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IMPLEMENTATION OF NESTED DILATED-BASED TRANS-R2UNET FOR SEGMENTATION AND ADAPTIVE EFFICIENTNET WITH REGION ATTENTION MECHANISM TO CLASSIFY DENTAL CARIES THROUGH CBCT IMAGES

Mohammed Khamees Khalaf ALBORISHA

Master's Thesis

Supervisor

Assoc. Prof. Dr. Sefer KURNAZ

İstanbul, 2025

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The thesis Titled IMPLEMENTATION OF NESTED DILATED-BASED TRANS-R2UNET FOR SEGMENTATION AND ADAPTIVE EFFICIENTNET WITH REGION ATTENTION MECHANISM TO CLASSIFY DENTAL CARIES THROUGH CBCT IMAGES prepared by MOHAMMED KHAMES KHALEF ALBORISHA and submitted on 16/05/2025 has been **accepted unanimously** for the degree of Master of Science in Information Technologies.

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

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Signature

DEDICATION

I would like to dedicate this thesis to my advisor Assoc. Prof. Dr. Sefer KURNAZ and to my family and friends.

PREFACE

I must extend my thanks and appreciation to my master's thesis supervisor, Assoc. Prof. Dr. Sefer KURNAZ, for his directives and instructions. He was very helpful to me, and I learned a lot from him. A special thank him for his sincerity, and I wish a happy life for him.

ABSTRACT

IMPLEMENTATION OF NESTED DILATED-BASED TRANS-R2UNET FOR SEGMENTATION AND ADAPTIVE EFFICIENTNET WITH REGION ATTENTION MECHANISM TO CLASSIFY DENTAL CARIES THROUGH CBCT IMAGES

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Dental caries is a highly prevalent oral disorder, and the strategies of deep learning have been employed for diagnosing caries with large populations by employing RGB images. The conventional attention-aided image categorization approaches have the issues of feature underutilization and simple interference by irrelevant and background data. The timely recognition of dental caries is significant for performing treatments. For this objective, the bitewing radiography is employed to provide the initial detection of caries. The utilization of deep structured models with neural network approaches helps process the large number of images that have been experimented nowadays and provides promising functionalities. The computer-assisted smart vision approaches applied by image processing and machine learning mechanisms are required to eliminate these drawbacks. Hence, deep learning mechanisms have accomplished remarkable diagnosis efficacy in the radiology sector. Hence, a novel deep learning-based dental caries detection and classification framework is designed in this work. Initially, Cone Beam Computed Tomography (CBCT) images utilized for the detection and classification of dental caries are collected from the benchmark resources. Further, the collected images are provided for the image segmentation phase. Here, the developed Nested Dilated-based Transformer Recurrent Residual Unet (NDT-R2Unet) framework is used to attain the segmented images and these images are provided as the input to the dental caries disease classification phase. In this phase, an Adaptive

Efficient Net with Region Attention (AdaENet-RA) is employed to classify dental caries among the individuals. Moreover, several parameters in developed AdaENet-RA are tuned using Arbitrary Updated Wild Geese Migration Optimization (AUWGO) and provide the dental caries disease classified outcomes. Later, various validations are executed in the developed framework to verify the effectualness of the suggested framework over the classical techniques.

Keywords: Nested Dilated-based Trans-R2Unet, Segmentation, Adaptive EfficientNet, Region Attention Mechanism, CBCT Images.

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ABBREVIATIONS

CNN	:	Convolutional Neural Network
DL	:	Deep Learning
DRL	:	Deep Reinforcement Learning
QLR	:	Quality Life Reputation
RLQR	:	Robust Linear Quadratic Regulator

1. INTRODUCTION

1.1 INTRODUCTION

Dental caries is one of the common dental disorders. The complex communication among the acid-generating bacteria caused the dental carries that adhere to the fermentable and dental carbohydrates [9]. The acids present in the dental plague demineralize the dentine and enamel in the cracks and the dental's smooth surfaces. The dental caries earlier sign is the whit spot lesion [10]. The white dot surfaces get pitted, if the demineralization starts. This creates tiny holes named cavities. It is specifically normal in older adults, teenagers, and children [11]. Nevertheless, anyone who has teeth, even if it is babies, is to have dental caries. The cavities can develop and affect the teeth's deeper layers if it is left untreated [12]. The cavities create severe infection, toothache, and dental loss. Diverse techniques are available for treating the dental caries [13]. Often, the caries extension is so tiny that it cannot be diagnosed and visualized without the help of radiographic images [14]. X-rays are one kind of the best techniques for detecting dental caries and threats to the root of the tooth. In the diagnosis of dental conditions including dental caries, the CBCT provides an important part [15]. It provides diverse merits such as low time of exposure, high accuracy, and multiplanar reconstruction. The identification of caries lesions via the existing radiographs continues to exist instead of an evasive approach [16]. The complexities inherent in conventional radiographs are high because of the caries lesion's 2D representations that are in reality 3D frameworks, and this may result in the loss of significant data [17].

Nowadays, dental caries diagnosis highly depends on dental X-ray and visual touch validation that is time-consuming and increases the patient's financial burdens. Therefore, there has been a requirement for devices that can diagnose and identify dental caries at low prices between huge populations [18]. The intraoral imaging approach largely employs intraoral periapical radiography in dental radiology and offers significant data regarding the teeth and their nearby bone. It offers significant data to support the recognition of the highly common dental disorders, most importantly periodontal bone loss, dental abscesses, dental caries, or gum disorder, and displays the teeth and their nearby alveolar bone, dental roots, and dental coatings [19]. The program can provide the chance to recognize the extra important findings, such as broken dental fragments or impacted teeth, restoration status, and changes in bone and dental anatomy [20]. The caries identification on the basis of periapical and panoramic imaging approaches is manually carried out by the dentists. Often the diagnosis of caries dental displayed on the radiography cannot be performed properly due to conventional dental caries can be overlooked because of the intense patient load or the inexperience of the physicians [21]. This scenario can result in caries progression, dental loss, and advanced dental infections. The automatic models that have been implemented according to the image processing as well as machine learning mechanisms to prevent these limitations and support the dentists to diagnose that attained significance [22]. Some of the dental disorders are cysts, impacted teeth, gingivitis, interdental bone loss, periodontitis, and dental caries.

In addition, the lesion's radiographic appearance can dramatically vary as a function of the selected projection geometry [23]. The digital detectors helped to replace the films, yet they didn't resolve the primary problems. Several conventional works displayed that the CBCT is an effective imaging mechanism in the intraoral digital imaging approaches. The deep learning has been largely employed in the CBCT images [24]. This method is employed in a lot of sectors such as the localization of landmarks, dental implants, sinus disorder, ibular joint, temporom, endodontics, tooth segmentation, bone-oriented disorder, inferior alveolar nerve segmentation, and upper airway segmentation. Convolutional Neural Networks (CNNs) are a kind of deep learning mechanism on the basis of neural networks in Artificial Intelligence (AI) that are utilized for object identification and image categorization in the images [25]. The CNNs can recognize the dental caries and validate the dental images to recognize the regions of caries. These models can recognize the dental caries present in the images, allowing timely caries identification utilizing the trained neural networks. The conventional works estimated the caries identification functionality of the deep learning mechanisms. Nevertheless, the existing works on the neural network's functionality in caries lesions with distinct radiographic locations and depths. Deep learning strategies have started to support the dental caries automatic diagnosis. Therefore, by considering the automated techniques, the developed work presented a new dental caries classification framework.

1.2 DENTAL CARIES

Dental caries is defined as a transmissible and multi-factorial infectious disease characterized by a root and crown structure's progressive destruction because of microbial activity. The Streptococcus mutans is the primary pathogen. Normally, caries grows because of the complex communication of cariogenic oral flora on the fermenting of dietary carbohydrates. Nevertheless, the immune system of the host, social status, oral hygiene, pH, bio-film, structure of the tooth, diet, and genetic susceptibility will impact whether an individual grows caries. For energy, the bacteria carbohydrates the biofilm metabolize into sugars, generating lactic acid as a byproduct [39]. During this period, this minimizes the plaque PH to severe stages and starts the calcium and phosphate removal from the dental structures developing the cavity. The minerals are formed again into enamel, after the restoration of equilibrium. If the demineralization signifies the remineralization, the enamel crystal's collapse generates the cavity, an operation that takes years or months. In the removal of substrates calcium provision, and buffering the plaque acid, the saliva plays an important part.

Thy dynamic caries operation includes rapid alternating times of tooth remineralization and demineralization, which, if total demineralization happens over enough time, the outcomes in the particular caries lesion's initiation at specific anatomical predilection regions on the teeth. It is significant to trade off the protective and pathological attributes that impact the progression and initiation of dental caries. The protective attributes improve lesion arrest, and remineralization, on the other hand, the pathological attributes shift the trade-off in the way of disease progression and the dental caries. The daily utilization of fluoride toothpaste is viewed by distinct authorities as a primary reason for the entire decline of caries globally. The action mode of certain toothpaste is regarded as shifting the trade-off of the oral biofilm towards health. This is not a correlation among the caries lesion's extension and whether discomfort and pain are felt.

Nevertheless, serious toothache, when it happens, can be sepsis, infection, and disabling happening because of the caries that propagate to include the dental pulp can often result in critical results including propagating local infection, tooth loss, and treatment-oriented death. The caries clinical identification is conventionally conducted by the thorough visual examination of clean teeth by experienced examines [40]. The sharp pointed dental probes are mostly utilized yet these are giving several damages. Supportive diagnostic approaches and dental radiographs are required in clinical practice to identify the lesions that are concealed to visual validation; most importantly those that happened on the surfaces of the tooth.

