Asian, Indian, and Caucasian) as all. Second, use the Asian

(600) image samples as one and the 1800 images samples from the (African, Indian, and Caucasian) as all. Third use the Indian (600) image samples as one and the 1800 images samples from the (African, Asian, and Caucasian) as all. Finally, use the Caucasian (600) image samples as one and the 1800 images samples from the (African, Asian, and Indian). Multi-Class-Classification will train and test all four races dataset (African, Asian, Indian and Caucasian) at once for all races datasets (600,600,600,600)

as all. Table 4.8 illustrate the model's training number of layers and parameters

Table 4.8: The model's number of layers and parameters.

Model	Layers	Parameters	Trainable parameters	Non-trainable parameters
RGCNN	12	1,500,401	1,500,401	0
MCCNN	12	1,500,401	1,500,401	0
ResNet50	50	36,418,370	12,853,570	23,564,800
VGG19	19	21,073,346	1,048,962	20,024,384
InceptionV3	48	24,162,466	2,359,682	21,802,784

This study used two approach One-Versus-All RGCNN and Multi-Class-Classification approach for training and testing dataset.

The rest Three models will do the same training and testing methodology with One against All approach as shown in Figure 4.5.

One against one approach will used for training and testing the gender model. the same models (InceptionV3, RGCNN, ResNet50, VGG19,) training and testing will be done in dividually. Only MCC-CNN will train and test for purpose of multi-Class-Classification To compare performance of both proposed approaches One-Versus-All and Multi-Class-Classification on race dataset. The dataset contains 1200 images for males and 1200 for females from (African, Asian, Indian, Caucasian). first model RGCNN will use the males (1200) images data as One and the 1200 images from the females. MCC-CNN will train, validate and test all 2400 images at once.

The facial races and gender recognition system steps shown in Figure 4.6. The system will start in case the image is loaded. After that the image will resized to (150 by 150) pixel. The Caffe Model will detect the face boundary. In case the Caffe Model did not detect the image face the system will start again by reading image step until the face will be detect. After that, you can select the model. The model will identify the image's race

and gender and display the results. The four models will train and test methodology with a one-versus-all approach, as shown in figure 4.5.

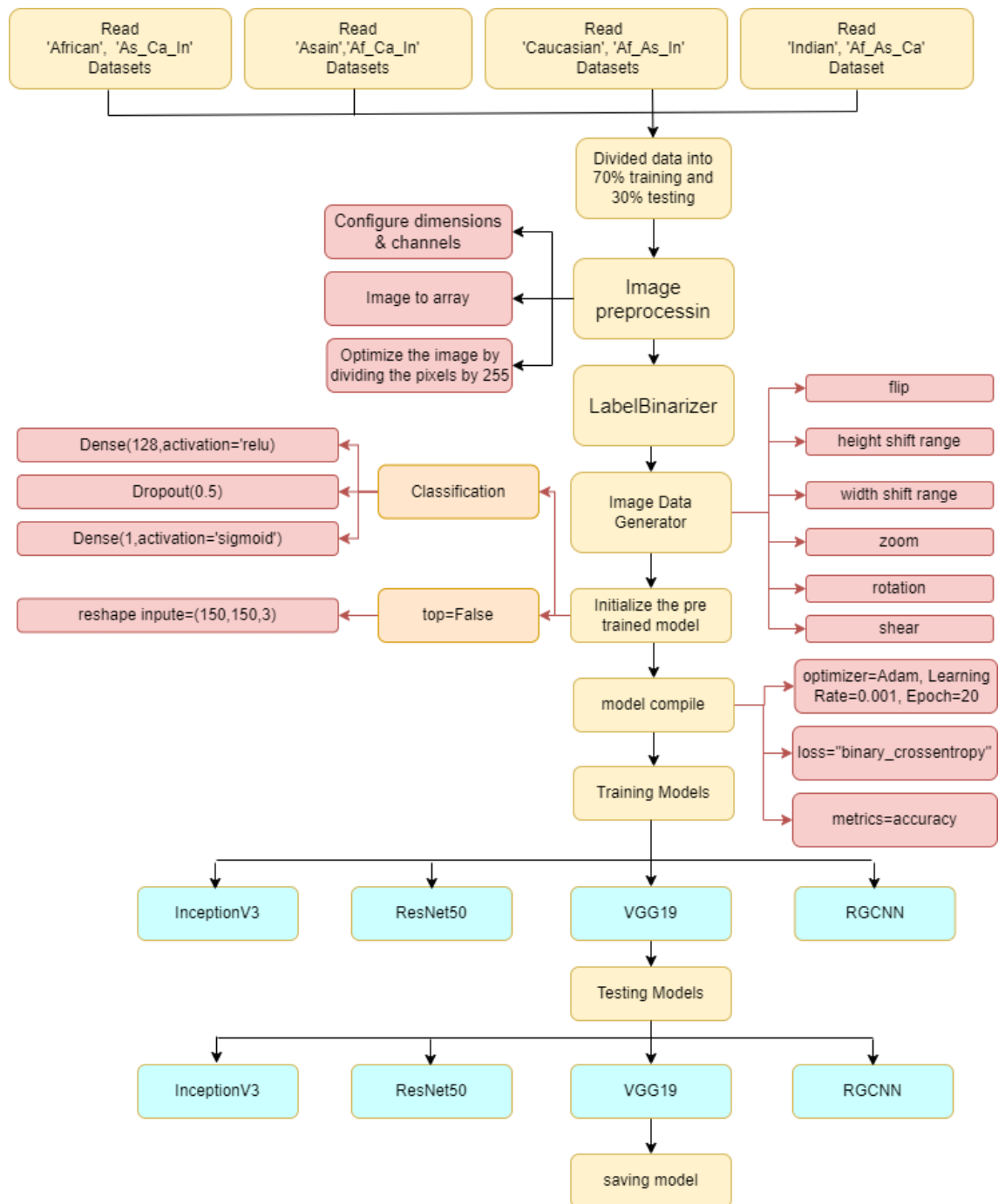


Figure (4.5): Training and testing the four CNN models on the four races.

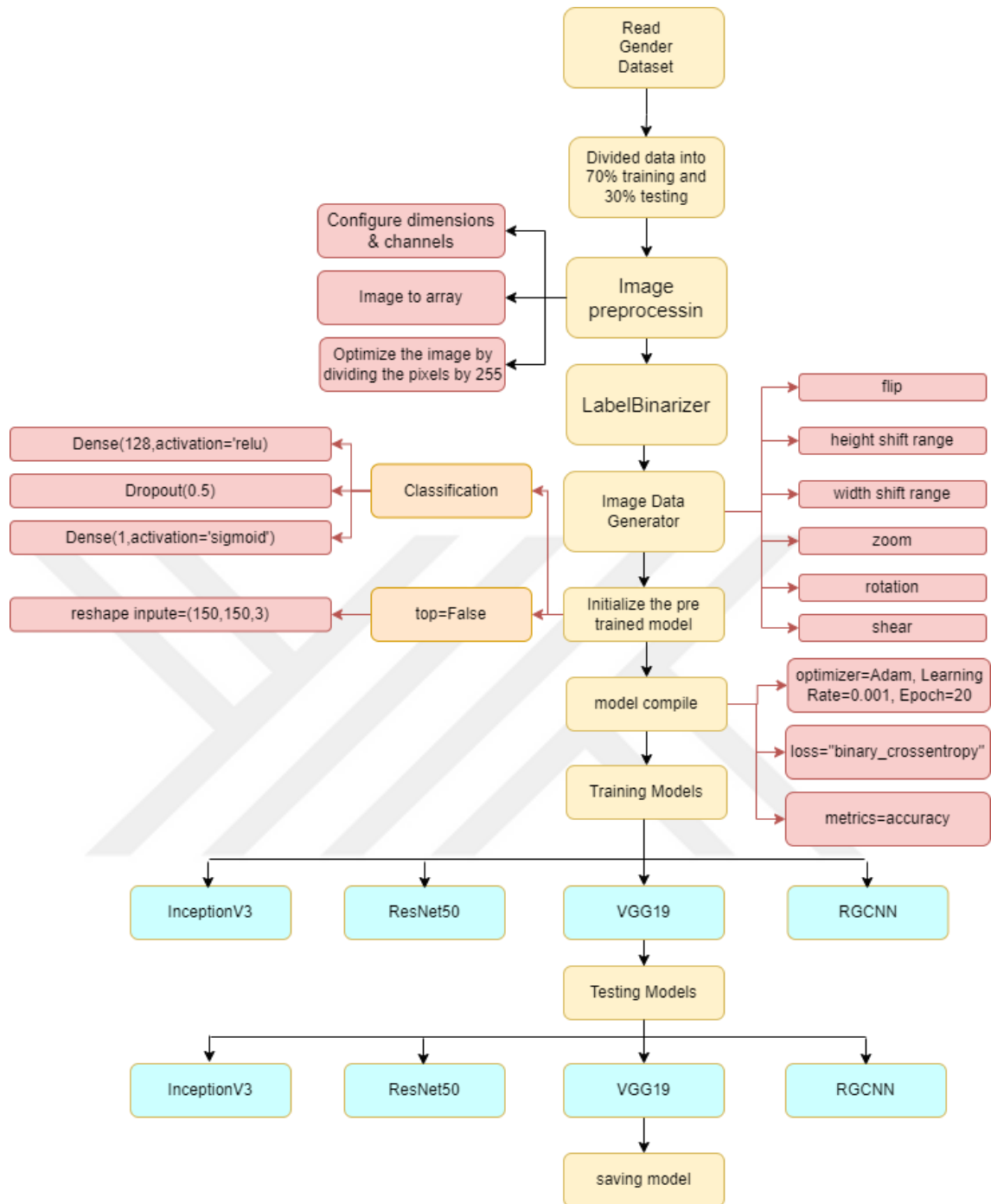


Figure (4.6): Training and testing the four CNN models on the Genders.

After training and testing all models on race and gender, the system will use those models for predicting the images or fame.

4.5 FRGCNN system structure

Figure 4.7 outlines the steps for the facial race and gender recognition systems. The system starts the process either by loading the image or by capturing a frame every 3 seconds. The system will then resize the image to 150 by 150 pixels. The coffee model

will detect the face-bound If the Caffe Model fails to identify the face in the image, the system will retry the image step until it detects the face. Following this, users can select their preferred model. The model will identify the image's race and gender and display the results.

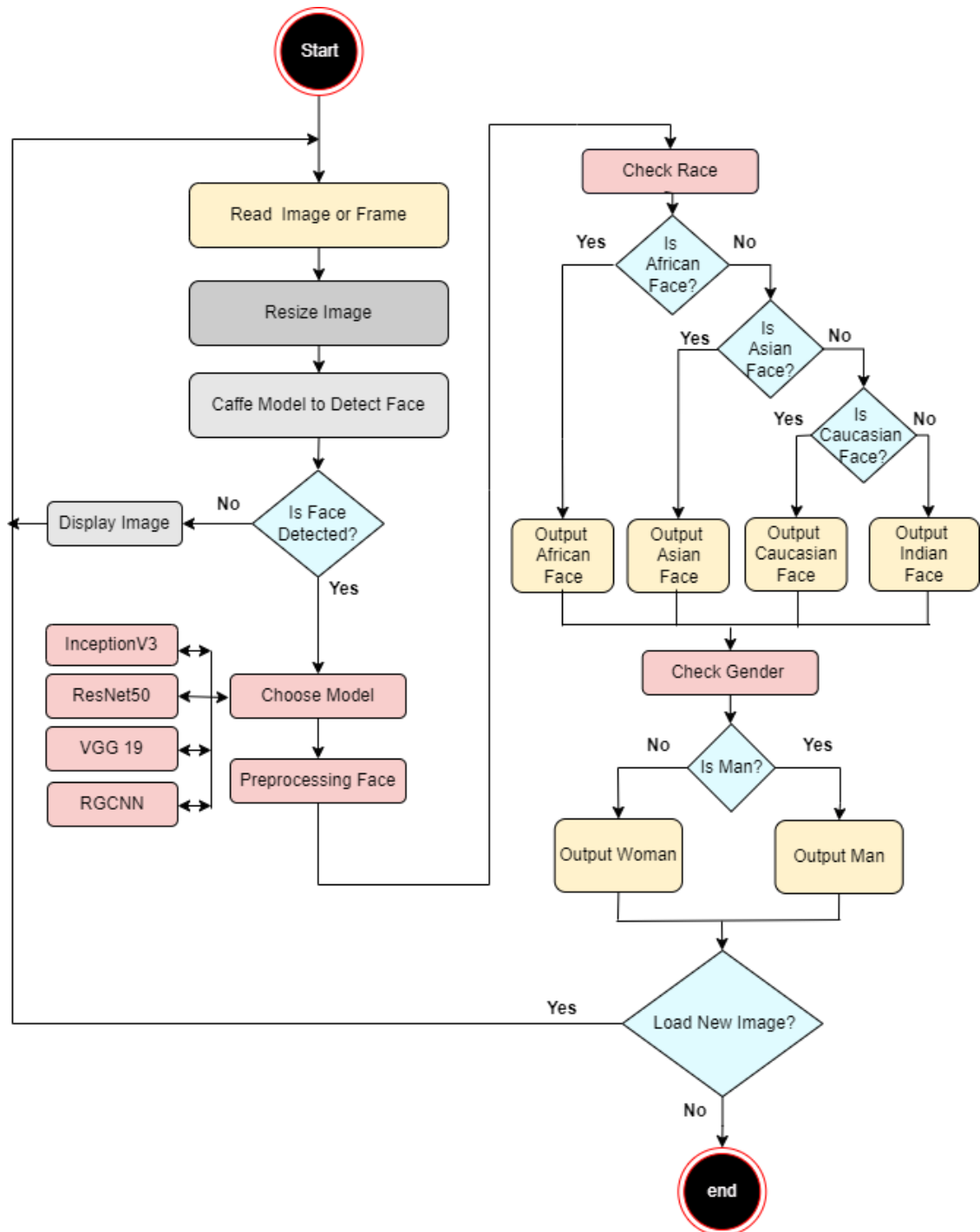


Figure (4.7): The proposed Races and gender system structure

CHAPTER FIVE

5. RESULTS AND DISCUSSIONS

5.1 Introduction

This chapter presents the results of the proposed methodologies, as outlined in Chapter Four, aimed at facial race and gender recognition using four races (African, Asian, Indian, and Caucasian), as well as gender (Male and Female). The performance evaluation of the proposed models was assessed using standard performance metrics commonly used to evaluate personal identification recognition systems, such as accuracy, recall, precision, Loss, and F-Score. The chapter commences with a review of the results obtained from utilizing the models (InceptionV3, ResNet50, VGG19, and RGCNN, MCC-CNN).

5.2 Implementation Results of the CNN Models

This thesis employs a one-versus-all methodology. That means each model will train and test four times for all races, as well as one more time for males and females. We extracted the accuracy and error after implementing the models for facial race and gender recognition training and testing.

5.3 The InceptionV3 Model Implementation

InceptionV3 Model implementation training and testing (20) epochs for the four races (African, Asian, Indian, Caucasian) dataset, the optimizer is ADAM, and the learning rate is 0.001. Additionally, there are 32 Batch sizes. Tables (5.1) illustrate performance evaluations for four races.

Table 5.1. The InceptionV3 model four races performance evaluation

Race	Precision	Recall	F1-score	Loss	Accuracy
African	0.98	0.99	0.99	0.012	0.994
As_Ca_In	1	0.99	1		
Asian	0.99	0.96	0.97	0.118	0.958
Af_Ca_In	0.88	0.97	0.92		
Caucasian	0.95	0.99	0.97	0.101	0.968
Af_As_In	0.97	0.83	0.89		
Indian	0.97	0.99	0.98	0.093	0.969
Af_As_Ca	0.98	0.89	0.94		

Table 5.2. illustrate the InceptionV3 Model African Races testing confusion matrix, while Figure 5.1 displays the model performance evaluation loss and accuracy.