Though the caries ravage can make the teeth occur to be largely susceptible to destruction by disorder, from a perspective of biology, the human teeth are highly precious organs involved in the processing and prehension of the fold, and also it can function in the phonetic articulation, sexual attraction, and the defense. The tooth crown's outer surface includes enamel, which is the hardest substance in the human body with a specialized fluid named defense. The saliva is secreted the entire day to maintain its integrity. The advanced definition's morphology has developed highly on the basis of dietary preferences that have altered over the years. The diets have high in sugar tend to be liquid and soft. The teeth are not needed for their ingestion that could define why the teeth are quickly lost. The primer concentrates on offering a balanced international dental caries overview, both as a multi-factorial, complex disorder and as a fluctuating disorder.

When validating adolescent dentition, it is significant to focus on that distinct teeth are at threat at distinct ages, as the teeth erupt into the mouth. It takes many years for caries to occur once the tooth erupts [41]. Moreover, the temporary teeth are more vulnerable to caries than the original teeth, and the existence of hypoplasia, maybe as the outcome of poor maternal health enhances the concern. Several experts discuss that girls have more predisposition to caries compared to boys. This can connect to the starting age of the teeth eruption in females. The molar's buccal and coronal caries is a specific disease pattern in children because of the unworn fissure's susceptibility in the teeth, and normally an adult's disorder. The unhandled caries can provide rise to lethal troubles including cavernous sinus thrombosis or meningitis or create chronic maxillary sinusitis.

1.3 CAUSES AND SYMPTOMS OF DENTAL CARIES

Dental caries, normally known as cavities or tooth decay, is one of the highly prevalent oral health problems globally. It negatively impacts people of all kind ages from children to elderly people. This can result in important long-term dental issues and discomfort if left unhandled. While distinct individuals understand the primary idea of cavities, there is still more information related to dental caries, such as its treatment options, preventive measures, stages, and causes. The primary causes as well as the symptoms of dental caries are explained below.

Dental caries is the dentin and the tooth enamel's destruction because of the bacteria action in the mouth. The operation starts when carbohydrates from drinks and foods integrate with bacteria on the teeth's surface. These bacteria generate the acids that damage the enamel, constantly breaking it down and generating holes or cavities in the teeth. The caries are classified into distinct phases on the basis of how deep the decomposition has penetrated the structure of the tooth.

The causes of the dental caries are explained below.
Age: While caries can influence all age kinds of people, older adults, and younger children may be susceptible because of distinct medical conditions, thinner enamel, and oral care habits.
Genetics: Several people are genetically predisposed to caries because of attributes such as teeth alignment, saliva composition, and enamel strength.
Bacteria in the mouth: The specific bacteria strains, most importantly, the Lactobacillus and Streptococcus mutans are famous for generating the acids that decompose the enamel of the tooth.
Dry mouth: The saliva supports neutralizing acids and washing away the food particles. Insufficient saliva created by medical conditions, specific medications, and dehydration can improve tooth decay.
Acidic diet and high sugar: The continuous consumption of acidic drinks and sugary foods increases the growth of bacteria and weakens the enamel, increasing the decay operation.
Poor oral hygiene: Improper flossing and brushing enable bacteria and plaque to occupy the teeth, enhancing the decay risk.
Vitamin deficiency: The deficiency in the body of vitamins and minerals included in the teeth's hard tissue's construction (vitamin C, phosphorus, fluoride, calcium, and so on) causes dental caries.
Diet: Consuming starchier, sugary drinks and foods or having extended contact with juice or milk as a child can increase the plaque-creating bacteria's growth.
Tooth surface: Low fluoride exposure, poorly calcified surfaces of the tooth, or an acidic environment can make the teeth highly vulnerable to the teeth.

Medications: Several medications can minimize the salivary flow that can result in caries. The dental caries mostly initiate silently with no proper symptoms until the decay has improved. Nevertheless, timely identification is significant in mitigating severe issues. The symptoms of dental caries are given as follows:

a. Swelling or Abscess: If an infection is created, swelling, foul taste in the mouth, or pus can occur, representing the requirement for immediate dental care.
b. Discoloration: Black, brown, or white stains on the surface of the tooth can represent advanced or early decay.
c. Bad breath: The bacteria is high accountable for tooth decay can also result in persistent bad breath.
d. Toothache: As the tooth decay grows, it irritates the nerves in the tooth, resulting in persistent or intermittent pain.
e. Tooth sensitivity: A normal early cavity sign, sensitivity can happen when consuming acidic, sweet, cold, or hot beverages and foods.
f. Holes or bits: If an infection occurs, there can be pits and holes.

1.4 TYPES AND STAGES OF DENTAL CARIES

Dental caries is the teeth's hard tissue's breakdown by the bacteria activity that generates the acids from the sugars in drinks and foods. Dental caries causes tooth loss, infection, and pain, and impacts the appearance of the teeth and the overall heath. There are distinct kinds based on the region, progression, and extent of the decay.

The dental caries types are explained as follows.

a. Fissure and pit caries: These are the normal type of dental caries, impacting the back teeth's chewing surfaces such as premolars and molars. Naturally, these surfaces have pits and grooves that can trap the bacteria and food, making them vulnerable to decay. The fissure and pit caries can be categorized into three.

i. Lingual- It affects the teeth's tongue side.
ii. Buccal-It affects the teeth's cheek side.
iii. Occlusal*:* It affects the teeth's top surface.

b. Smooth surface caries: This type of caries is the second most common kind of dental caries, affecting the teeth's smooth surfaces that are not related to other teeth. These surfaces include the back teeth's side and front teeth's side such as canines and incisors. The caries of smooth surfaces can be then categorized into two.

i. Cervical: It affects the region near the gum line.

ii. Interproximal*:* It affects the spaces among the teeth.

c. Root caries: These are the kinds of dental caries that impact the teeth's roots and are generally enclosed by the bone and gums. Root caries can happen when the gums recede because of the brushing to hard, gum disorder, and aging, revealing the roots to bacteria and plaque. This kind of caries can create tooth loss, infection, and sensitivity if left unhandled.

d. Secondary caries: These kinds of caries happen around conventional dental restorations including implants, bridges, crowns, or fillings. Secondary caries can happen when the restoration is poorly fitted, damaged, and defective, enabling bacteria and plaque to occupy the margins or gaps. This caries can compromise the function of the tooth, restoration, and integrity.

The caries has some stages, based on the region of enamel damage, and are explained below.

a. Initial caries: In this, the caries re in the spot phase or as it is also referred white caries. In this phase, a matte light spot is constructed on the surface of the enamel at the enamel demineralization's place. After some time, the operation can start from an acute shape to a chronic one and stop for a while, and the color of the stain becomes darker.

b. Superficial caries: The acute operation's suspension at the phase of the spot does not mean that the infection has retreated. After some time, in the region where the stain has been generated, roughness occurs that specifies the carious operation's active stage, and the enamel's destruction starts.

c. Medium caries: In this stage, the infection attacks, and starts to damage the dentin tissue. The operation proceeds separately for each patient for someone it is already at this phase, for another one it is imperceptible, the teeth's sensitivity is enhanced, and pain and discomfort occur.

d. Deep caries: A huge carious cavity generated from the internal tooth, the infection impacts a majority of the dentin, gets near to the pulp, or even starts the pulp bundle's inflammation.

1.5 PREVENTION AND TREATMENT OF DENTAL CARIES

The best news is that dental caries is highly mitigated with effective lifestyle changes and oral hygiene practices. The following ways help to minimize the threat of tooth decay.

a. Floss daily: The flossing eliminates the plaque and the food particles in the teeth, where the brushing sometimes may not reach. At least one day, flossing to maintain the health of the gum and eliminate the decay in these regions.
b. Brush properly and regularly: At least twice a day, brushing the teeth by employing fluoride toothpaste. Ensure to brush the teeth's entire gums and surfaces, utilizing a soft bristled brush, and circular, gentle movements.
c. Limit acidic foods and sugary: Minimize the consumption of drinks and sugary snacks including fruit juices, sodas, and cadies that lead to acid generation and feed bacteria in the mouth. Focus on consuming a balanced diet with more vegetables, fruits, and whole grains.
d. Chew sugar-free gum: The chewing process of sugar-free gum can improve the production of saliva and support minimizing plaque buildup during meals.
e. Stay hydrated: Consume water often, most importantly after the meals, to support rinse away the bacteria and food particles. Also, the water improves the production of saliva that supports neutralizing the threatening acids.
f. Utilize fluoride products: The fluoride improves the enamel of the tooth and supports eliminating cavities. Utilize fluoride toothpaste and refer fluoride treatments from dentists, most importantly if the risk of the cavity is high.
g. Regular dental checkups: Do visit the dentists every six months for professional examination and cleaning. The timely identification of caries enables highly conservative treatments and eliminates the decay from the growing.

If dental caries grows despite preventive efforts, the treatment of dental caries is significant to evade the damage. The kind of treatment relies on the decay stage.

a. Tooth extraction: The extraction is helpful, in critical cases where the tooth is beyond cure. After that, the dentists can suggest a dental bridge or implant to exchange the tooth.
b. Root canal therapy: If the decay has attained the pulp of the tooth, crating the abscess or infection, a root canal can be needed. This operation includes eliminating the affected

pulp, cleaning the canals of a root, and sealing the tooth to eliminate the subsequent infection.

c. Dental crowns: In situations where the decay is large and has strengthened the tooth, a crown can be significant to obtain its normal function and shape. The crowns cover the overall tooth.
d. Dental fillings: For cavities that have improved beyond the enamel, the dentists can eliminate the decayed section of the tooth and fill the region with material including composite gold, amalgam, or resin.
e. Fluoride treatments: In the starting phases of dental caries, the standard fluoride treatments can support remineralizing the enamel and undoing the decay. These treatments are more focused than the products of over-the-counter fluoride and are employed the dentists.

1.6 SIGNIFICANCE OF DENTAL CARIES CLASSIFICATION

Dental caries has been referred to as relatively prevalent with its timely lesions existing in the majority of the populations. Based on the recent experiment, the unhandled caries in the permanent definition have become the globally normal condition. Some of the significance of classifying dental caries are explained below.

a. Accurate diagnosis: The classification of dental caries supports in proper detection and diagnosis of caries at the timely stages.
b. Prevention methods: The classification supports recognizing high-risk patients, enabling targeted prevention mechanisms.
c. Treatment planning: The classification assists the treatment planning, allowing dentists to choose the most proper treatment plans.
d. Monitoring progression: The classification allows caries progression monitoring, enabling timely analysis.
e. Epidemiological experiments: The classification supports epidemiological experiments, supporting tracking the caries trends and prevalence.
f. Research and development: The classification reports the new caries treatment and identification approach’s research and development.
g. Clinical decision-making: The classification process encourages clinical decision-making, guaranteeing evidence-aided and consistent care.

h. Patient education: The classification helps the people understand their status of caries, improving self-care and education.
i. Risk assessment: The classification allows risk validation, recognizing the patients with high threats of caries growth.
j. Resource allocation: The classification explains the resource allocation, guaranteeing the effective utilization of healthcare resources.
k. Quality assurance: The classification supports the quality assurance, observing the efficacy of caries treatment and diagnosis.
l. Communication: The classification operation standardizes communication between healthcare analysts, guaranteeing consistency and clarity.
m. Data analysis: The classification allows the data validation, offering insights into caries trends and patterns.
n. Public health planning: The classification task reports public health planning, assisting the implementation of caries prevention applications.
o. Evidence-aided practice: The classification helps evidence-aided practice, guarantying that the caries treatment and diagnosis are grounded in scientific proof.

1.7 AI IN DENTISTRY

In history, humanity has faced an enhancement in the normal state of well-being, resulting in notable improvements in human health. A significant attribute involving this criterion is the promising improvement performed in the medical technology sector. The importance of maintaining better oral health and securing natural teeth has become highly significant in an advanced society. The teeth play a significant part in a human's ability to enjoy the happiness of the delicious food. The teeth play as important components in breaking down and chewing the food, performing as the primary step in the digestion process of the body. Nevertheless, it is also significant to consider that the oral cavity is a natural habitat for distinct microorganisms.

In addition, the oral cavity is the resident for distinct microorganisms. Nutrient absorption is negatively affected by the poor dental conditions. Hence, the oral health is highly connected to the normal health. The oral cavity offers a special complexity as it is not simply observable, making the timely identification of signs or changes of the disorders very challenging. Distinct persons tend to reactively seek dental treatment, most of the time waiting until the individuals experience discomfort and pain. This mechanism results in more treatment expenses yet also leads to high discomfort for the individuals. It is significant to emphasize that the threat created by the cavities is not reversible and can lead to tooth loss if not correctly considered. Therefore, the timely identification, as well as treatment of dental caries, is significant to eliminate the irreversible threat and guarantee optimal oral health.

AI is a famous computer science sector that nowadays was experimented with in the belief that the computing power's computation could mimic the thinking ability of humans and make proper responses related to those of humans to support them fulfill their operations. With the support of the Internet of Things (IoT) mechanism, distinct furniture can communicate with individuals via data transmission, making the lives of people highly convenient and comfortable. As a primary content, rapidly driverless cars are implemented, though driverless cars are still far from being originally commercialized. Employing AI-aided translation components in the translation work supports the translators in high-quality and effective translation. It also supports the individuals who have distinct languages to interact. It is also explained that AI can fulfill the implementation requirements of some of the sectors and improve the organizations further. The health care sector has included the AI mechanism to support the medical analysis with quantitative comparative validations of tumor regions to enhance the reliability and accuracy of the healthcare diagnosis.

Nowadays, the dental organization is entering the sector of AI. Data imaging is one of the fundamental concepts for detecting oral disorders via the imaging of soft and hard oral cavity tissues. The AI allows the smart identification and validation of dental imaging data, resulting in smart oral disorders diagnosis. Some of the AI models involved in dentistry are explained as follows.

a. Traditional machine learning**:** Machine learning is referred to as a sector of computer science that includes the utilization of statistical approaches and algorithms to allow computer devices to understand and improve their expertise without being specifically programmed. Deep learning helps to simplify the learning operation and the algorithmic validation on the basis of conventional machine learning. It also helps to attain high accuracy in particular regions that conventional machine learning models cannot, for instance, medical images, text translation, behavior identification, face identification, and so on. Nevertheless, it does not mean that the conventional machine learning approaches are behind either. Machine learning has been implemented over the years and has pervaded via distinct sectors. The conventional machine learning approaches can conduct a majority of the everyday operations without building alternative attributes. Hence, the urge to utilize deep learning is much less when simple techniques can be addressed.

b. Support Vector Machine (SVM*):* It is a flexible and powerful supervised-aided machine learning approach. For each sample's feature vector in the data, the source is specified as a point in the space. This model tries to split the object's two classes utilizing a plane or line. The plane or line that splits the classes is named hyperplane. Even if new points are later included in the space, the hyperplane will be capable of categorizing them. Normally, there have been distinct hyperplanes, all can conduct the classification task. The primary objective of SVM is enhancing the margin of the classification. The margin is referred to as the lowest value of the distance between the hyperplane and the point. Enhancing the margin enables the hyperplane to be properly categorized, even if the objects are later included.

c. Cluster analysis: The supervised and unsupervised learning rely on whether the data present in the data source has been manually labeled and categorized. As there are no specific labels, unsupervised learning does not end up with a constant outcome. The region of data is the sample's distribution in the data source. Cluster validation is the kind of supervised learning, that categorizes the data according to the proximity of the relations among the data present in the data source. In the cluster class images, each class is named cluster. The higher the data similarity presents in the cluster, the higher the spacing of the cluster, and the better the effect of clustering. Figure 1.1 displays the cluster analysis process's schematic illustration.

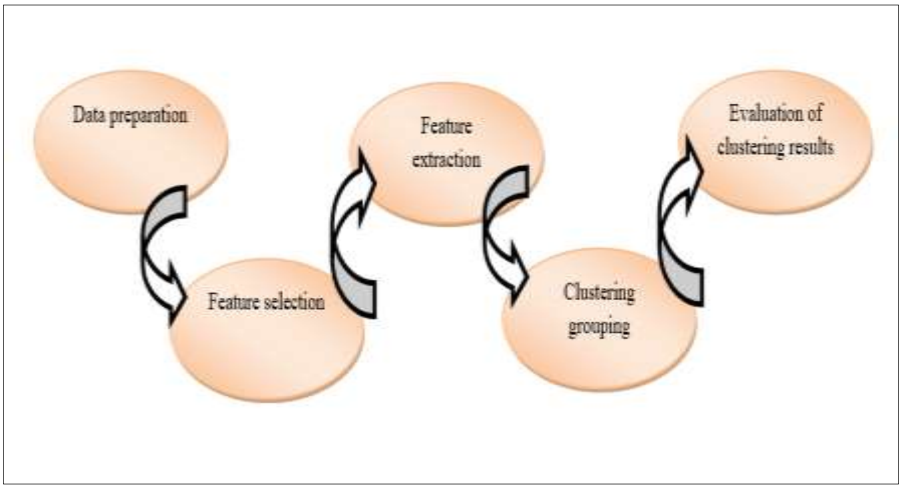


Figure 1.1: Cluster analysis process's schematic representation.

d. Random forest: It is a very famous technique in machine learning. This technique includes two keywords such as 'forest' and 'random'. The term 'forest' defines that this technique employs decision trees as a primary blow, borrows the combination concept to collect some decision trees with a similar working objective, further gathers the outcome, and utilizes distinct comprehensive validations to enhance the outcome. Though each decision tree has a similar objective, if the decision tree is the same, the last mean outcome will also be the same; hence the phase of averaging after the collection has no meaning. This is the concept where the point of 'randomization' becomes significant. The input data for each decision tree is arbitrarily sampled from the data source, and distinct attributes are chosen for designing. Therefore, the resulting decision tree is not relied on by each other and is as special as possible. Figure 1.2 presents the random forest model's flowchart.

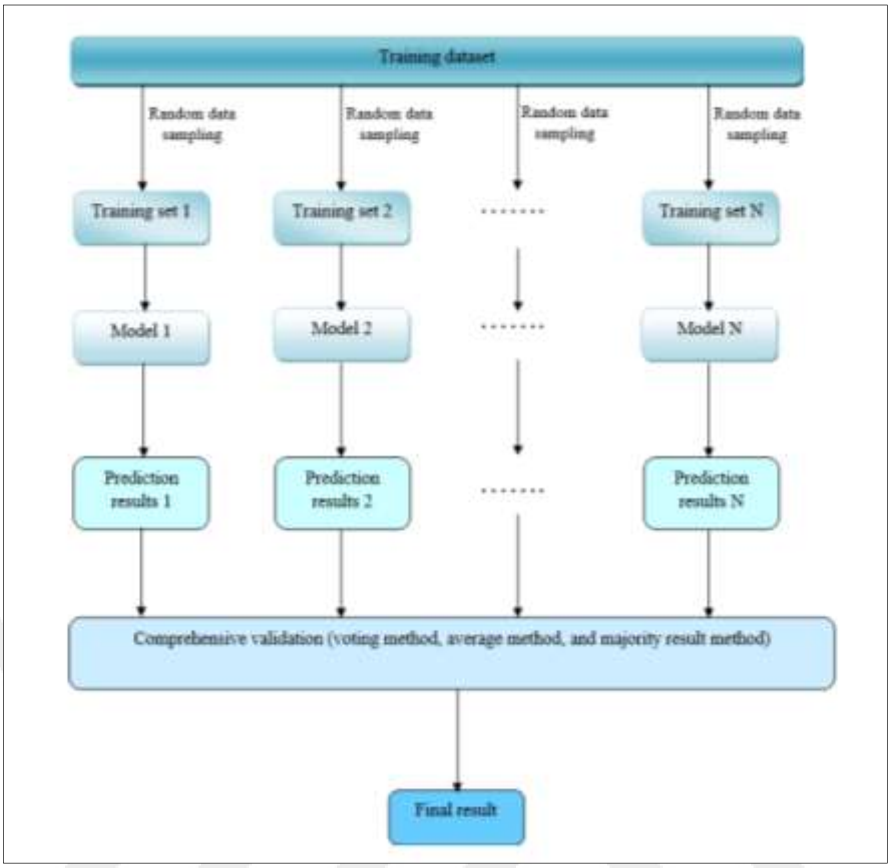


Figure 1.2: Flowchart of Random Forest.

e. Deep learning: It is a kind of machine learning. It is an AI approach that understands the features by constructing multi-level networks. The term 'deep' specifies the utilization of deep learning mechanism and the term 'learning' specifies that feature learning is the objective. In contrast to conventional machine learning, deep learning does not demand manual feature extraction but rather the model's training of the techniques from a huge amount of samples. The objective of deep learning is to generate neural networks that copy the human brain for learning purposes. In the neural network, the input layer attains the data, the mathematical estimations are performed by the hidden layer, and then the classification outcomes are attained from the output layer. Figure 1.3 displays the conventional machine learning workflow by comparing it with the deep learning workflow.