Table 5.2. The InceptionV3 model confusion matrix for African races

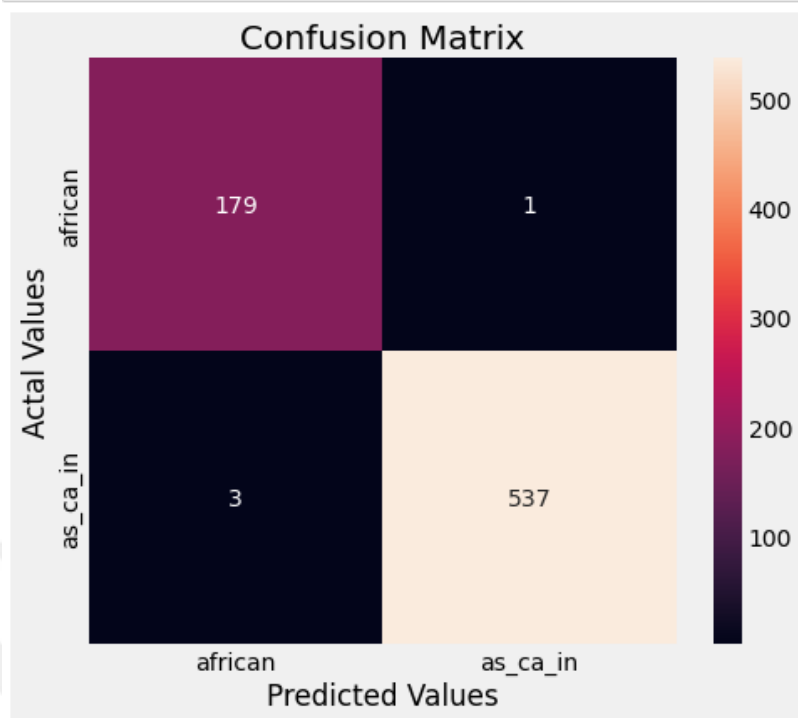


Figure 5.1. The InceptionV3 model loss and accuracy for African race

Table 5.3. illustrate the InceptionV3 Model Asian Races testing confusion matrix, while Figure 5.2 displays the model performance evaluation loss and accuracy.

Table 5.3. The InceptionV3 model confusion matrix for Asian races

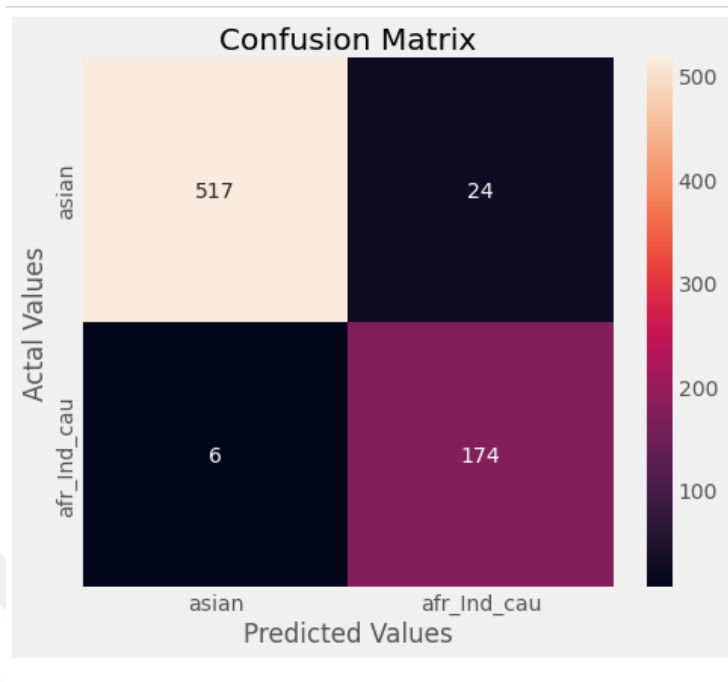


Figure 5.2. The InceptionV3 model loss and accuracy for Asian race

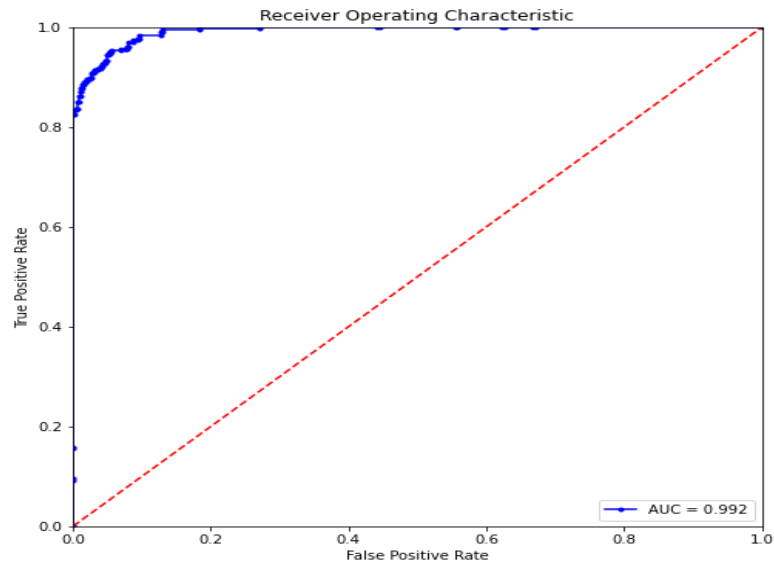


Figure 5.3. The InceptionV3 model ROC accuracy for Asian race

Table 5.4. illustrate the InceptionV3 Model Caucasian Races testing confusion matrix, while Figure 5.3 displays the model performance evaluation loss and accuracy.

Table 5.4. The InceptionV3 model confusion matrix for Caucasian races

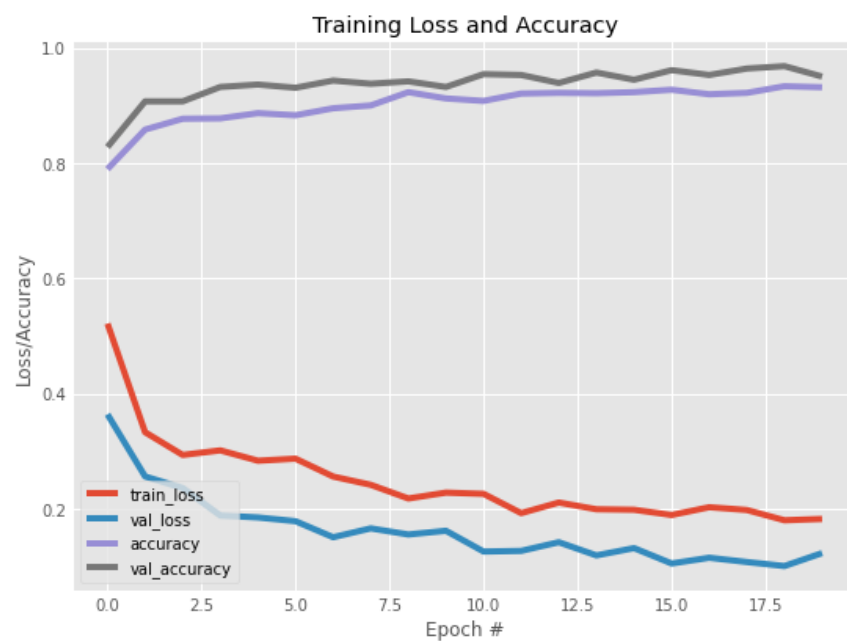
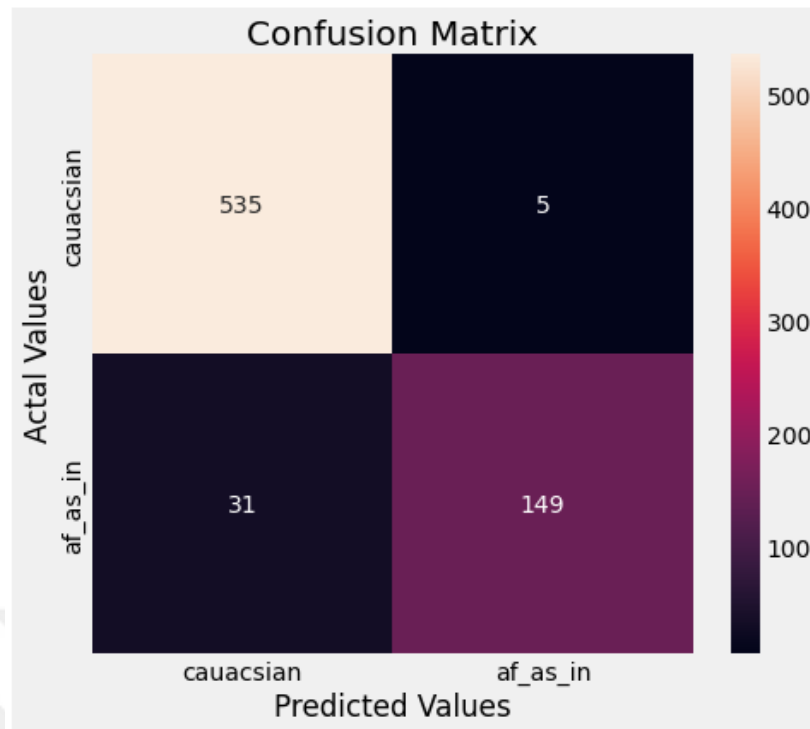


Figure 5.4. The InceptionV3 model loss and accuracy for Caucasian race

Table 5.5. illustrate the InceptionV3 Model Indian Races testing confusion matrix, while Figure 5.4 displays the model performance evaluation loss and accuracy.

Table 5.5. The InceptionV3 model confusion matrix for Indian races

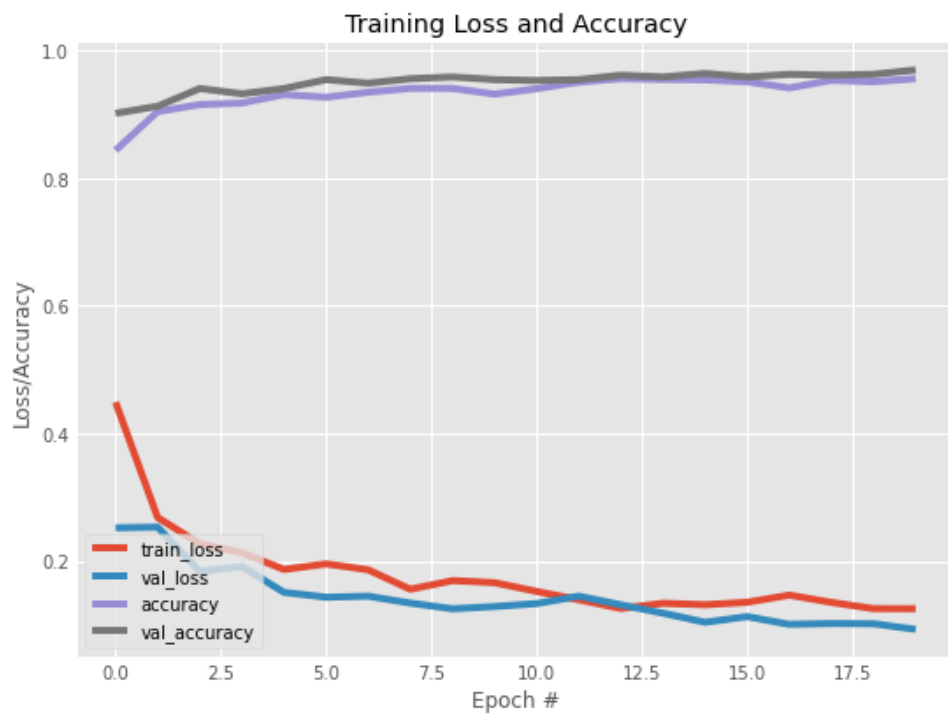
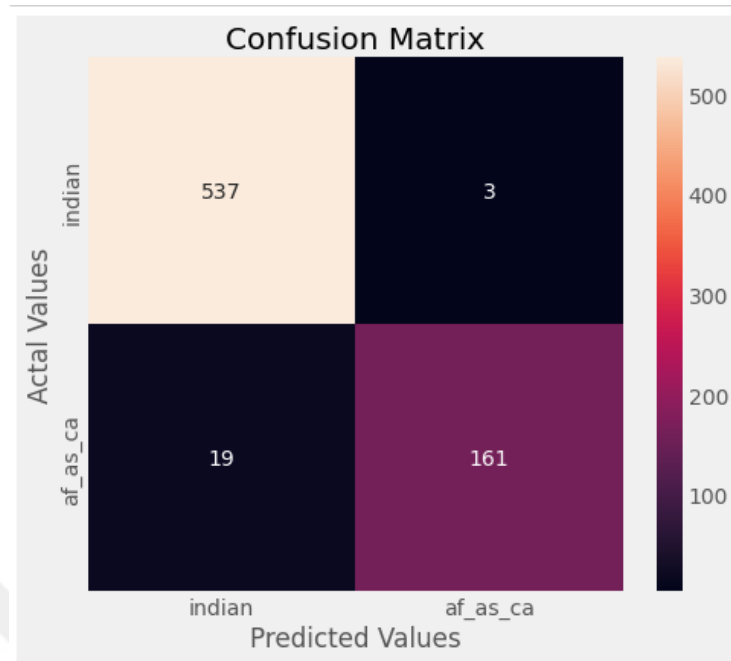


Figure 5.5. The InceptionV3 model loss and accuracy for Indian race

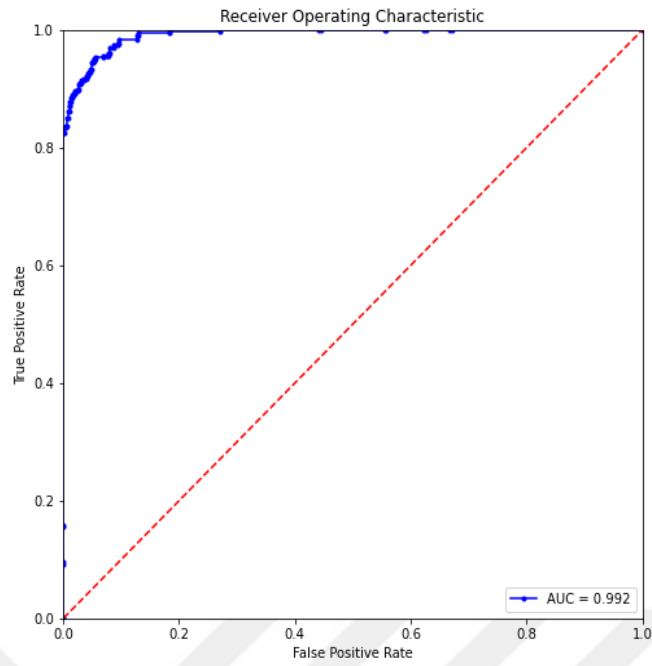


Figure 5.6. The InceptionV3 ROC accuracy for Indian race

Tables (5.6) illustrate the training and testing (20 epochs) of the InceptionV3 Model on the gender (male and female) dataset, while Tables (5.7) illustrate the confusion matrix for the gender. Figure 5.5 displays the model's loss and accuracy.