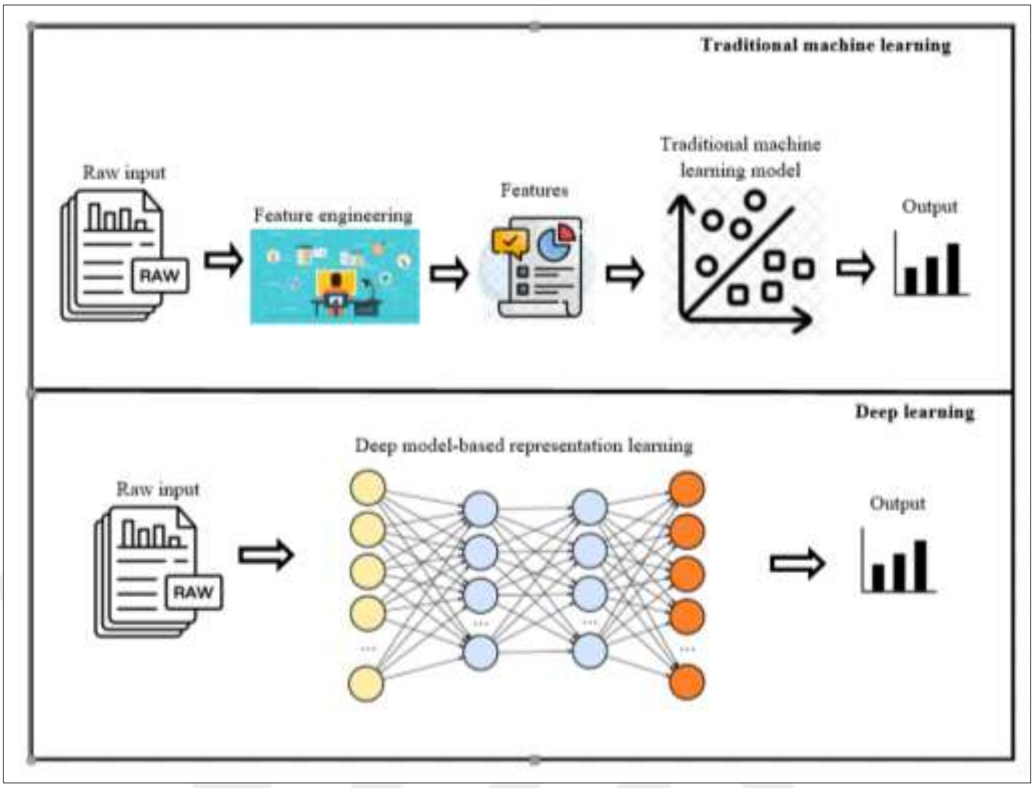


Figure 1.3: Displays the Conventional Machine Learning Workflow by Comparing it with the Deep Learning Workflow.

f. Convolutional Neural Network (CNN): The primary structure of the CNN includes an output layer, an activation layer, a convolutional layer, and an input layer. The convolution task is conducted by moving a set size filter across the image in an orderly from left to right and top to bottom based on the step size. The convolution task's outcome is attained by multiplying each position's filter elements with the specific input elements and adding them to attain the output value. Moreover, the convolution layer requires to be accompanied by the activation function to enhance the CNN model's complexity, permitting the CNN to be processed to distinct scenarios to resolve the complex tasks. Distinct from the convolutional layer, the pooling layer has no learning responsibility and does not need a structure, yet it is general.
g. Recurrent Neural Network (RNN): The real feed-forward neural network was employed for extracting the entire features and mapping them to the outcome. Nevertheless, if the input is speech or text, then there is a requirement to pay attention to the approach for ordering the words to each other. The RNN technique utilizes recursions or loops when

handling the distinct length's input content, dividing the input into same-length chunks and allocating them orderly.

h. Generative Adversarial Network (GAN): It is trained by employing 2 adversarial NNs. The fake images produced by one of the NNs are included in the real data source. The other NN technique concentrates on differentiating among the dataset images and the fake images. The two distinct NNs constantly enhance their corresponding functionality in the adversarial task and automatically attain the optimal functionality. The noise is arbitrarily produced and utilized with the support of a generator to fabricate the forged images. These forged images are further integrated into the data source for the discriminator to analyze. At first, the output of the generator is weak yet with iterations, both the discriminator and generator improve.

2. LITRATURE REVIEW

In 2024, Esmaeilyfard *et al.* [1], have recommended deep learning strategies to recognize the tooth caries and categorize the dental caries location and extension in the CBCT images. The image data source of CBCT included 403 non-caries molar samples and 382 molar teeth with caries. The data source was split into an implementation set for validation, a test set, and the training. For each case such as coronal, sagittal, and axial, three images were acquired. The test data sources were offered to distinct input CNN. The model provided predictions concerning the absence and the presence of dental decay and categorized the lesions based on their types and depths for the offered samples. The values of F1 score, specificity, accuracy, and sensitivity were calculated for the identification as well as classification of dental caries. The CNN technique provided high accuracy, specificity, and sensitivity in categorizing caries locations as well as extensions. This experiment illustrated that deep learning strategies could properly recognize dental caries and categorize their kinds and depths with more specificity, accuracy, and sensitivity. Deep learning's promising application in this sector efficiently supports patients and medical practitioners in enhancing the treatment and diagnostic planning in dentistry.

In 2022, Imak *et al.* [2], have implemented a mechanism for dental caries automated diagnosis according to the periapical images. The recommended model employed a new approach named Multi-Input Deep CNN Ensemble (MI-DCNNE). Most importantly, a score-assisted ensemble approach was implemented to enhance the success of the implemented MI-DCNNE technique. Both original periapical images and an improved version of it were the inputs of the implemented mechanism. The score integration was conducted in the suggested multi-input CNN model's SoftMax layer. In the research tasks, a periapical image data source with 340 images enclosing both non-caries as well and caries images was employed for the functionality estimation of the recommended mechanism. Based on the experiments, it was displayed that the suggested approach was promising in dental caries detection. The obtained accuracy of the model was 99.13%. These solutions were displayed so that the developed model could efficiently contribute to the dental caries categorization.

In 2022, Li *et al.* [3], have developed a model improved by the self-attention block for small segmentation of dental plaque. The primary objective was to employ the oral endoscope images directly and obtain accurate segmentation outcomes of pixel-level dental plaque. The model required performing the self-attention at the level of superpixel and integrating the local to global feature's super pixels. The developed model afforded the continuous integration of distinct scale complementary data assisted by the effective paradigm of deep learning. The complex integrated data included the plaque color's statistical distribution, the Heat Kernal Signature (HKS)-aided relationship of local-to-global structure, and the local texture pattern in the neighborhood locations centering on the plaque region. In order to further refine the integrated distinct scale attributes, the experiments suggested an attention approach according to the CNN model that could easily focalize the Regions of Interest (RoI) in the plaque, most importantly for distinct complex cases. The detailed validations and estimations ensured that, for a small-scale data source, this model could perform better than the conventional mechanisms. The user experiments validated the claim that the developed model was more accurate than the existing dental practice performed by experienced medical analysts.

In 2024, Li *et al.* [4], have introduced a new mechanism for exploring AI's application in the dental medicine sector. The primary stages of this mechanism were to recognize the symptoms of dental such as (i) identifying the tooth position, and (ii) identifying the symptoms. This work integrates the image enhancement mechanisms and the identification of tooth position utilizing the Gaussian filtering, the data pre-processing was by the adaptive binarization, supported by the YOLOv4 technique to accurately mark the positions of the tooth. The work further improved the visibility of the symptom region with the support of contrast enhancement, by employing the CNN technique and, most importantly, the AlexNet technique with enhancements in the accuracy of the caries identification, and the accuracy of the restorations identification contrasted to the previous experiments. In addition, the incorporation of periodontal disorder symptoms attains high accuracy. By employing the techniques of deep learning on the basis of CNN techniques, this experiment improved the precision of the diagnosis, minimized the error, and enhanced the efficacy of dentists, thus offering swift and meticulous patient care. This technology saved time and was also implemented in preventive and remote medicine.

In 2022, Kumari *et al.* [5], have developed a deep-learning strategy for efficiently segmenting the dental caries. Initially, the Contrast Limited Adaptive Histogram Equalization (CLAHE) model was supported for the contrast enhancement, and the bilateral filtering was supported for the noise filtering under the stage of pre-processing. After that, the caries segmentation was conducted by employing the Fused Optimal Centroid K-means with K-Mediods Clustering (FOC-KKC). It was improved by an optimization model named Hybrid Sea Lion-Squirrel Search Optimization (HSLnSSO). After the caries segmentation, the image's post-pre-processing was conducted with the help of morphological tasks. In the end, the caries identification from the segmented image was utilized with the help of Meta-Heuristic-based ResneXt with Recurrent Neural Network (M-ResneXt-RNN). In this architecture, some of the modifications were carried out with the support of HSLnSSO. This work for caries identification has offered superior performance when contrasted to the traditional approaches.

In 2024, Szabó *et al.* [6], have recommended an AI-aided model that supported the healthcare operations in the caries diagnosis on intraoral radiographs. The 323 chosen teeth's proximal surfaces on the intraoral radiographs were estimated with the support of two separate monitors utilizing an AI-aided model. The absence or presence of carious lesions was stored during the first stage. The AI-assisted human observers after 4 months estimated in the second stage, and the improved CNN revalidated the radiographic information in the third phase. Further, in the fourth phase, the information reflecting disagreements was eliminated. For each stage, the Fleiss and Cohen kappa rates, as well as the diagnostic accuracy, negative, and positive predictive rates, specificity, and sensitivity were estimated. The suggested approach helped the intraoral radiograph validation for caries detection as estimated by consensus among the AI device and human observers.

In 2024, Guilherme *et al.* [7], have implemented Self-Supervised Learning (SSL) operations to enhance the dental caries classification in the CBCT images. Encountered the complexities of inadequate annotated healthcare images, this experiment utilized SSL to employ unlabeled data thus enhancing the functionality of the approach. The developed work implemented a pipeline utilizing the extraction of unlabeled data from the CBCT validations and further model training utilizing the SSL operations. This model was the combination of image processing mechanisms with the SSL operations, along with discovering the requirement for the unlabeled information. This experiment concentrated on recognizing the highly efficient image processing mechanisms for extracting the data, and the highly effective deep learning models for classifying the caries. The outcomes recommended that

SSL could highly improve the efficiency and accuracy of the caries categorization in the CBCT images.

In 2023, Jiang *et al.* [8], have suggested a classification model with an attention approach for detecting dental caries. Most importantly, it included 4 phases, (i) Multi-Spectral channel Attention Module (MSAM) that could attain the supportive frequency factors in the feature map, (ii) the feature dependencies were captured by the Position Attention Module (PAM) in the spatial dimension, (iii) the highly significant feature points was discovered by the Discriminative Point Selection strategy (DPS) and finally the aggregate feature points at feature map's distinct scales were concentrated by the Graph Convolution and Aggregation module (GCA). In order to improve the capacity to draw out the significant features, the MSAM and PAM were fused into the backbone network to include the network of feature extraction with an attention approach. The distinct feature points at different feature map scales were drawn out by DPS and the global discriminative features were drawn out by GCA.

2.1 PROBLEM STATEMENT

In dentistry, diagnosing dental caries is a complicated task as it needs more precise and accurate detection in the initial stages. Accurate identification of dental caries helps to prevent dental caries and other periodontal diseases. Moreover, current dental examination procedures face more limitations in detecting dental caries without employing the medical dyeing reagent as it offers a minimal contrast between healthy teeth and dental caries-affected teeth. Multiple limitations presented while designing dental caries detection techniques are listed as follows.

a. Conventional dental caries disease detection techniques are prone to misclassification issues and also they are prone to more errors due to noisy and poor-quality data. Hence, to tackle these issues the developed framework used the required images from the standard dataset that helps to enhance the disease detection accurate of the developed framework by eliminating the errors in detecting the tiny lesions.
b. Conventional dental caries detection techniques face more misclassification issues in the network and also create more complications in observing the disease-affected regions in a blurry and noisy background. So, it is important to rectify multiple challenges presented

in the classical techniques by including the segmentation procedure in the suggested framework. Using segmentation procedures in the suggested technique helps to recognize the disease-affected regions more precisely.

c. Existing dental caries disease detection models use machine learning techniques for the detection, but these techniques don't have the efficiency to detect the abnormalities in a limited time and also lead to probability errors. Thus, to overcome these issues, the suggested technique utilized deep learning techniques as it effectively reduced the validation complication and offered higher accuracy-based disease-detected outcomes.
d. The classical dental caries disease detection framework didn't use the optimization mechanism, because this existing framework faces overfitting issues and also requires more memory space for the validation. To rectify these issues, the suggested framework employs a novel optimization mechanism that helps to enhance the accuracy of denial caries disease detection and rectify the overfitting issues.

Multiple advancements and complications presented in the classical dental caries detection models are offered in Table 2.1. Hence, it is essential to overcome several limitations presented in the classical dental caries disease detection model with a novel deep learning-based framework.

Table 2.1: Features and Challenges of Classical Dental Caries Disease Detection Framework.

Author [citation]	**Methodology**	**Features**	**Challenges**
Esmaeilyfard *et al.* [1]	CNN	• It offers a deep observation about the presence and absence of dental decay. • It provides superior disease-detected outcomes with labeled data.	• It needs to overcome the interpretability issues. • It requires reducing the training time in the network.
Imak *et al.* [2]	MI-DCNNE	• It effectively enhances the generalizability and also rectifies the overfitting issues.	• It always needs human supervision in all stages. • It needs to rectify the interpretability issue.
Li *et al.* [3]	CNN-AM	• It easily enhances the training efficiency of the entire network and also reduces the hardware load.	• It always needs the labeled data for validation.

Table 2.1: Features and Challenges of Classical Dental Caries Disease Detection Framework (Table Continued).

Li *et al.* [4]	YoloV4 and CNN	• It effectively minimizes errors and also improves disease detection efficiency in a complicated environment.	• It needs to rectify the overfitting issues and also the localization errors.
Kumari *et al.* [5]	ResneXt	• It effectively resolves the computation issues and enhances the efficiency of learning. • It accomplishes higher efficiency in a complicated environment.	• It needs to enhance the robustness of the developed model.
Szabó *et al.* [6]	CNN	• It easily reduces the redundancy between the learned features and also uses simple procedures for training.	• It needs to speed up the training process. • It needs to offer better outcomes for the sequential data.
Guilherme *et al.* [7]	SSL	• It provides superior dental caries-detected outcomes by using unlabelled data. • It easily reduces the similarity among the images by reducing the loss functions.	• It needs to enhance the performance of the entire system. • It requires tackling the generalization errors.
Jiang *et al.* [8]	MSAM	• It easily collects the feature dependencies and discriminative features in the spatial dimension.	• It needs to reduce the validation time.

2.2 RESEARCH MOTIVATION

Dental disorders are normal in humans and gradually enhancing, though majority of the people are conscious regarding tooth protection, and are becoming a primary health issue in distinct regions and affect people their entire life time, creating deformity, uneasiness, and pain, and related with other non-communicable disorders such as diabetes, chronic respiratory disorder, cancer, and cardiovascular disorder. In the initial days, the caries are recognized by the visual examination of the variations in the enamel breakdown and structure. The recent improvements in technology have introduced a new vista in the way of dental informatics that combines telecommunications, information science, computer science, cognitive sciences, and dentistry for disease treatment and diagnosis in a time-effective way. In the medical and dental science sector, a huge amount of data is gathered from high-quality medical imaging models including CT and radiographs. The identification of dental disorders by validating the radiograph images, and smartphone dental photos via computer applications minimize the burden on the dentists and false diagnosis. Though radiography is suggested as a diagnostic approach, the identification of dental caries utilizing radiographs is subjective. The primary variations present among experts concerning whether the caries tumors are identified, even utilizing a similar radiograph.The attributes such as the time length per examination, variability across examiners, the expectations of the dentists, viewing conditions, and the radiograph's quality are causing inconsistencies in the agreement of the interpreter. The CBCT plays an important part in detecting dental conditions including dental caries. The CBCT provides distinct merits such as low exposure time, high accuracy, and multiplanar reconstruction. The caries lesion identification via the conventional radiographs remains a complex operation. The complexities present in conventional radiography are high because of the caries lesion's 2D representations that are 3D formats in original, and this may result in the loss of significant data. Distinct restoration and retention techniques that have been developed and enhanced for dental caries treatment have been implemented over the previous years. Nevertheless, there has not yet been an important enhancement in the diagnostic approach for identifying dental caries because of the distinct anatomical teeth morphologies and the restoration shapes. Most importantly, when the secondary lesions, tight interproximal contacts, and deep fissures are present, it is complex to identify the early phase disorder and originally distinct lesions are identified in the advanced dental caries stages. Hence, though radiography and the explorer are highly regarded and employed to be largely reliable diagnostic components for the identification of dental caries, the majority of the screening and the last diagnosis result depends on empirical proof. To forecast diseases from oral health details, machine learning strategies are employed to rectify the problems without the intervention of humans.

The performance and the efficiency of the network are highly based on the model and the data employed for training the technique. According to the probabilistic and statistical approaches, the machines enhance their decision-making concerning new data ordering, discovering new forms, and predictions, by learning from prior samples. Deep learning has largely been employed in the CBCT images. This model is employed in distinct sectors such as landmark localization, dental implant, sinus disorder, endodontic, tooth segmentation, bone-oriented disorder, inferior alveolar nerve segmentation, and upper airway segmentation. The conventional experiments validated the caries identification functionality of the deep learning strategies. Nevertheless, there are very limited experiments on neural network functionality in caries lesions with distinct radiographic locations and depths. This is significant to treatment decision-making and health economic perspectives, since the treatments of dental caries including tooth extraction, root canal therapy, cavity filling, and remineralization change with lesion location and depth. Moreover, very less amount of experiments examined the variations that are obtained from employing deep learning strategies in clinical situations or how dentists can benefit from the approaches of deep learning.

2.3 RESEARCH OBJECTIVES

The research objectives of the implemented classification framework of dental caries are explained below.

a. To develop an automated dental caries classification system for mitigating the subjective, and tedious tasks of the dentists.
b. To suggest an advanced deep learning strategy for segmenting the abnormal regions present in the CBCT images that help to classify dental caries with more clarity.
c. To present an adaptive deep network for classifying dental caries that efficiently resolves the existing model's complexities such as computational burdens, overfitting, and more inference time thus providing highly accurate classifications.
d. To design an enhanced heuristic algorithm by improving the existing algorithm that helps to optimally select the deep network's parameters and improves the performance rates of the classification task.