Table 5.6. The InceptionV3 model gender performance evaluation

Gender	Precision	Recall	F1-score	Loss	Accuracy
Female	0.95	0.91	0.93	0.173	0.934
Male	0.92	0.96	0.94		

Table 5.7. the InceptionV3 model confusion matrix for gender

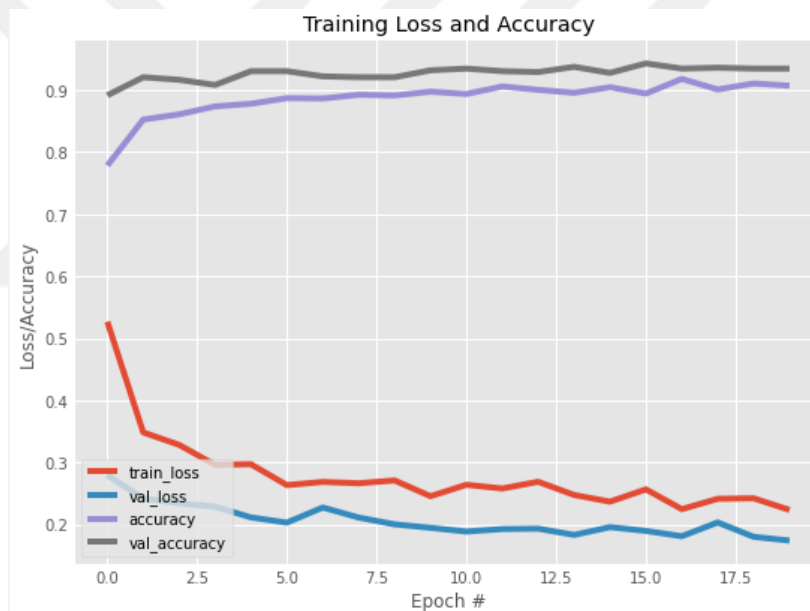
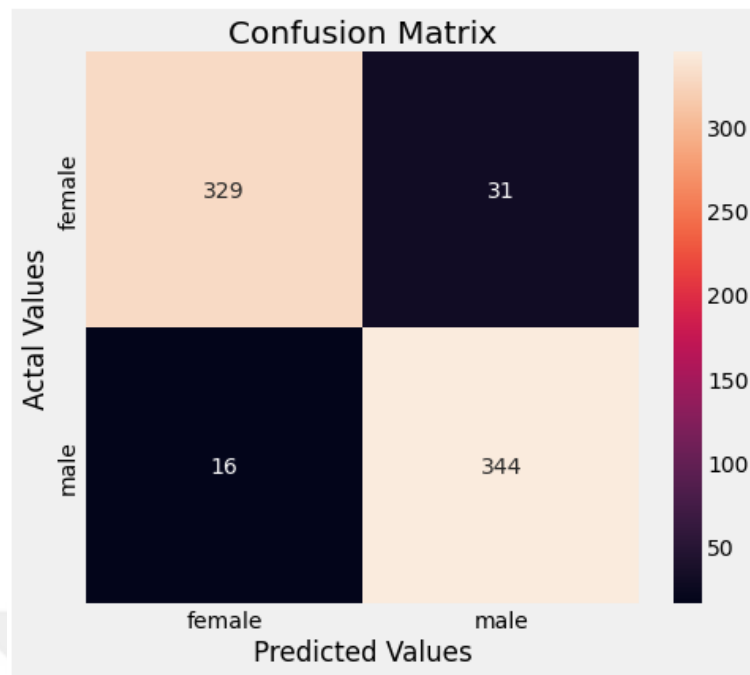


Figure 5.7. The InceptionV3 model loss and accuracy for gender

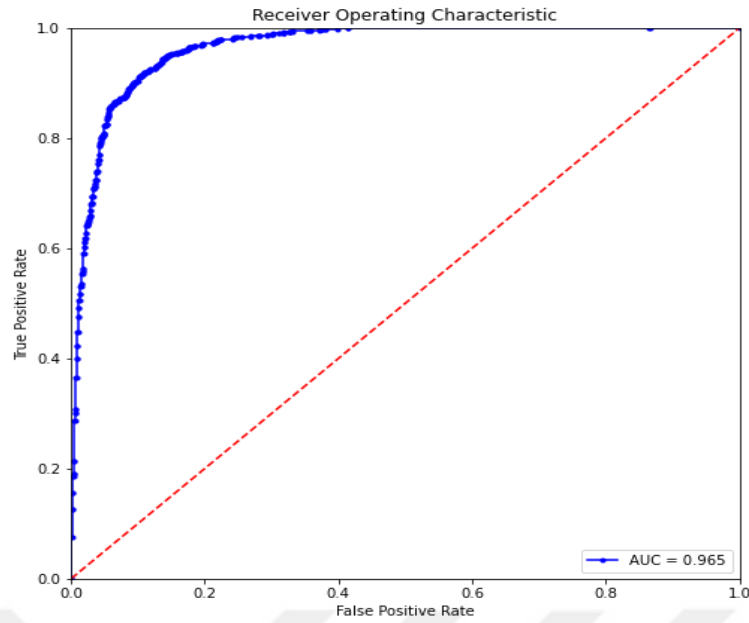


Figure 5.8. The InceptionV3 model ROC accuracy for gender

5.4 The ResNet50 Model Implementation

ResNet50 Model implementation training and testing (20) epochs for the four races (African, Asian, Indian, Caucasian) dataset, the optimizer is ADAM, and the learning rate is 0.001. Additionally, there are 32 Batch sizes. Tables (5.8) illustrate performance evaluations for four races.

Table 5.8. The ResNet50 model four races performance evaluation

Race	Precision	Recall	F1-score	Loss	Accuracy
African	0.99	0.99	0.99	0.005	0.997
As_Ca_In	1	1	1		
Asian	0.98	0.97	0.98	0.077	0.966
Af_Ca_In	0.92	0.94	0.96		
Caucasian	0.96	1	0.98	0.064	0.970
Af_As_In	0.99	0.89	0.94		
Indian	0.97	1	0.98	0.071	0.976
Af_As_Ca	0.99	0.92	0.95		

Table 5.9. illustrate the ResNet50 Model Caucasian Races testing confusion matrix, while Figure 5.6 displays the model performance evaluation loss and accuracy.

Table 5.9. The ResNet50 model confusion matrix for African race

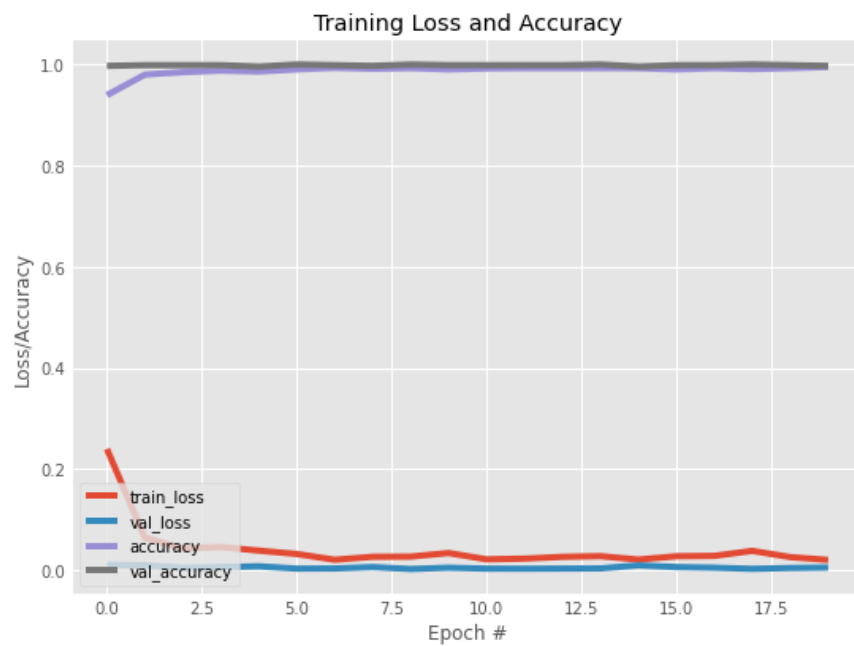
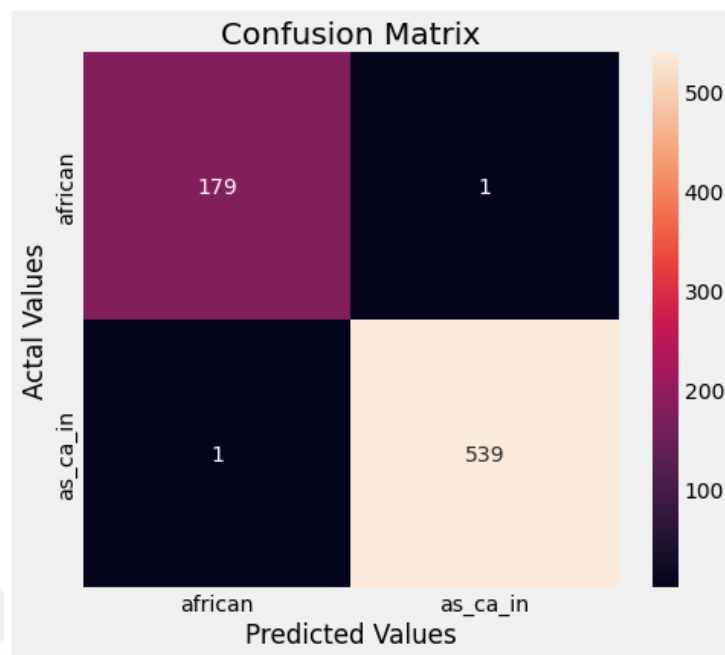


Figure 5.9. The ResNet50 model loss and accuracy for African race

Table 5.10. illustrate the ResNet50 Model Asian Races testing confusion matrix, while Figure 5.7 displays the model performance evaluation loss and accuracy.

Table 5.10. The ResNet50 model confusion matrix for Asian race

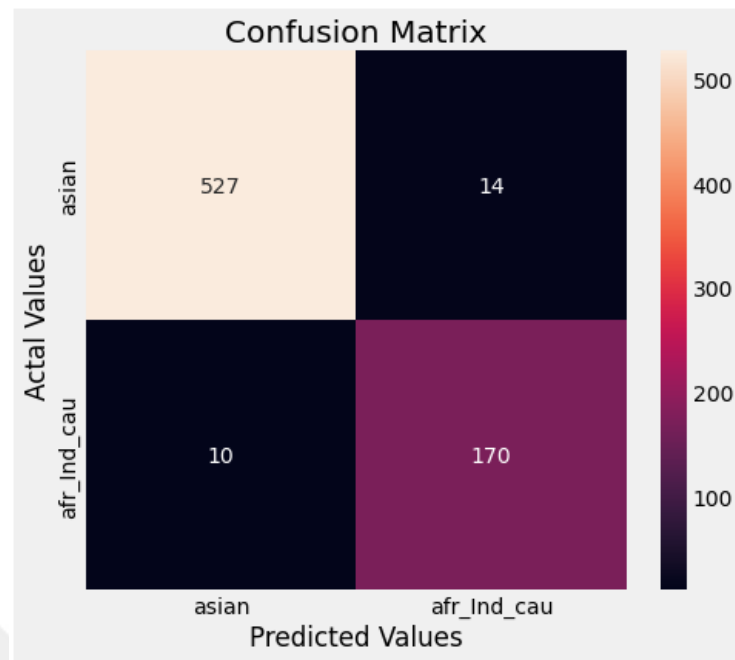


Figure 5.10. The ResNet50 model loss and accuracy for Asian race

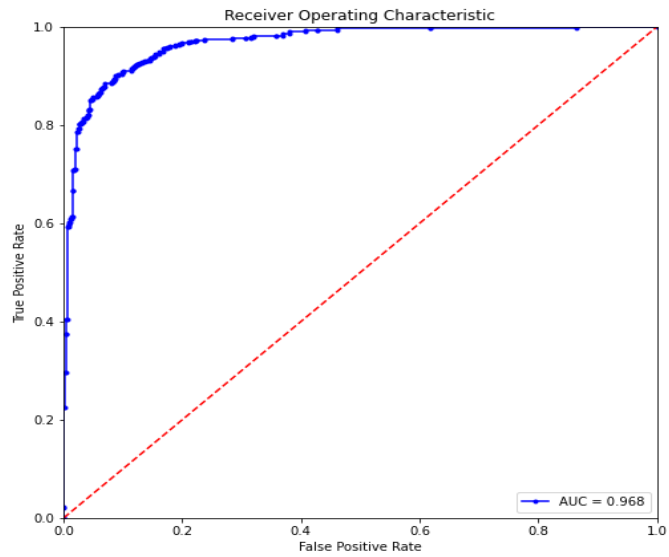
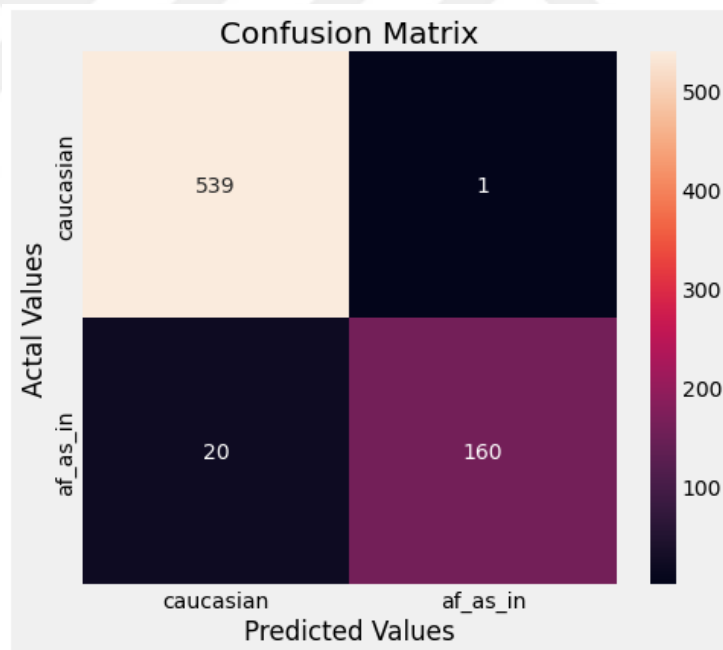


Figure 5.11. The ResNet50 model ROC for Asian race

Table 5.11. illustrate the ResNet50 Model Caucasian Races testing confusion matrix, while Figure 5.8 displays the model performance evaluation loss and accuracy.

Table 5.11. The ResNet50 model confusion matrix for Caucasian race



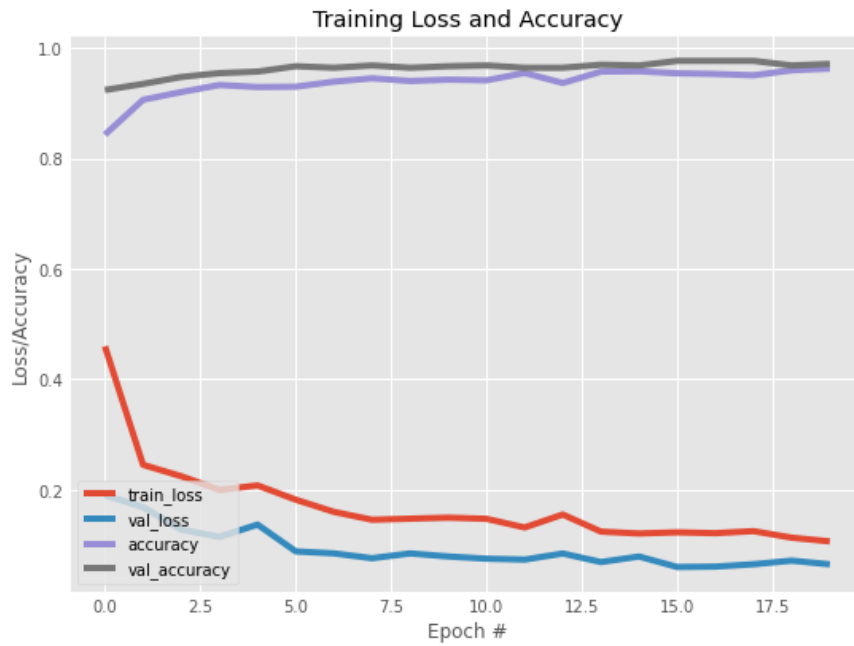
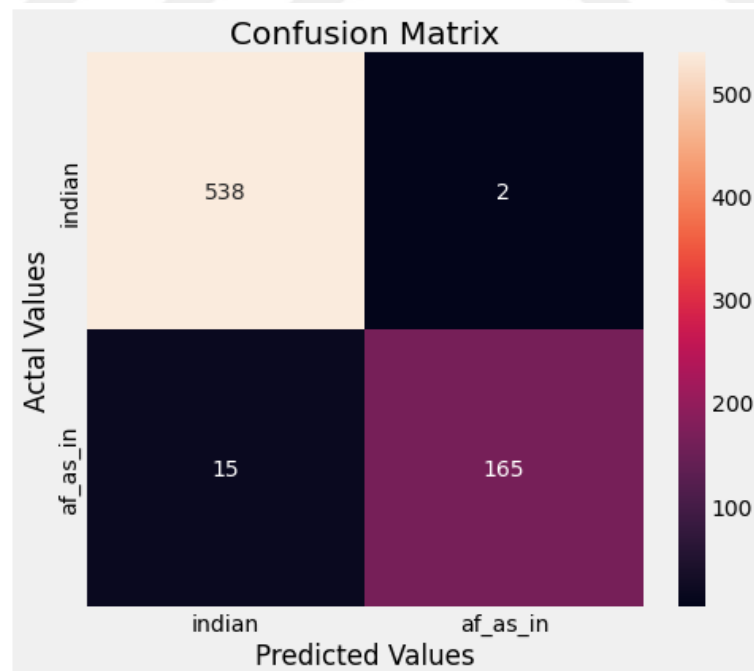


Figure 5.12. the ResNet50 model loss and accuracy for Caucasian race

Table 5.12. illustrate the ResNet50 Model Indian Races testing confusion matrix, while Figure 5.9 displays the model performance evaluation loss and accuracy.

Table 5.12. The ResNet50 model confusion matrix for the Indian race



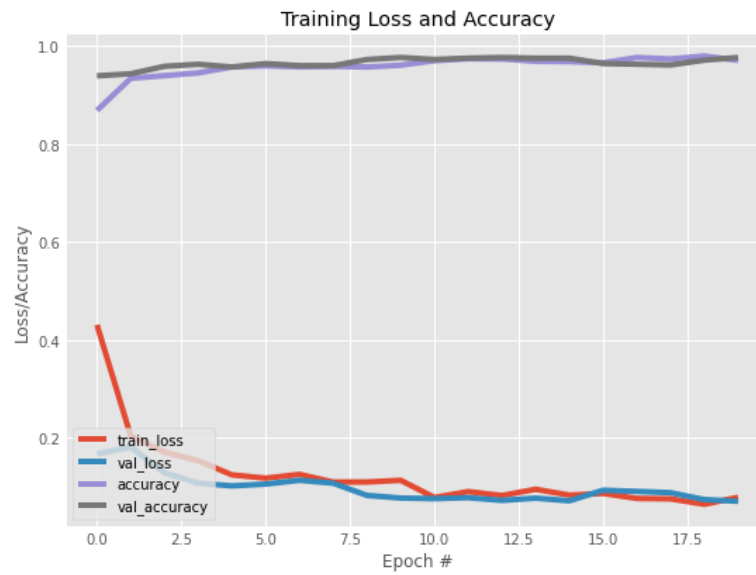


Figure 5.13. the ResNet50 model loss and accuracy for Indian race

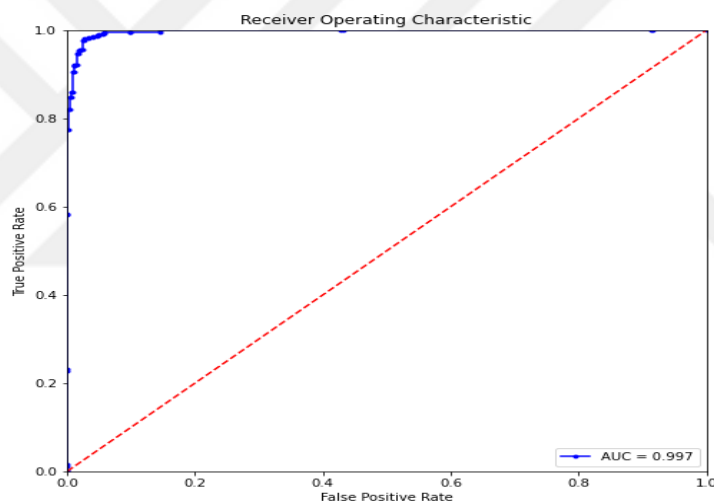


Figure 5.14. the ResNet50 model ROC accuracy for Indian race

Tables (5.13) illustrate the training and testing (20 epochs) of the ResNet50 Model on the gender (male and female) dataset, while Tables (5.14) illustrate the confusion matrix for the gender. Figure 5.10 displays the model's loss and accuracy.

Table 5.13. The ResNet50 model gender performance evaluation

Gender	Precision	Recall	F1-score	Loss	Accuracy
Female	0.91	0.96	0.94	0.180	0.934
Male	0.96	0.91	0.93		

Table 5.14. The ResNet50 model confusion matrix for the gender

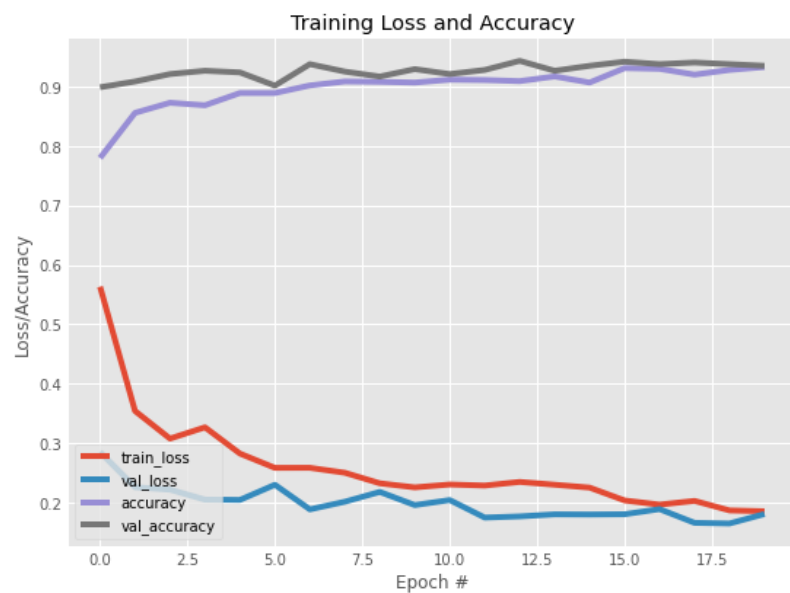
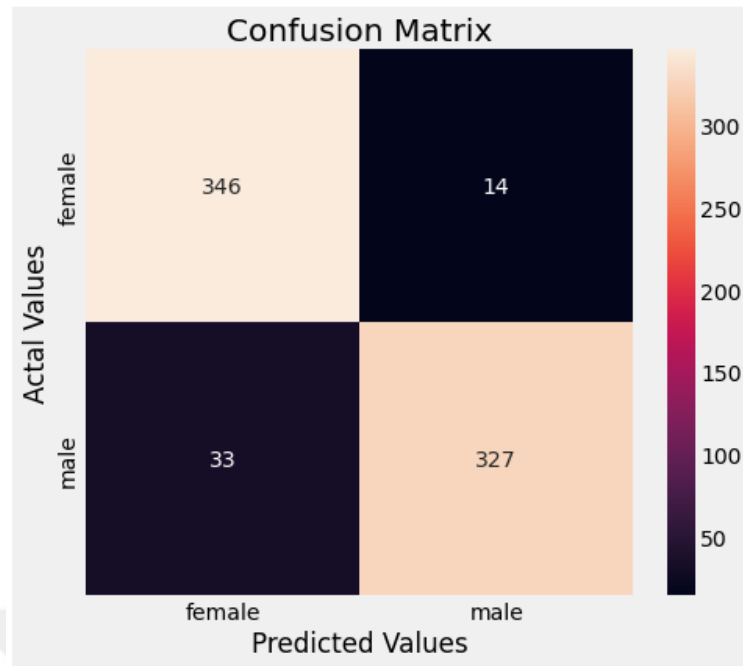


Figure 5.15. the ResNet50 model loss and accuracy for the gender

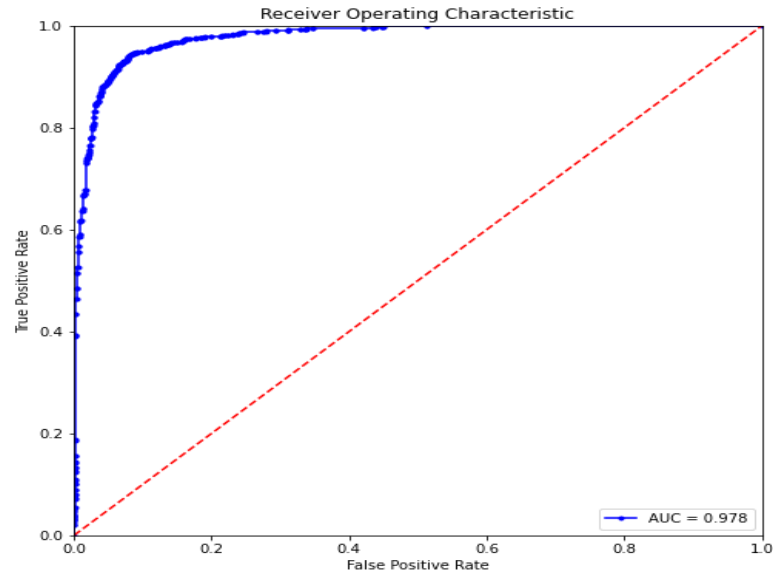


Figure 5.16. the ResNet50 model ROC accuracy for the gender

5.5 The VGG19 Model Implementation

VGG19 Model implementation training and testing (20) epochs for the four races (African, Asian, Indian, Caucasian) dataset, the optimizer is ADAM, and the learning rate is 0.001. Additionally, there are 32 Batch sizes. Tables (5.15) illustrate performance evaluations for four races.

Table 5.15. The VGG19 model four races performance evaluation

Race	Precision	Recall	F1-score	Loss	Accuracy
African	1	0.99	1	0.008	0.998
As_Ca_In	1	1	1		
Asian	0.98	0.96	0.97	0.103	0.958
Af_Ca_In	0.89	0.94	0.92		
Caucasian	0.96	0.99	0.98	0.100	0.966
Af_As_In	0.98	0.89	0.93		
Indian	0.97	0.97	0.97	0.137	0.951
Af_As_Ca	0.90	0.91	0.95		

Table 5.16. illustrate the VGG19 Model African Races testing confusion matrix, while Figure 5.11 displays the model performance evaluation loss and accuracy.

Table 5.16: The VGG19 model confusion matrix for African race

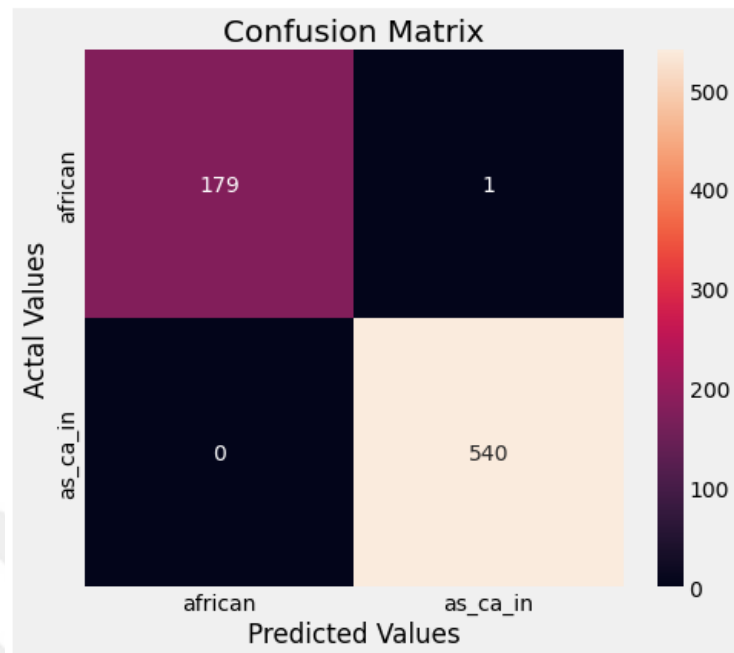


Figure 5.17. The VGG19 model loss and accuracy for African race

Table 5.17. illustrate the VGG19 Model Asian Races testing confusion matrix, while Figure 5.12 displays the model performance evaluation loss and accuracy.

Table 5.17. The VGG19 model confusion matrix for Asian race

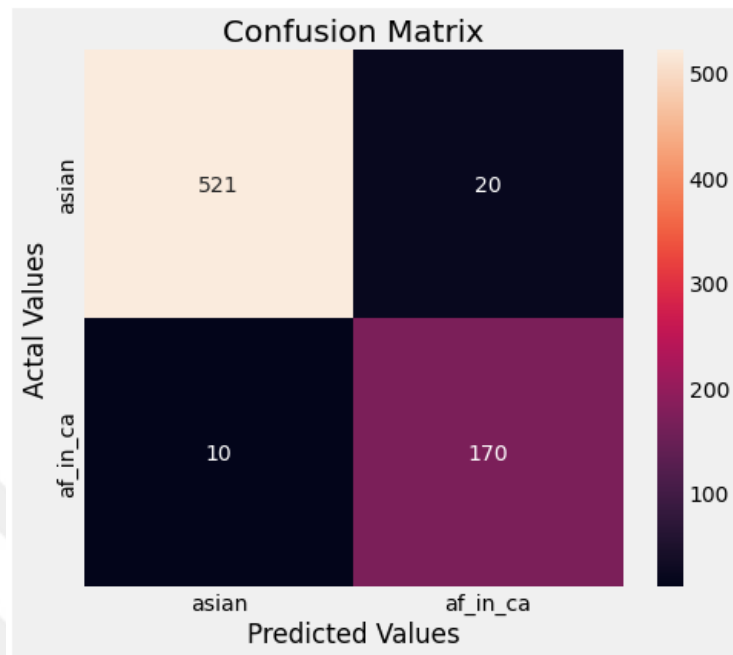


Figure 5.18. The VGG19 model loss and accuracy for Asian race

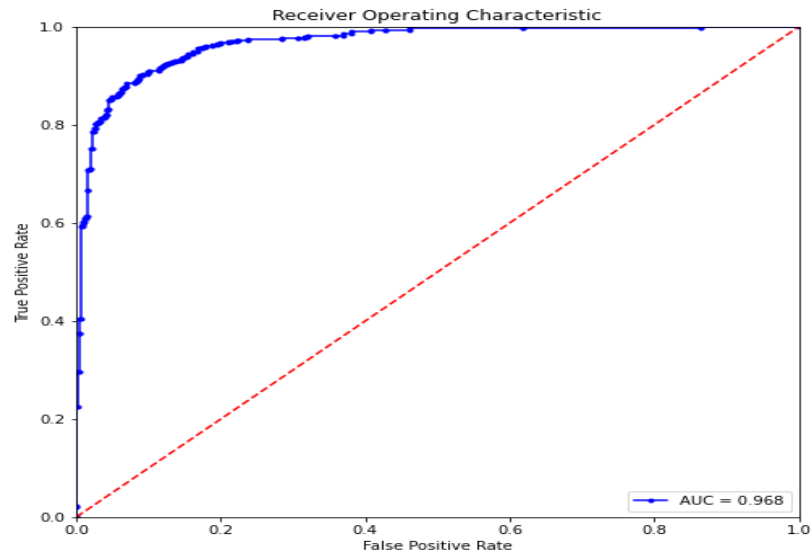
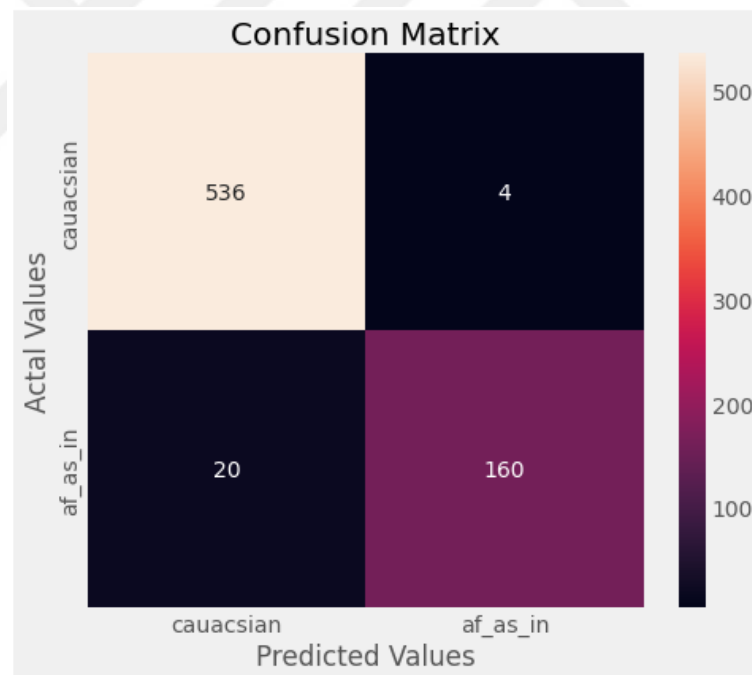


Figure 5.19. The VGG19 model ROC accuracy for Asian race

Table 5.18. illustrate the VGG19 Model Caucasian Races testing confusion matrix, while Figure 5.13 displays the model performance evaluation loss and accuracy.