2.4 RESEARCH CONTRIBUTION

The research objectives of the implemented classification framework of dental caries are explained below.

a. To introduce a novel and new classification framework for dental caries by introducing powerful deep learning mechanisms that help in the early identification of caries. This automated framework improves efficiency by rapidly validating the CBCT images thus enhancing the treatment planning capabilities and providing a highly precise assessment of dental decay contrasted to the conventional visual examinations. Moreover, this model prevents reliance on experienced dentists and offers a promising and comprehensive analysis of dental caries.
b. To develop an NDT-R2Unet model for segmenting the abnormal regions in the CBCT images. The NDT-R2Unet technique comprises the T-R2Unet model with nested dilation. Here, the T-R2Unet model captures the global context and the long-range dependencies in the input images. Also, the model learns the highly complex features to enhance the accuracy of the segmentation. The model efficiently handles the intricate object boundaries and mitigates the vanishing gradient problems. The nested dilation in the NDT-R2Unet technique minimizes the computational burdens and captures the multi-scale contextual data. Thus, the NDT-R2Unet accurately segments the abnormal regions in the CBCT images and improves its image resolution thus improving the classification phase.
c. To design an AUWGO algorithm for optimally selecting the parameters of the efficient net in the classification phase. The suggested AUWGO algorithm introduces a new flight step size and modifies the flight operation in the existing WGO. This operation relatively increases the performance and the convergence rates of the AUWGO algorithm. In addition, the AUWGO enhances the accuracy and the Critical Success Index (CSI) values in the dental caries classification.
d. To implement an AdaENet-RA network for classifying dental caries. The AdaENet-RA exploits the efficient net as a primary model, which has better feature extraction capabilities and is suitable for distinct image sizes. Moreover, the efficient net efficiently recognizes the disease features. The region attention is included in this network for focussing on the related and target features from the segmented images. Moreover, to prevent overfitting complexities, the AUWGO-aided adaptive concept is included in this network to improve the accuracy and efficiency of the dental caries classification.

3. METHOLOGY

3.1 DESCRIPTION OF PROPOSED DENTAL CARIES CLASSIFICATION SYSTEM

Dental caries is a highly common dental disorder. If the dental caries are left unhandled then it causes dreadful consequences. The dental caries diagnosis poses an important complexity in dentistry, necessitating early and precise identification for efficient management. Distinct techniques are available for detecting dental caries. Often, the caries extension is so tiny that it cannot be diagnosed or visualized with the help of radiographic images. X-rays are one of the suitable techniques for detecting dental caries and threats to the root of the tooth. The CBCT specifies advancement in the dental imaging mechanism, providing a thorough dental anatomy in 3D view. This imaging method is significant for distinct diagnostic programs such as surgical intervention plans, estimation of low bone density diseases, tooth demineralization validation, and endodontic treatments. The CBCT enables the professionals of oral health to validate distinct dental layers and identify the cavities timely such as interproximal caries thus improving the detailed experiment's inclusion and the diagnostic reports comprehensiveness. Nowadays, image processing has been implemented in the dentistry for timely identification and diagnosis of dental caries-oriented disorders. It normally categorizes the kind of dental disorder infections. Diverse experts have been carried out for the identification of dental caries concerning the distinct methods and tough cases are suggested for the dental caries classification. However, no certain technique is satisfactory to categorize the layer-wise caries. Diverse machine learning strategies are included for categorizing and validating the image data. Amongst, the Deep Neural Network (DNN) and Artificial Neural Network (ANN) techniques of machine learning provide significant performance. Although there are distinct techniques for the timely identification of caries, it is significant to develop an accurate caries identification model, helpful for dentists. Therefore, this work implements a new strategy for classifying the dental caries.

The developed classification framework of dental caries is introduced in this work by employing deep learning. The developed work employed the CBCT images for classifying dental caries. The CBCT images provide some merits in the classification of dental caries because of their capacity to offer a thorough 3D teeth view, enabling better identification and the validation of the caries lesions. Most importantly, in the hard-to-see regions such as inter-proximal surfaces, contrasted to the conventional 2D radiographs resulting in highly accurate treatment planning and the diagnosis. Therefore, the developed work considered the CBCT images. These images are fetched from the available datasets. These images are then subjected to the segmentation module, where the NDT-R2Unet is employed for segmenting the abnormal areas in the CBCT images. The developed NDT-R2Unet technique integrates the advantages of the Unet model's efficient segmentation abilities with the transformer's long-range dependency designing, along with the advantages of residual and recurrent connections, resulting in enhanced feature extraction capacity and better functionality in the complex segmentation operations, most importantly in medical imaging, where the properly localization of fine details is significant. Here, the nested dilated convolution is included, which enhances the receptive field while managing the computational efficacy, handling the technique to obtain the long-range dependencies with very less amount of parameters. It makes the model highly significant for operations, where the detailed information is significant. Thus, the segmentation is carried out. Further, the obtained segmented images are passed to the AdaENet-RA technique for categorizing the caries disease. The efficient net technique minimizes the computational and memory demands, performing an effective classification for dental caries. Moreover, the region's attention is included with this technique for focusing on the important image features from the segmented images. In this classification phase, the CSI and the accuracy are maximized by the implemented AUWGO. The AUWGO is developed from the existing WGO, where the random integer is updated by the newly designed concept. Thus, an effective caries classification is conducted and the model provides effective and accurate solutions. Performance validations are performed for the designed framework for ensuring the efficacy of the implemented approach. The implemented dental caries classification framework's schematic representation is presented in Figure 3.1.

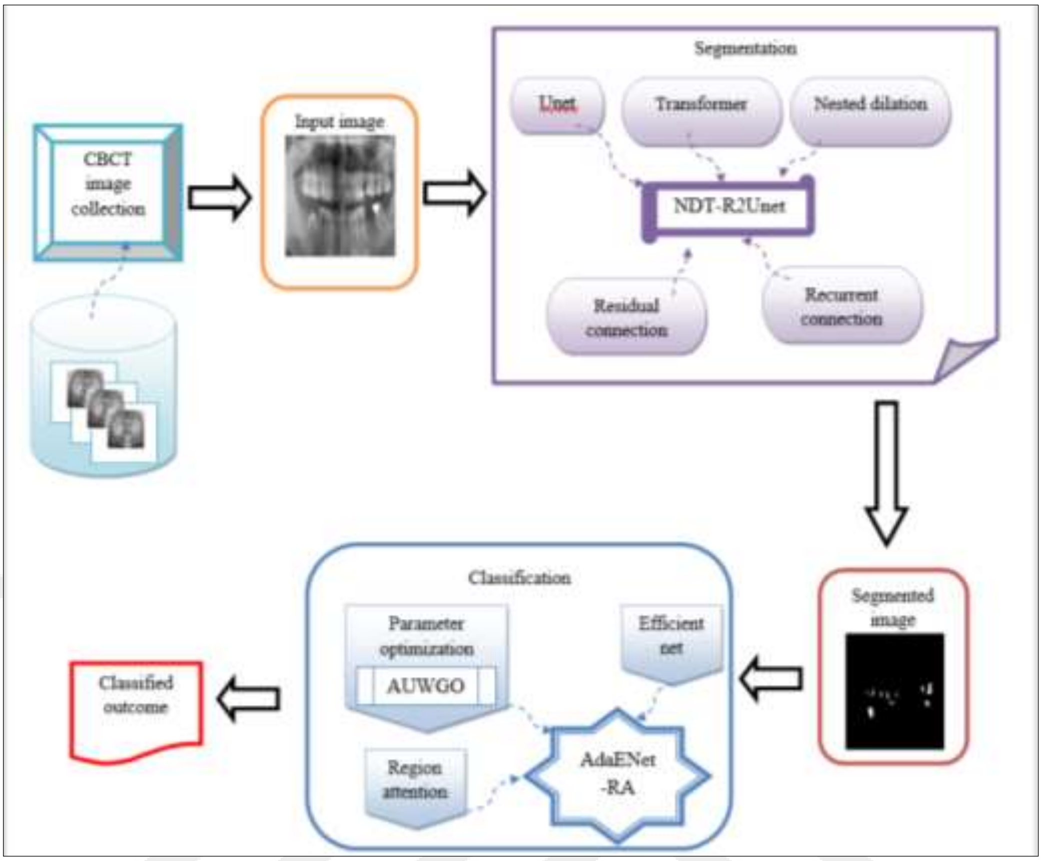


Figure 3.1: Schematic Representation of Implemented Dental Caries Classification.

3.2 ACQUISITION OF CBCT IMAGES

The CBCT images are a set of 3D digital images generated by the CBCT scanner. It offers detailed anatomical data regarding the structure of the bone, most importantly in the maxillofacial and dental regions. This is relatively important in dentistry for effective diagnosis and treatment planning to visualize the difficult anatomical attributes in distinct planes, enabling accurate estimations and a better understanding of the criteria including root canal morphology, bone density, and impacted teeth contrasted to the conventional 2D radiographs. Thus, the developed model employs the following dataset for gathering the CBCT images.

Dataset (Panoramic Dental Dataset): This dataset includes an image collection and their specific segmentation masks of dental caries. These images are fetched utilizing the link https://www.kaggle.com/datasets/thunderpede/panoramic-dental-dataset: access link: 2024-12-16. This data source includes:

a. Labels: It is a full-size caries segmentation mask.
b. Images: It is a full-size dental X-ray image.
c. Labels_cut: It is a full-size caries segmentation mask at the teeth border.
d. Images_cut: It is the crop dental x-ray images at the teeth border.
e. Annotations.bboxes_teeth: Each tooth's Bboxes in the full-size images.
f. Annotations.bboxes_caries: Each area's Bboxes of caries in the full-size images.