Table 5.18: The VGG19 model confusion matrix for the Caucasian race



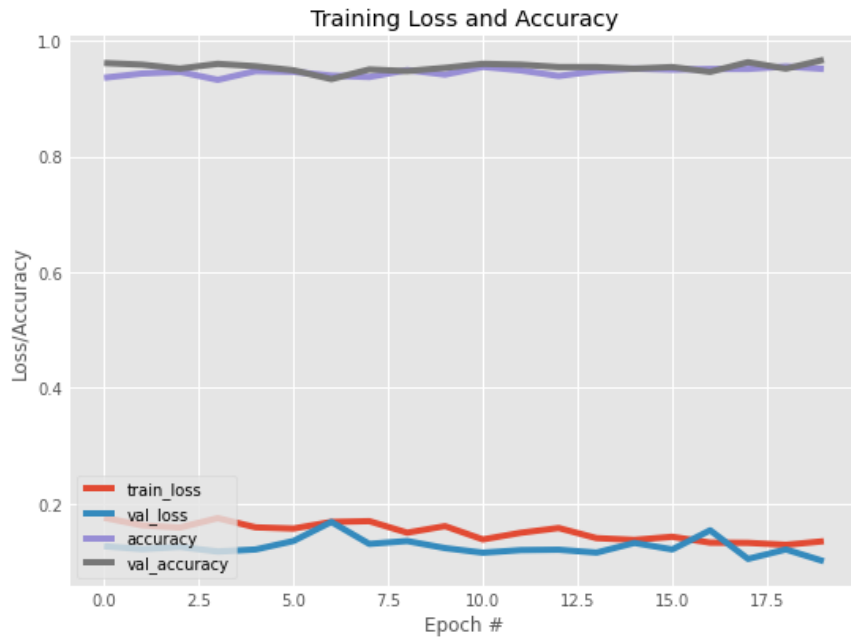
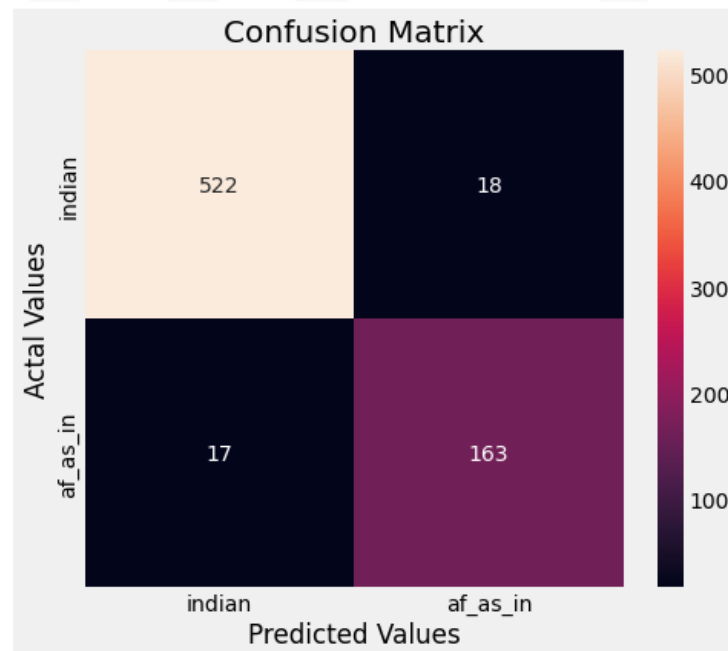


Figure 5.19. The VGG19 model loss and accuracy for the Caucasian race

Table 5.19. illustrate the VGG19 Model Indian Races testing confusion matrix, while Figure 5.14 displays the model performance evaluation loss and accuracy.

Table 5.19: The VGG19 model confusion matrix for the Indian race



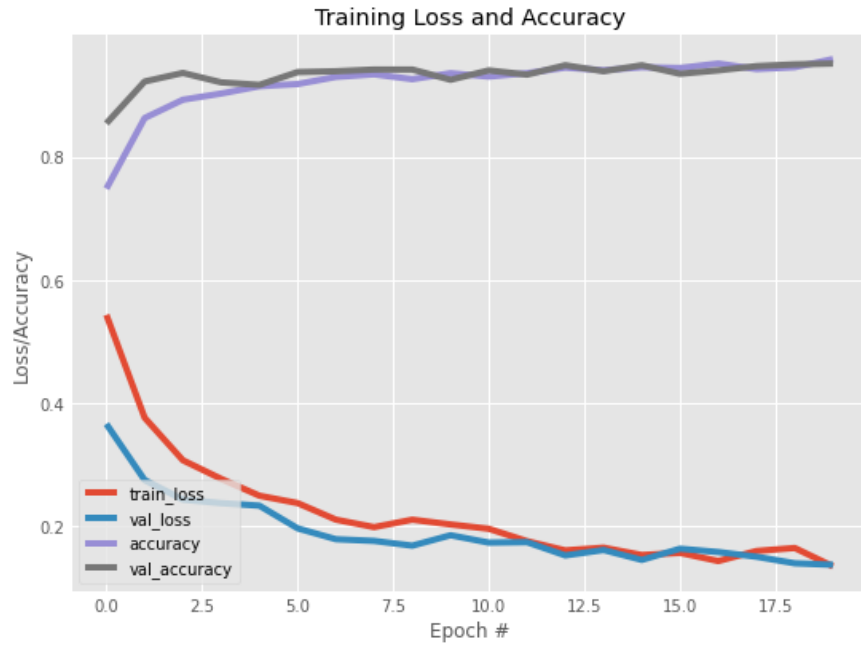


Figure 5.20. The VGG19 model loss and accuracy for the Indian race

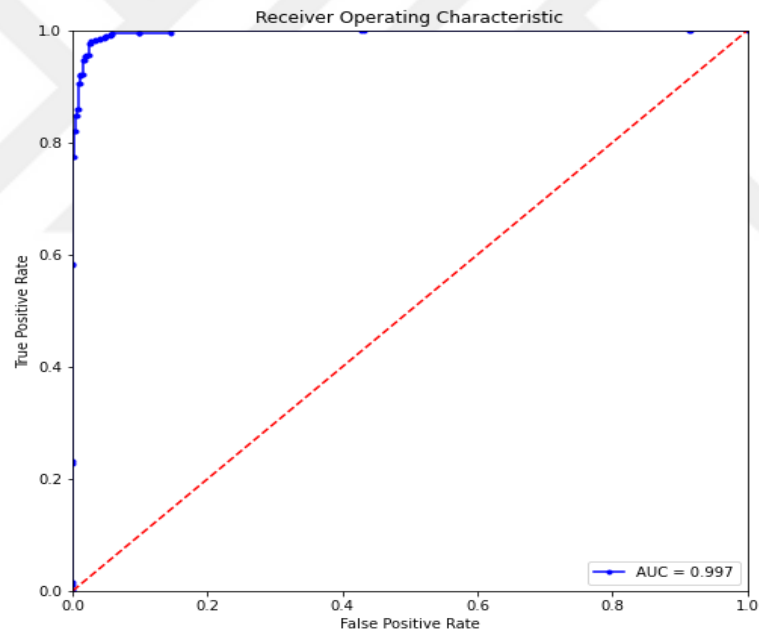


Figure 5.21. The VGG19 model ROC accuracy for the Indian race

Tables (5.20) illustrate the training and testing (20 epochs) of the VGG19 Model on the gender (male and female) dataset, while Tables (5.21) illustrate the confusion matrix for the gender. Figure 5.15 displays the model's loss and accuracy.

Table 5.20: The VGG19 model gender performance evaluation

Gender	Precision	Recall	F1-score	Loss	Accuracy
Female	0.85	0.90	0.87	0.297	0.870
Male	0.90	0.84	0.87		

Table 5.21: The VGG19 model confusion matrix for the gender

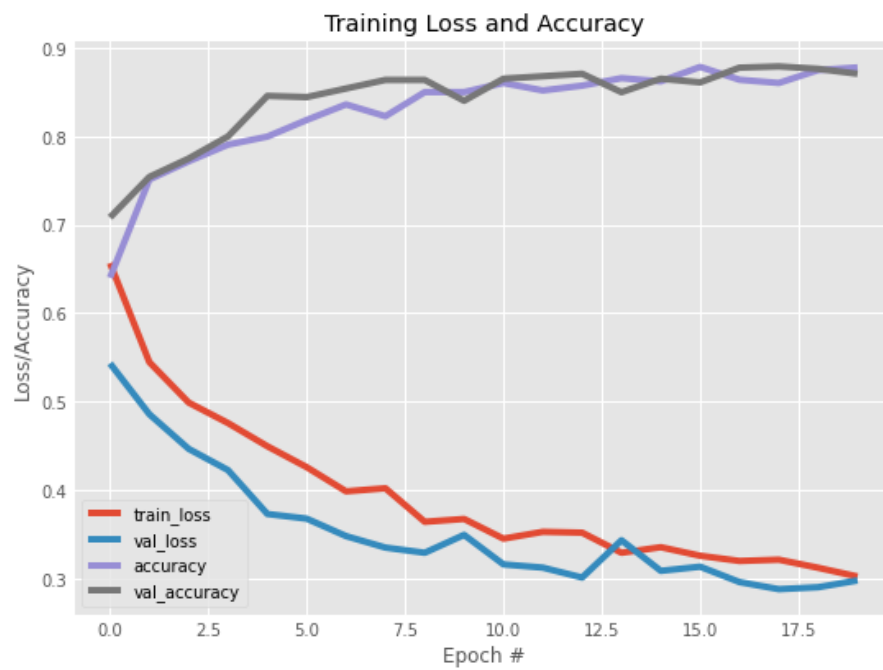
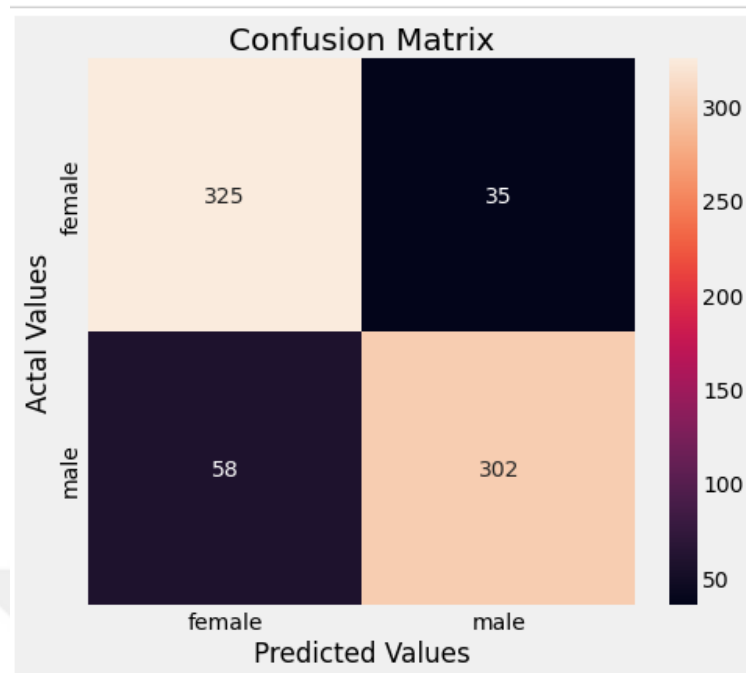


Figure 5.23. The VGG19 model loss and accuracy for the gender

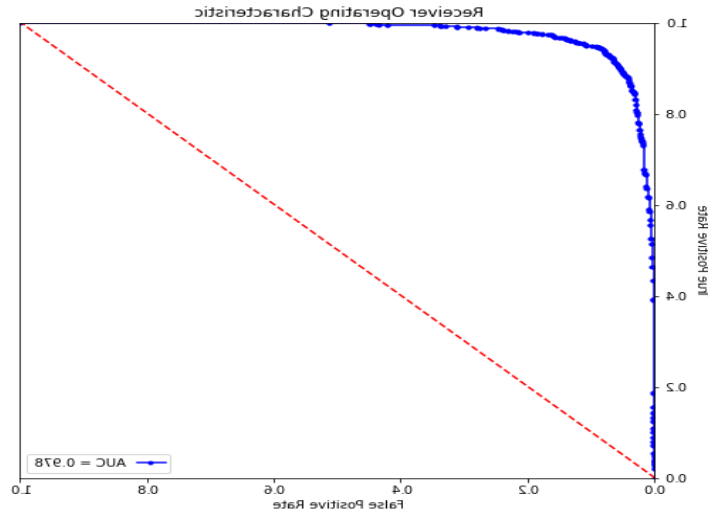


Figure 5.24. The VGG19 model ROC accuracy for the gender

5.6 The RGCNN Model Implementation (One-Versus-All)

RGCNN Model implementation training and testing (20) epochs for the four races (African, Asian, Indian, Caucasian) dataset, the optimizer is ADAM, and the learning rate is 0.001. Additionally, there are 32 Batch sizes. Tables (5.22) illustrate performance evaluations for four races.

Table 5.22: The RGCNN model four races performance evaluation

Race	Precision	Recall	F1-score	Loss	Accuracy
African	0.99	0.99	0.99	0.0148	0.995
As_Ca_In	1	1	1		
Asian	0.98	0.96	0.98	0.077	0.973
Af_Ca_In	0.95	0.94	0.95		
Caucasian	0.98	1	0.99	0.075	0.980
Af_As_In	0.99	0.93	0.96		
Indian	0.99	0.97	0.98	0.077	0.966
Af_As_Ca	0.91	0.97	0.97		

Table 5.23. illustrate the RGCNN Model African Races testing confusion matrix, while Figure 5.16 displays the model performance evaluation loss and accuracy.

Table 5.23: The RGCNN model confusion matrix for the African race

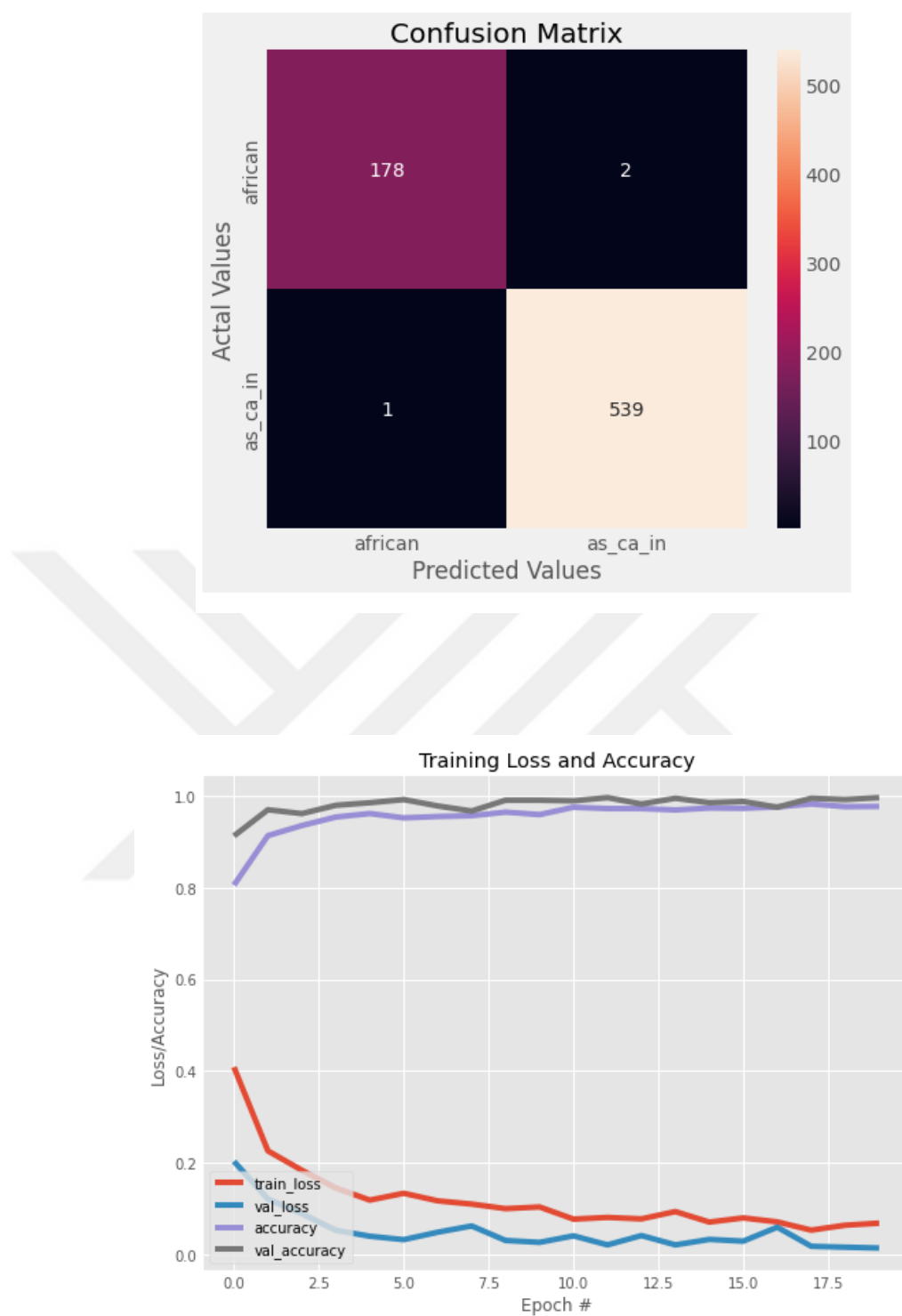


Figure 5.25 The RGCNN model loss and accuracy for the African race

Table 5.24. illustrate the RGCNN Model Asian Races testing confusion matrix, while Figure 5.25 displays the model performance evaluation loss and accuracy.

Table 5.24: The RGCNN model confusion matrix for Asian race

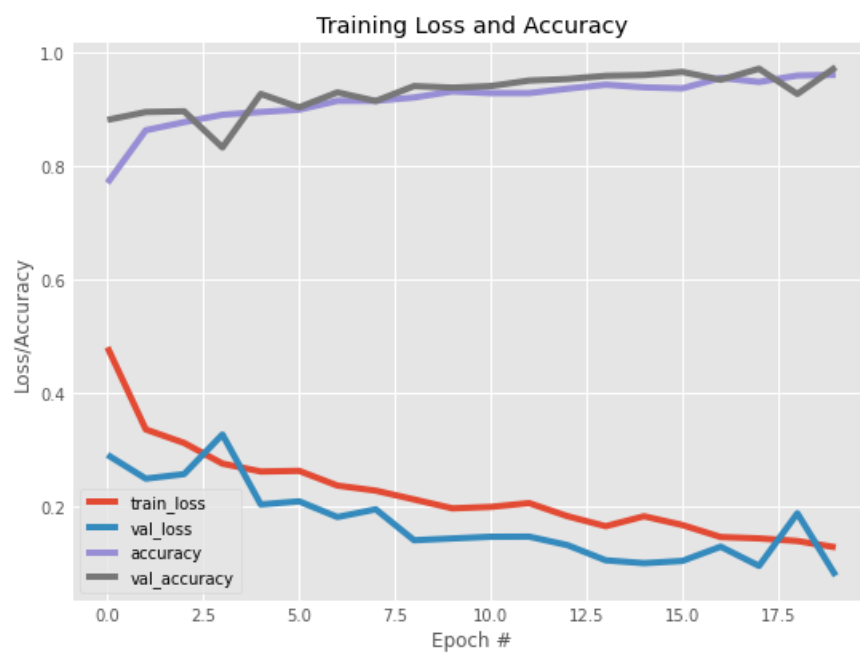
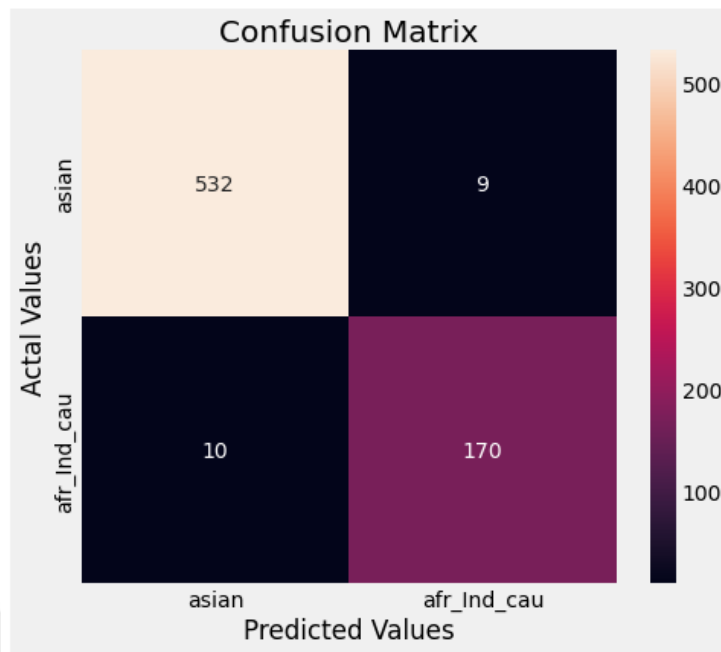


Figure 5.26: The RGCNN model loss and accuracy for Asian race

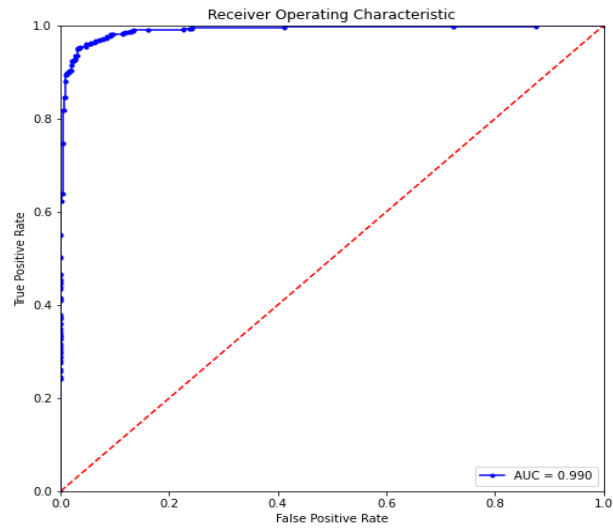
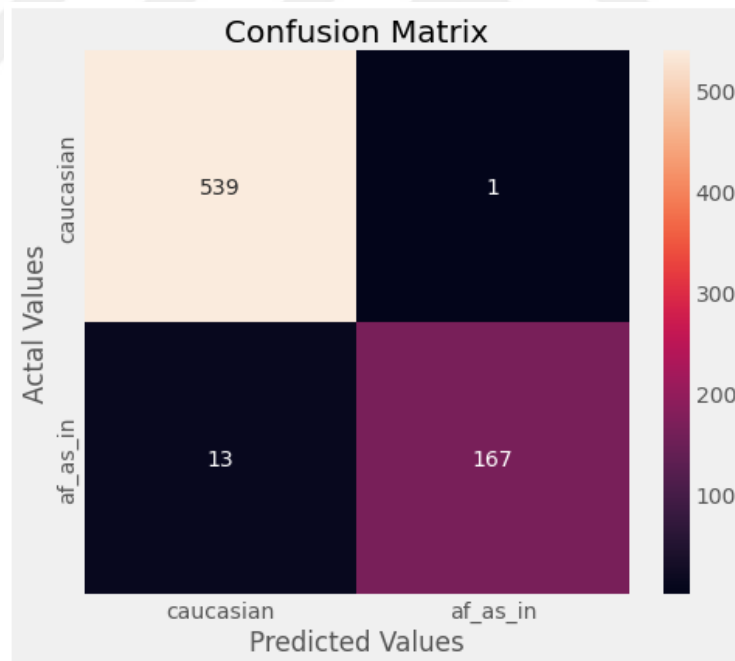


Figure 5.26: The RGCNN model ROC accuracy for Asian race

Table 5.25. illustrate the RGCNN Model Caucasian Races testing confusion matrix, while Figure 5.28 displays the model performance evaluation loss and accuracy.

Table 5.25. the RGCNN model confusion matrix for the Caucasian race



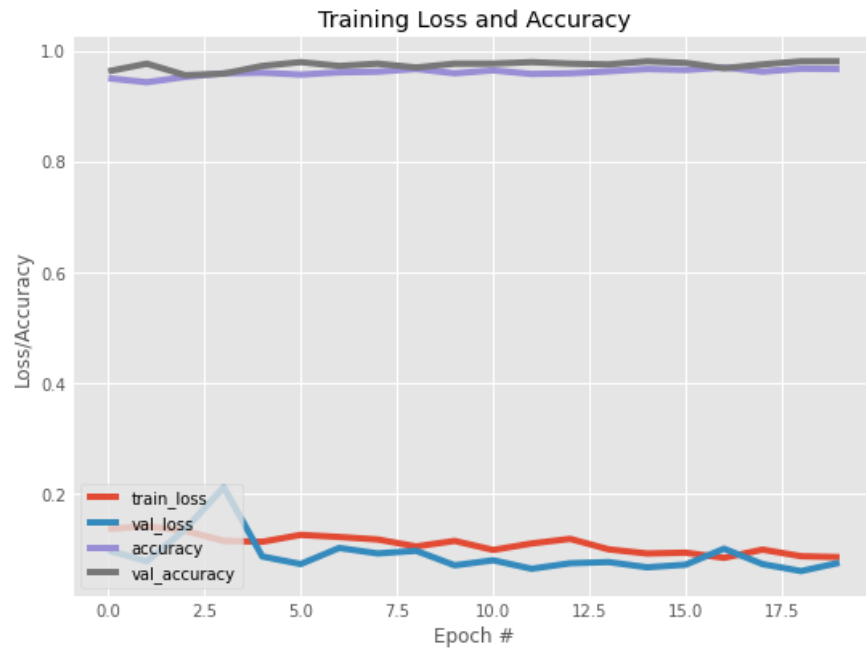
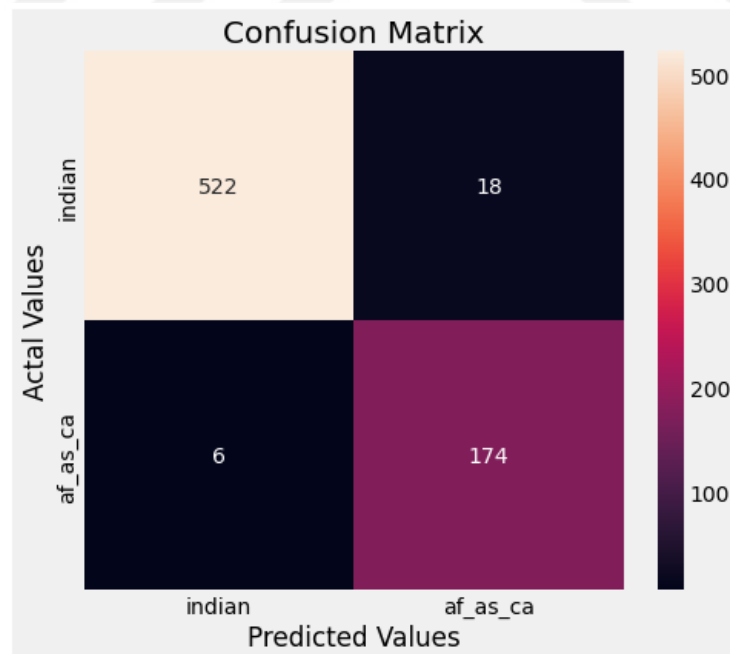


Figure 5.28. The RGCNN model loss and accuracy for the Caucasian race

Table 5.26. illustrate the RGCNN Model Indian Races testing confusion matrix, while Figure 5.29 displays the model performance evaluation loss and accuracy.

Table 5.26: The Indian model confusion matrix for the Indian race



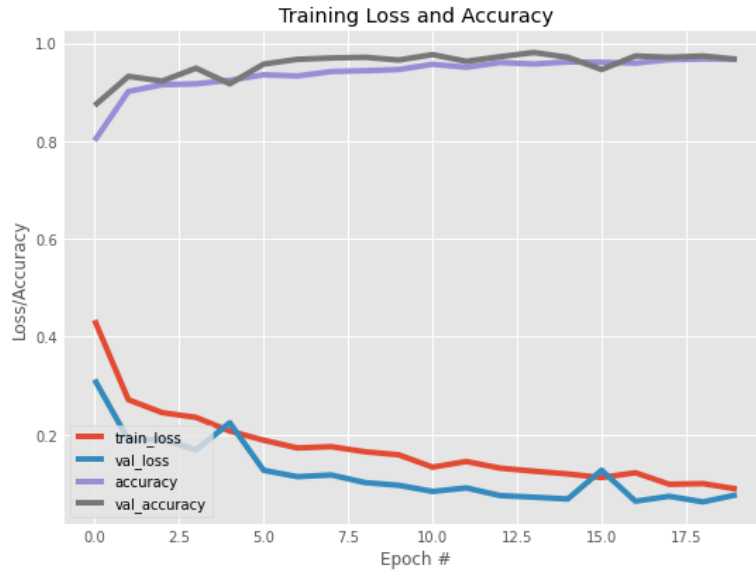


Figure 5.29. The RGCNN model loss and accuracy for the Indian race

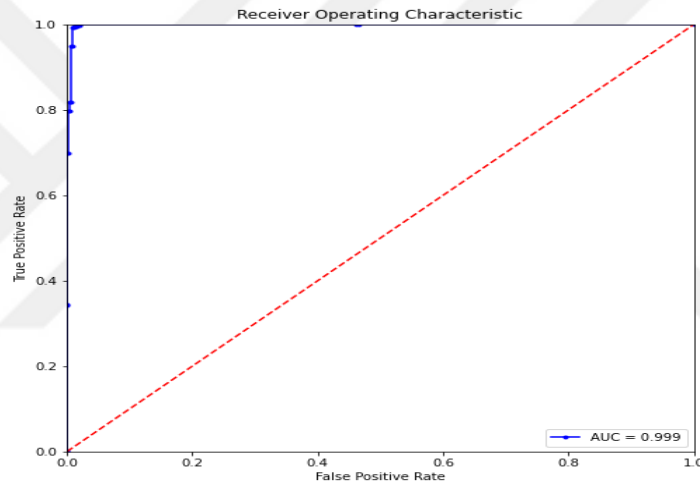


Figure 5.30. The RGCNN model ROC accuracy for the Indian race

Tables (5.30) illustrate the training and testing (20 epochs) of the RGCNN Model on the gender (Male and Female) dataset, while Tables (5.31) illustrate the confusion matrix for the gender. Figure 5.20 displays the model's loss and accuracy.

Table 5.27: The RGCNN model gender performance evaluation

Gender	Precision	Recall	F1-score	Loss	Accuracy
Female	0.93	0.96	0.95	0.143	0.944
Male	0.95	0.93	0.94		

Table 5.28: The RGCNN model confusion matrix for the gender

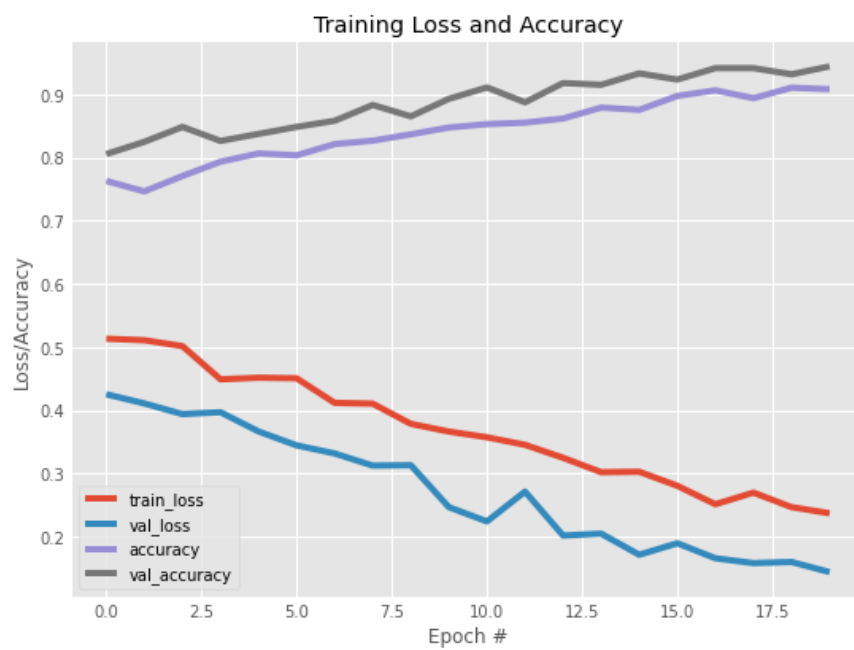
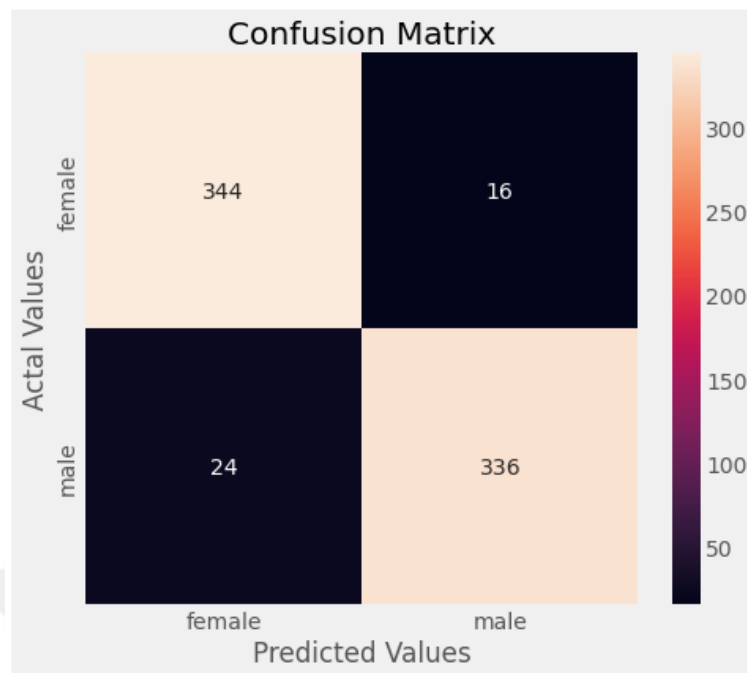