Further, the number of images in this resource is 200, where the images are split into 150 for training and 50 for testing. There are 2 classes in this data source such as crop dental X-ray images at the teeth border (100 images), and full-size dental X-ray images (100 images). From this dataset, the fetched CBCT images for the classification operation are taken as $Y_b,\ here\ \ b = 1,2,...,B$. Here, the attribute B indicates the overall count of the gathered CBCT images. The sample images of the implemented classification system of dental caries are provided in Figure 3.2.

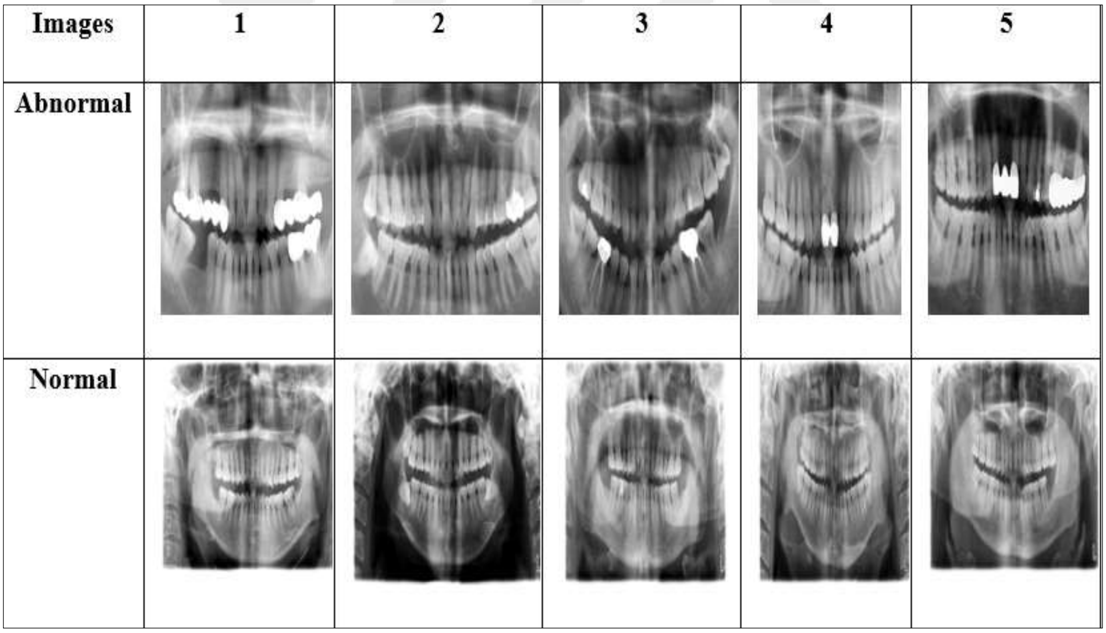


Figure 3.2: Sample Images of the Developed Classification System of Dental Caries.

3.3 TRANSFORMER R2UNET MODEL

The transformer-based R2Unet technique is implemented for segmenting the abnormal areas of dental caries images. This technique utilizes two techniques such as transformer and R2Unet models. The R2Unet technique [27], is inspired by the deep residual, RCNN, and

Unet models. The RCNN model offers satisfactory functionality in object recognition operations. According to the improved residual models, the recurrent residual convolutional operations are demonstrated. The Recurrent Convolution Layers (RCL) operations are performed by protecting the multiple time series that are formulated according to the RCNN model. Consider RCNN's input sample z_v of n^{th} layer and the pixel deployed in the provided sample on the m^{th} feature maps. In addition, assume the result of the network Q^n_{klm} is at the time series v. The result is provided in Eq. (1).

$$Q^n_{klm}(v) = \left(y^h_m\right)^T * z_n^{h(k,l)}(v) + \left(y^t_m\right)^T * z_n^{t(k,l)}(v-1) + d_m \tag{3.1}$$

Here, the attributes $z_n^{h(k,l)}(v)$ *and* $z_n^{t(k,l)}(v-1)$ considered as the input of the convolutional and n^{th} RCL layers accordingly. The attributes y^h_m *and* y^t_m represent the weights of the convolutional layer and the RCL's weights in the feature map. Further, the bias is denoted as d_m, and the result of the RCL is passed to the function h named Rectified Linear Unit (ReLU) and is given in Eq. (2).

$$H(z_n, y_n) = h\left(Q^n_{klm}(v)\right) = \max\left(0, Q^n_{klm}(v)\right) \tag{3.2}$$

In this, the result of the n^{th} layer is pointed as $H(z_n, y_n)$ in the block of RCNN. The outcome of $H(z_n, y_n)$ is employed for the layers of downsampling as well as the upsampling in the convolutional encoding and the decoding blocks of the R2Unet approach. The final result of the RCNN block in the R2Unet context is forwarded through the residual module. Consider the solution of the R2CNN model's outcome is z_{m+1} and is validated by Eq. (3).

$$z_{n+1} = z_n + H(z_n, y_n) \tag{3.3}$$

Here, the input sample of the R2CNN technique is provided as z_n. The sample z_{m+1} serves as the sub-sampling and the upsampling layer's input in the encoding as well as decoding convolutional modules of R2Unet.

The suggested R2UNet technique is a highly efficient approach and exploits fewer network parameters. The recurrent and the residual connections do not increase the amount of parameters involved in the network. However, the R2Unet model's testing as well as the training functionality is not yet enhanced. In addition, the generalization ability of the suggested R2Unet model is relatively poor. To address these limitations, the transformer model is incorporated with this model.

The transformer [28], is designed to address the constrained parallel execution. Moreover, this technique improves the generalization capability of the R2Unet technique by enhancing the testing and training operations. This model includes the self-attention approach, which is the enhancement of an attention method. This approach depends on the image feature data's internal correlation and allocates distant weights to multiple pixel data. This approach changes the given image into three sets of matrix data such as query R, key F, and value matrices B accordingly. The final outcome is displayed in Eq. (4).

$$atn(R, F, B) = soft\max\left(\frac{RF^T}{\sqrt{d_F}}\right)B \tag{3.4}$$

The multi-headed self-attention approach is the primary factor of the transformer that is the integration of m^{th} self-attention blocks. Here, the attributes Y_g^R, Y_g^F, Y_g^B represent the g^{th} self-attentive linear transformation matrix.

The last self-attentive output matrix is constructed by Eq. (5) and Eq. (6).

$$head_g = atn\left(RY_g^R, FY_g^F, BY_g^B\right) \tag{3.5}$$

$$multi(R, F, B) = concat\left(head_g, ..., head_p\right)Y^o \tag{3.6}$$

The Multi-Layer Perceptron (MLP) highly includes a linear integration of 2 fully connected layers and ReLU. The position embedding is included in the transformer network to understand the image's position embedding data.

3.4 ELUCIDATION OF NDT-R2UNET FOR SEGMENTATION

The NDT-R2Unet approach is implemented in this work for abnormal caries region segmentation. The CBCT images Y_b which are obtained from the benchmark dataset are given as input to this technique. The NDT-R2Unet technique utilizes the metrics of multiple and effective approaches such as recurrent, residual connections, Unet, transformer, and nested dilation. The recurrent and residual connections in the R2Unet technique allow the technique to understand the complex features via the accumulation of the features, enhancing the segmentation outcome's accuracy. Importantly, when handling intricate object boundaries, these connections perform well. Moreover, during training, the vanishing gradients are relatively minimized by these connections. The Unet technique accurately localizes the abnormal regions because of its skip connections, and effective and rapid processing with its fully convolutional framework. The Unet architecture also provides better performance on the multi-class segmentation operations, and the capacity to manage the high-resolution images while handling the fine-grained details. Thus, the R2Unet technique efficiently performs the segmentation task. The NDT-R2Unet approach-aided CBCT image segmentation is shown in Figure 3.3.

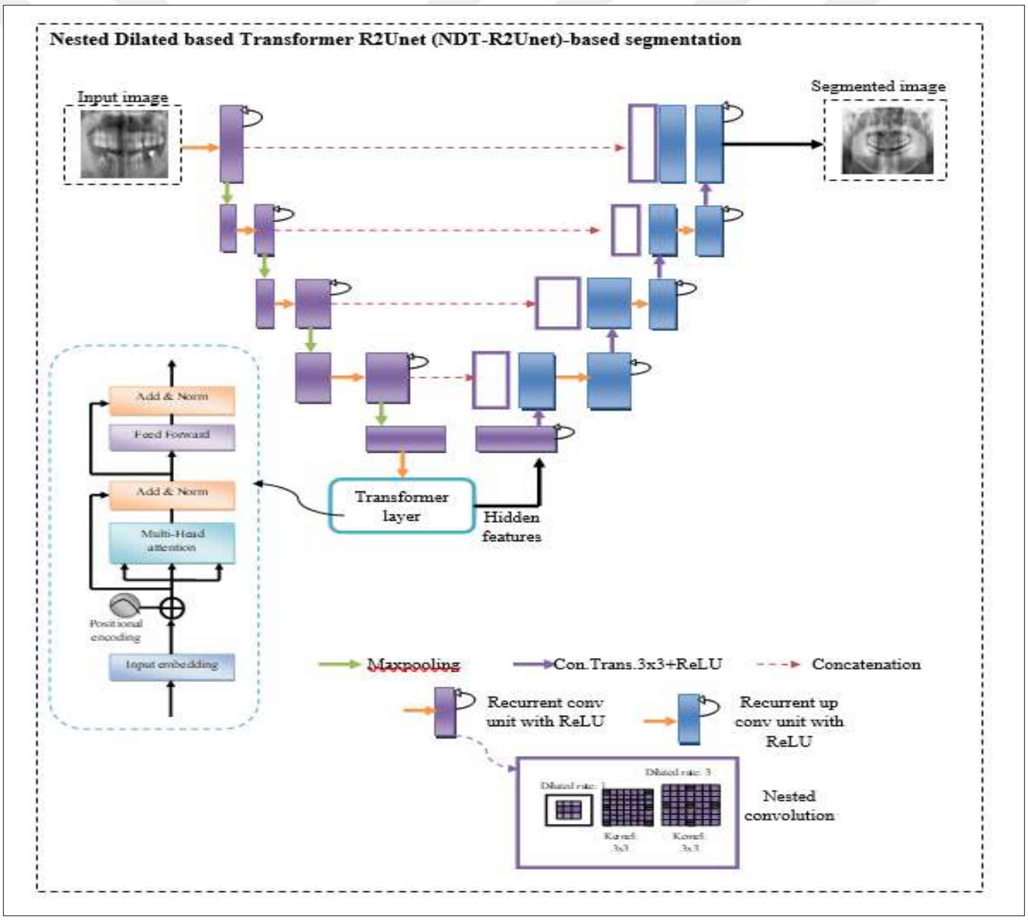


Figure 3.3: Functional View of Developed NDT-R2Unet-Aided Dental Caries Segmentation.