Figure 5.31. The RGCNN model loss and accuracy for the gender

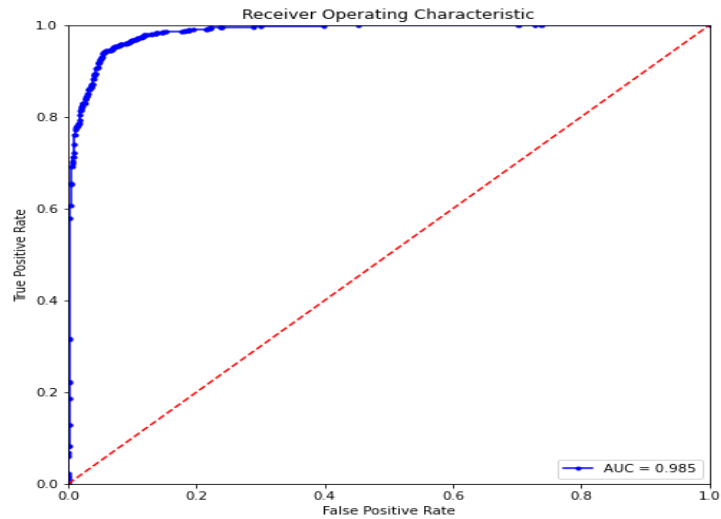


Figure 5.32. The RGCNN model ROC accuracy for the gender

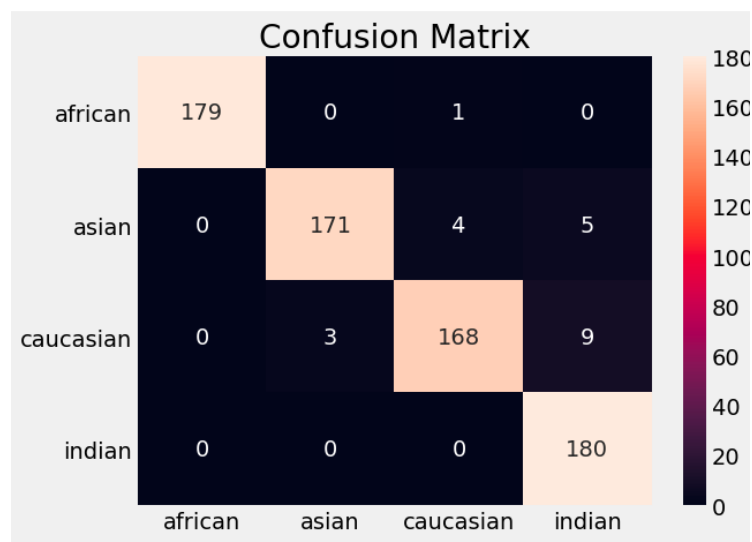
5.7 The MCC-CNN Model Implementation (Multi-Class-Classification)

RGCNN Model implementation training and testing (20) epochs for the four races (African, Asian, Indian, Caucasian) dataset, the optimizer is ADAM, and the learning rate is 0.001. as illustrate table 5.30

Table 5.29: The MCC-CNN model The Multi-Class-Classification performance evaluation

Precision	Recall	F1-score	Loss	Accuracy
97	97	97	0.110	96

Table 5.30: The Multi-Class-Classification confusion matrix.



Training Loss and Accuracy for all races

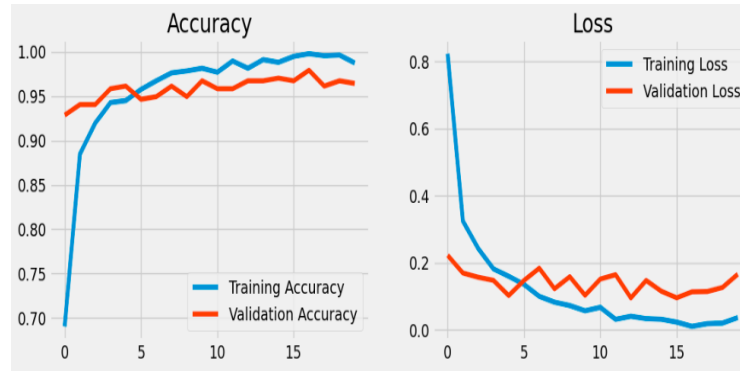


Figure 5.33. The RGCNN model loss and accuracy for four races

ROC Accuracy for all races

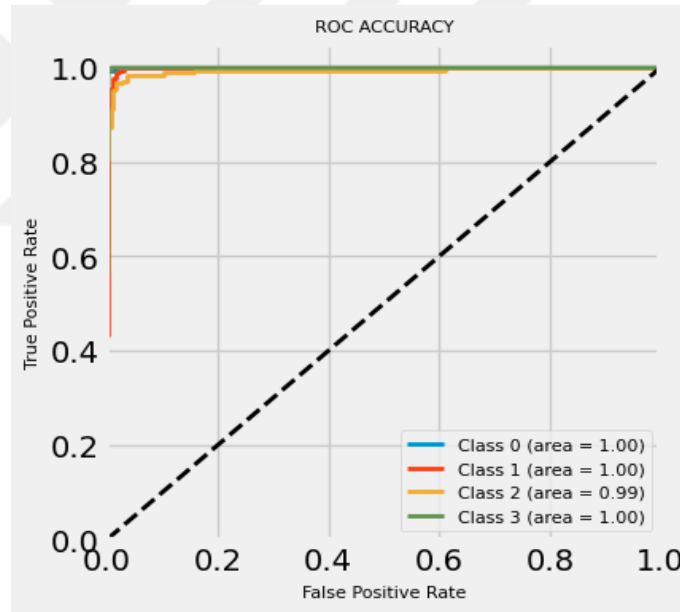


Figure 5.34. The RGCNN model ROC accuracy for four races

5.8 The Race and Gender system Implementation

All models trained and tested, including InceptionV3, ResNet50, VGG19, and RGCNN, used the two new datasets: race and gender. All the models will be saved. At first, the system will give the user the option to select an image or capture the frame from the camera. The system will preprocess the image size and detect the face. After that, the user will also select the model. The race and gender system implemented in many

images produces excellent results and is accurate. The four models implemented a sample of all race images including both genders, as shown in bellow Figures.

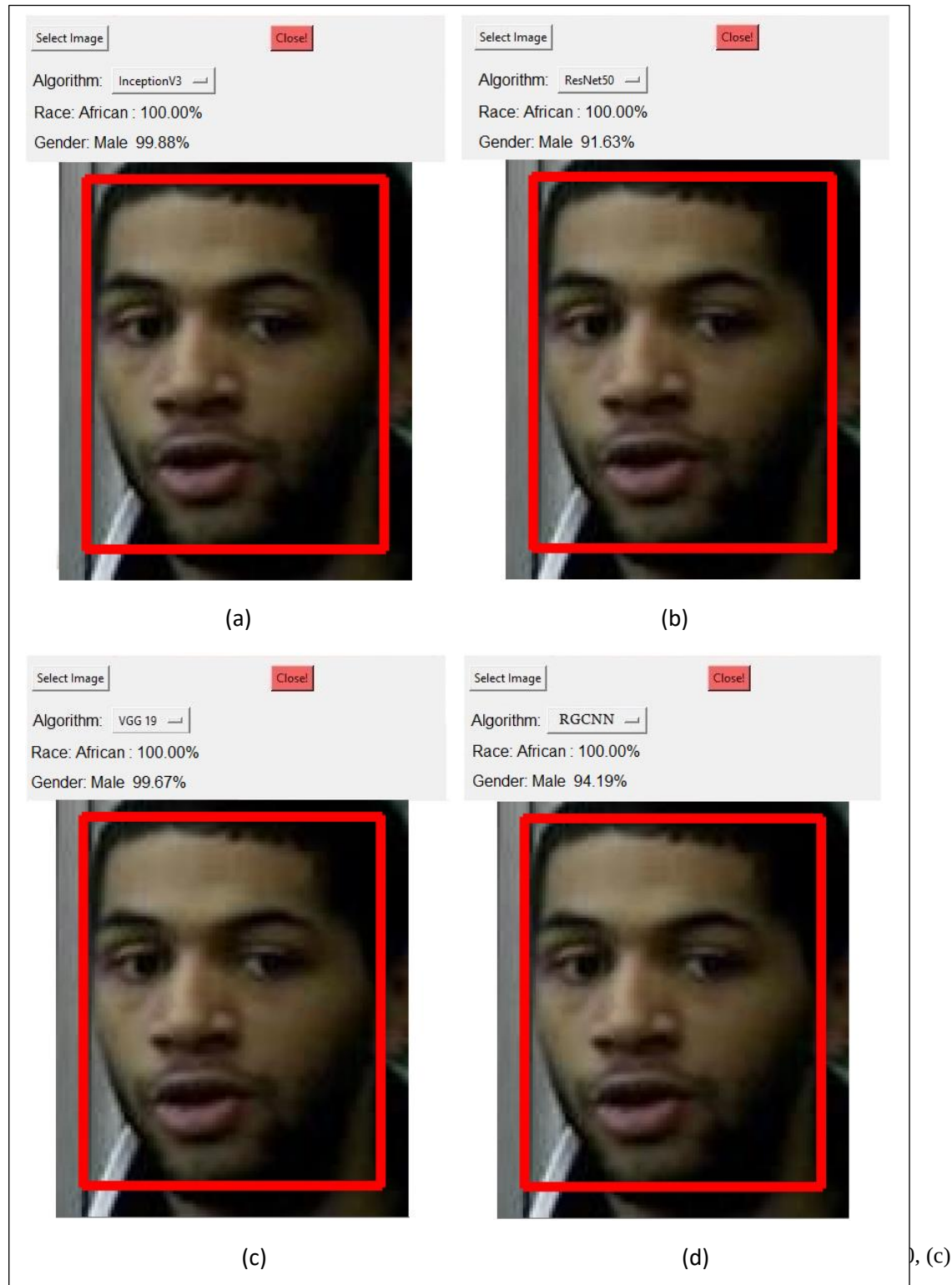


Figure 5.36 provides a sample of African female images applied to the four models.

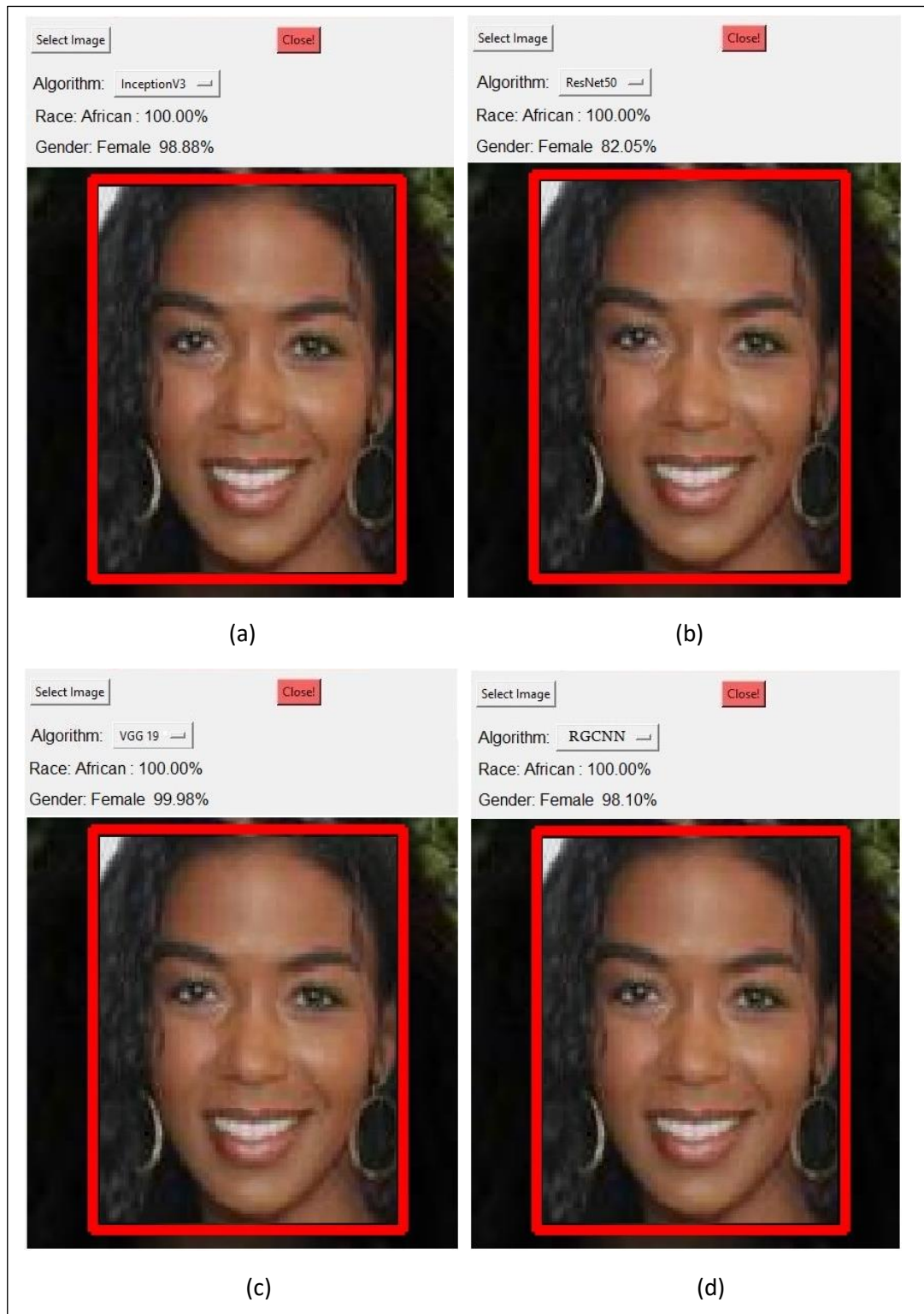


Figure 5.37 provides a sample of Asian male images applied to the four models.

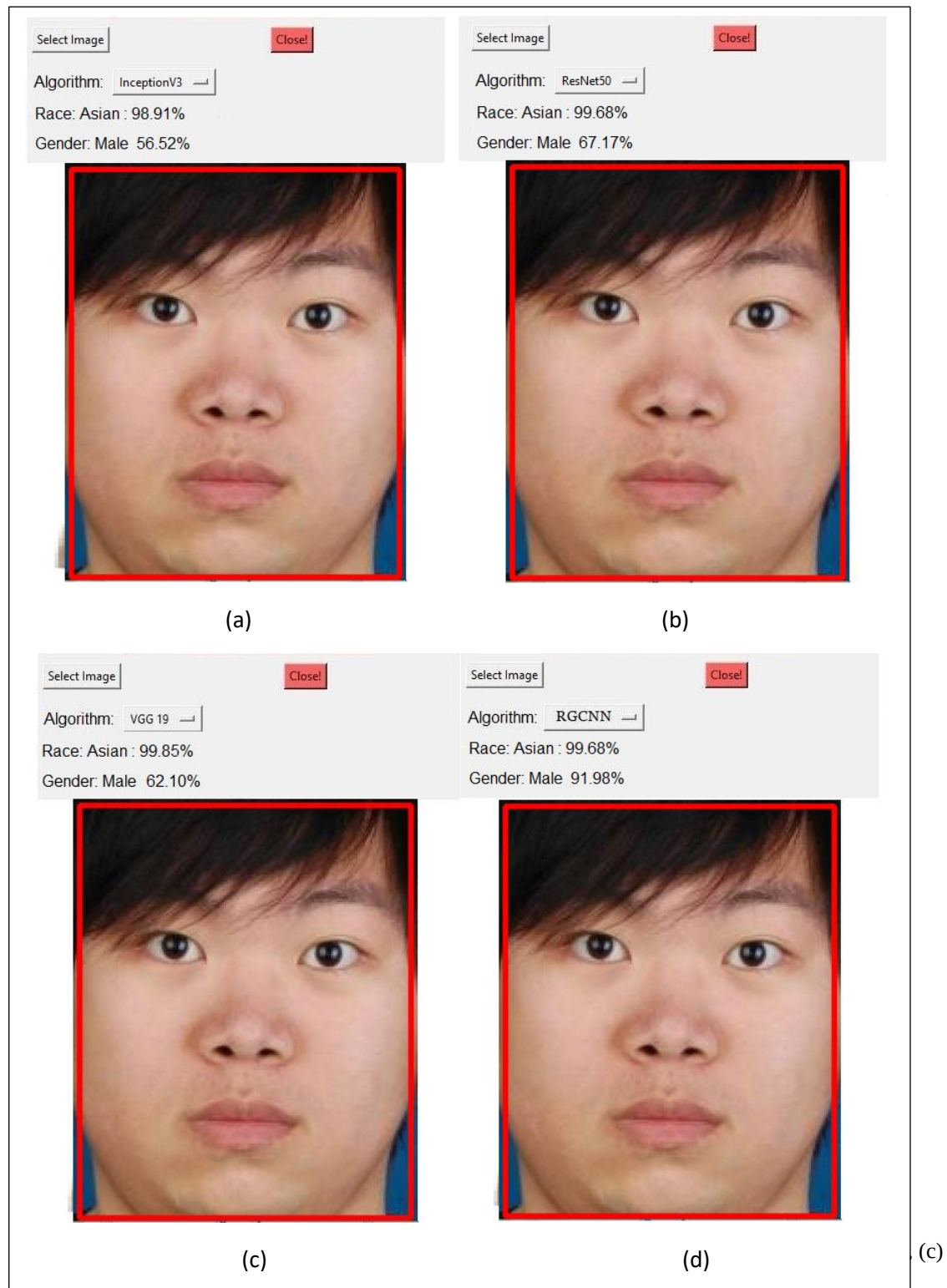


Figure 5.38 provides a sample of Asian female images applied to the four models.

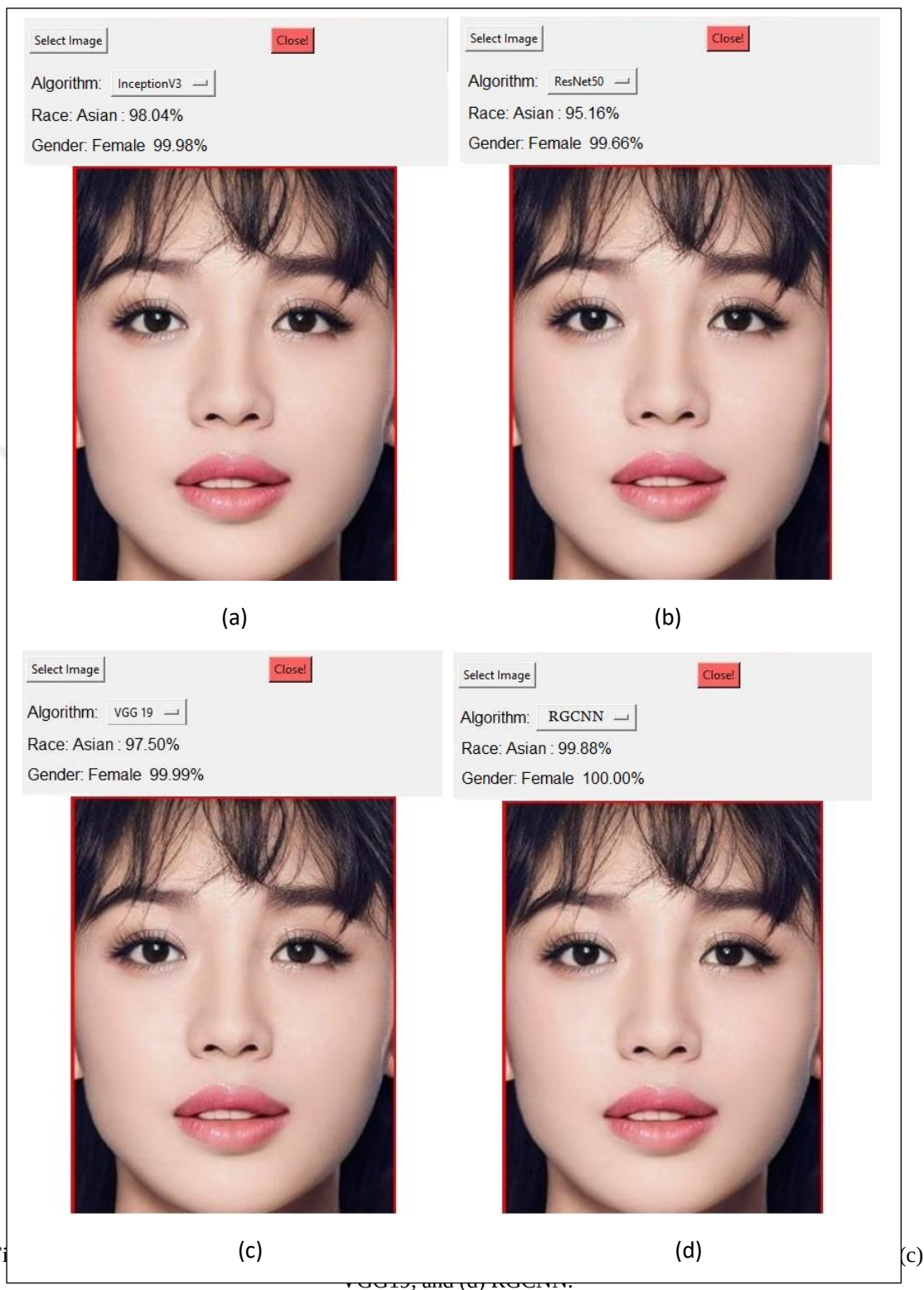


Figure 5.39 provides a sample of Caucasian male images applied to the four models.

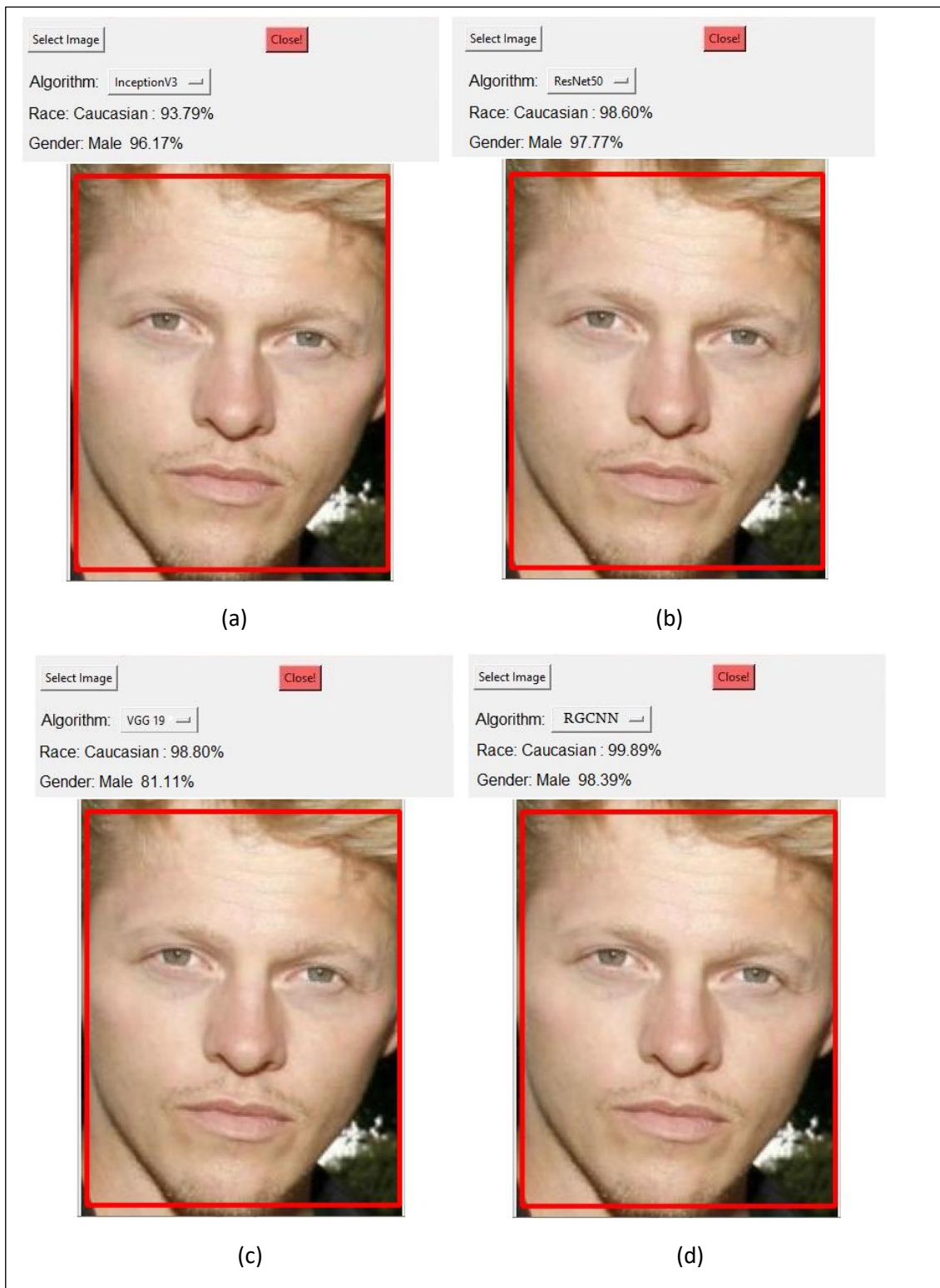




Figure 5.40. The female Caucasian facial race is recognized by the model's (a) InceptionV3, (b) ResNet50, (c) VGG19, and (d) RGCNN.

Figure 5.41 provides a sample of Indian male images applied to the four models.



Figure 5.42 provides a sample of Indian female images applied to the four models.



Figure 5.42. The female Indian facial race is recognized by the model's (a) InceptionV3, (b) ResNet50, (c) VGG19, and (d) RGCNN.

5.9 Comparison with Previous Works

This section compares the performance and results of the proposed methodology with previous works in facial race and gender recognition. Table 5.29 shows a comparison overview of the comparisons between the proposed methods and alternative approaches from various years and authors.

Table 5.32: Comparisons with Previous Works

Author's	Dataset	Race	Models	Accuracy
[37]	CNSIFC (1650)	Indian	CNN-based features	62%
[72]	RFW, GBU, and IJB-A	African, Asian, Indian, and Caucasian	IMAN	
[47]	visible and multi-distance infrared images	Asian or Caucasian	deep network	95%
[45]	FERET	Asian, African, American Black, Hispanic, Middle Eastern, and White	Weber local descriptors	Asian: 97.74%, Black: 96.89%, Hispanic: 92.06%, Middle: 98.33%, White: 99.53%.
[58]	Yale, FERET	Caucasoid, Negroid, Mongoloid.		
[3]	UTK and CFD		R-Net	97%
[78]	FG-NET	Black, gender	DML	MAE=1.6
[67]	AFAD, UTKFace	gender		
Proposed Method	new facial race	African,	InceptionV3	96.8%
		Asian,	ResNet50	97.7%
		Caucasian,	VGG19	97.2%
		Indian	RGCNN	97.8%
		African,	InceptionV3	93.4%
	new gender	Asian,	ResNet50	93.4%
		Caucasian,	VGG19	87.0%
		Indian	RGCNN	94.4%
		All Race	MCC-CNN	96.4

Many researchers work on race and gender, as illustrated in Table 5.31. They used a different number of races, ranging from one to four. It is clear that they used one or two datasets. This study creates two new datasets for facial race and gender (African, Asian, Caucasian, and Indian) and gender (Male and Female). The new model, RGCNN, gives a better accuracy rate and less execution time with the minimum number of parameters of the three models used. The proposed methodology's versatility in achieving high recognition rates for both facial race and gender using various models demonstrates its potential for robust and accurate biometric recognition applications.

CHAPTER SIX

6. CONCLUSION AND SUGGESTIONS FOR FUTURE WORKS

6.1 Conclusion

The most important productions relating to this study are:

1. a new dataset created for facial race and gender, containing 2400 samples of four races (African, Asian, Caucasian, and Indian), of which 1200 are female and the rest are male.
2. The three convolutional neural network models We trained, validated, and tested on the new facial race dataset. The performance accuracy rate of the models InceptionV3, ResNet50, and VGG19 is 97.2 %,97.7%, 96.8%, and, respectively.
3. The three convolutional neural network models We trained, validated, and tested on the new gender dataset. The performance accuracy rate of the models InceptionV3, ResNet50, and VGG19 is 93.4%, 93.4%, and 87.0%, respectively.
4. The newly created model (RGCNN) was trained, validated, and tested on the new facial race and gender datasets. The new model's performance accuracy rate on the new facial race dataset is 97.8%, and on the new gender dataset, it is 94.4%, which is better than InceptionV3, ResNet50, and VGG19 with less executing time.
5. The system's predictive capabilities, encompassing race and gender classifications across a sample size of 40 individuals, achieve an impressive 98% accuracy rate.
6. Additionally, this study used multiclass classification approach for classifying 4 races. The excremental shows that for classifying four races One-Versus-All approach outperform multi class classification. The result for multi class classification is 96.64 accuracy. For One-Versus-All is 97.8 % accuracy.

6.2 Suggestions for Future Works

The following are some possible paths this thesis could take in the future:

1. Implementing the new model (RGCNN) with different types of datasets.
2. Using the other convolutional neural network models (except VGG19, ResNet50, and InceptionV3) on the new facial race and gender dataset.
3. Evaluating the proposed method on larger and more diverse datasets would be helpful to validate its generalizability and applicability to real-world scenarios.
4. Add new parameters to improve performance of MCC-CNN model for racial and other datasets.

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Viyan Shukri Mikael (CV)

Duhok, KRG

EDUCATION:

Gaziosmanpaşa University/ Tokat Province/ Turkey	Feb2022 July2024
MSc in Computer Science	
UOD /College of science	July2008-Oct2012

LANGUAGES:

KURDISH: Mother tongue.

ENGLISH: Excellent (Reading, writing, listening and fluent speaking).

ARABIC: good (Reading, writing, listening and good speaking).

TURKISH: Excellent (Reading, writing, listening and fluent speaking)

AREA OF EXPERTICE:

- | | |
|---------------------------------|-----------------------------------|
| • Computer proficiency | • Good in financial statements. |
| • ERP data management software. | • Excellent in office management. |
| • Problem solving. | • Time management. |
| • Adaptable and flexible. | • Advanced customer service |
| • Attention to Detail | • Excellent communication. |
| • Interpersonal. | • Collaborative team player. |
| • Critical thinking. | • Highly disciplined and focused. |

PROFESSIONAL EXPERIENCES:

Duhok Agriculture Company	Feb2019-May-2021
Administration and Finance Officer	Duhok

Duties and Responsibilities:

- Ensure smooth operations by overseeing supplies, records, systems, and customer relations.
- Provide management support by updating policies, calendars, reports, and ensuring compliance.

- Manage workplace logistics by coordinating travel, events, maintenance, and office supplies.
- Maintain financial health through analysis, managing accounts, monitoring expenses, preparing

for audits, conducting financial planning, and facilitating stakeholder communication.

TearFund ORG

April 2018-Dec2018

Protection Officer

Nineva

Duties and Responsibilities:

- Lead project activities; foster team building; ensure compliance; represent externally.
- Prioritize vulnerable beneficiaries, innovate assistance methods, and prepare status reports while ensuring proper document filing.

- Manage security systems, emergency response, and access control.
- Write reports, provide support, assess risks, collaborate with authorities, and train staff.
- Maintain equipment, adhere to regulations, and resolve conflicts.

ACTED ORG

Oct2017-Feb2018

Child Protection Team leader

Nineva

Duties and Responsibilities:

- Overseeing staff attendance and ensuring accurate reporting across all centers.
- Assisting the mobile activities supervisor in coordinating operations and facilitating payments for staff involved in cash-for-work programs. and representing externally to stakeholders and partners.

- Report complaints, feedback, and issues to the direct supervisor without delay

Internation Medical Corps

Oct2016-July2017

Gender Based Violence Officer

Ninava

Duties and Responsibilities:

- Represent the organization in collaborative meetings, ensuring effective engagement.
- Engage in outreach and coordination efforts to represent the organization's interests.
- oversee staff attendance, manage absences efficiently, maintain accurate records, and monitor progress, including reporting.

Harikar NGO

April2013-Oct2016

Registration Clerk

Duhok

Duties and Responsibilities:

- Assist with registration forms and maintain organized filing systems.
- Register individuals in software systems for accurate record-keeping.