To improve the training process and generalization ability, the transformer model is included with the R2Unet model. The transformer in the T-R2Unet model improves the generalization capacity and training operation. Moreover, this technique allows capturing the global context and long-range dependencies within the image that is highly beneficial for the critical scenarios where the objects can be propagated across the huge regions or have intricate relations with the nearby elements. Thus, the T-R2Unet model helps in the caries segmentation process. However, the T-R2Unet faces computational complexities during the segmentation. To eliminate this problem, the nested dilated convolution [29] is included. Thus, the NDT-R2Unet technique is formed. The nested dilation in the NDT-R2Unet model was developed via the stacked dilated convolutions. It enables the model to capture the multi-scale contextual data without enhancing the computational burdens. This technique relatively minimizes the computational complexities, allowing better region segmentation with distinct shapes and sizes across images. Most importantly, the nested dilated convolution is relatively helpful for analyzing the thorough structure of the objects in the images with distinct scales. By stacking the dilated convolution with enhancing the dilation rates, the developed NDT-R2Unet approach can efficiently view the huge region around each pixel, enabling it to incorporate the global detain in the segmentation task. Thus, the NDT-R2Unet approach segmented the abnormal regions in the input CBCT images, and the acquired segmented images are provided as Y_b^{seg} .

3.5 RECOMMENDED HEURISTIC ALGORITHM: AUWGO

The AUWGO is designed for enhancing the diagnosis operation of dental caries.
Purpose: The AUWGO helps in the classification operation of dental caries by performing parameter optimization. The developed work constructs a new model named AdaENet-RA for classifying dental caries. Here, the parameters such as activation function, number of epochs, and the hidden neurons of an efficient net model may cause the complexities. To prevent the burdens caused by these parameters in the classification task, the AUWGO is invented. The developed AUWGO helps to optimally choose these parameters in the classification task thus enhancing the CSI and accuracy values in the overall process. Therefore, the suggested classification framework of dental caries not only becomes effective but also becomes accurate and robust.

Reason for selecting WGO: The AUWGO is implemented by utilizing the significant features of the traditional WGO [26]. The WGO is a recent meta-heuristic algorithm. The wild geese swarm's natural behavior is the inspiration of the WGO's inspiration. The WGO shows relatively better computational performance and also provides accurate optimization outcomes. The suggested WGO provides highly competitive solutions in the challenging issues with the unknown search space. The WGO has also explored suitable solutions with a limited amount of time. Therefore, the WGO is considered for this work.

Novelty: The existing WGO is relatively provides competitive solutions. However, the WGO also has one significant issue. The flight process in the WGO includes the flight step size factor. This factor is selected from the interval of [0, 1]. The flight step size of the WGO most of the times struggle to select the proper value and sometimes it provides the value, which is unexplainable. This relatively minimizes the efficiency and also the rate of convergence also becomes slow. To conquer these problems, the AUWGO is invented. The AUWGO modifies the flight step size of the WGO by exploiting the values of fitness. The improved flight step size S is shown in Eq. (7).

$$S = \frac{\left(B_f + C_f\right)}{\left(B_f + W_f + \left(\frac{C_f + M_f}{2}\right)\right)} \tag{3.7}$$

In this, the terms $B_f, C_f, W_f,\ \ and\ \ M_f$ indicate the best, current, worst, and mean fitness rates correspondingly. This formulated new step size S is then updated in the flight process of WGO. This updated flight process is shown in Eq. (8).

$$d_v^{t+1} = d_v^t + \mathbf{S}\left(d_{best}^t - d_b^t\right) + a\left(d_y^t - d_b^t\right) \tag{3.8}$$

Here, the modified step size is indicated as S, which is formulated in Eq. (7). Further, the variables $d_b^t\ \ and\ \ d_v^t$ represent the head goose and the candidates in the migration group. The new position of the v^{th} member is taken as d_v^{t+1} for the $t+1^{th}$ iteration. The global optimal member is specified as d_{best}^t and an arbitrarily chosen head goose member is considered as d_y^t. The term is employed to handle the proportion of the experience detail of the other head goose. Thus, the AUWGO is designed by modifying the flight process of WGO. This increases the efficiency and also the convergence of the overall process. The pseudo-code of the AUWGO is presented in Algorithm 1.

Algorithm 1: Developed AUWGO
Input: The hyper-parameters such as activation function, number of epochs, and hidden neuron counts of efficient net
Output: The optimally selected above-mentioned hyper-parameters of efficient net
Set the algorithm parameters and initialize the population D
Set the highest iteration count M_{itr}
For i to M_{itr}
For v to D
Randomly select the head goose individuals
Design a new flight step size by Eq. (7)
Formulate the migration group
Update the flight process in the migration group by Eq. (8)
Individual’s free foraging in a small range
Choose the optimal individual in each migration group as the new head goose
Upgrade the radius value
End for
Save best individual solutions
End for
Return the optimal solutions

3.6 EFFICIENT NET

The efficient net [30], technique is an effective CNN model with more speed and parameter efficacy. It employs a simple and scaling approach to scale up the CNN techniques in a structured form by scaling the dimensions of the network such as resolution, depth, and width uniformly. In the classification operations, the efficient net is employed as a spatial feature extraction framework. There are seven efficient net variations exist from efficient net B0 to efficient net B7. The efficient net B0 technique can surpass the Resnet 50 technique with the sample amount of input and also the parameter utilization of efficient net B0 is also much less than the other models. The efficient net B0 technique has a better ability for feature extraction. The efficient net B0 technique is split into 7 modules on the basis of some channels, convolutional filter size, and striding. The efficient net B0 model's primary module is an inverted bottleneck (MBConv) that is according to the Mobilenet model's concept. There are two distinct convolutional layers in the MBConv. For channel expansion, the initial convolutional layer is utilized. For minimizing the parameters count, the depthwise convolution is utilized. For concentrating the connection among the channels, the squeeze and excitation module is supported. For compressing the channels, the second convolution layer is utilized. The efficient net model's structure is offered in Figure 3.4.

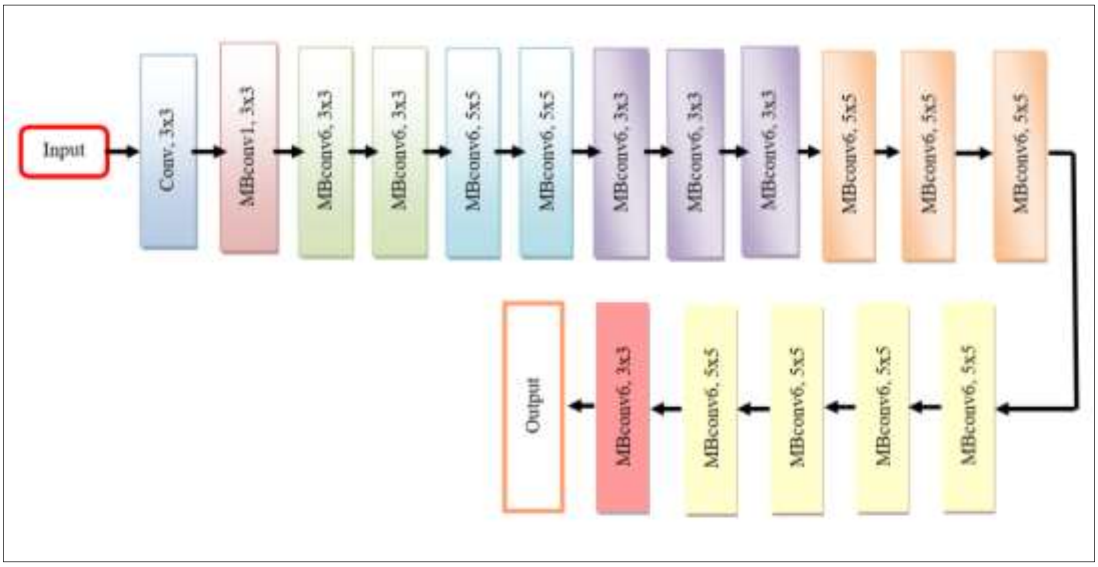


Figure 3.4: Structure of Efficient Net Model.

3.7 DEVELOPED ADAENET-RA FOR CARIES CLASSIFICATION

The AdaENet-RA is introduced for classifying the dental caries in the suggested work. This network employs the segmented images Y_b^{seg} as input. The developed AdaENet-RA employs the efficient net as the primary model in the classification. The efficient net provides some significant merits in the dental caries classification tasks including its high accuracy, and scalability across distinct dimensions such as resolution, width, and depth, making it suitable for distinct image sizes. The efficient net has the capacity to attain strong functionality even with constrained computational resources, making it effective for real-time applications. The efficient net model also has excellent feature extraction abilities, most importantly helpful for identifying the subtle dental caries features in the segmented images. Therefore, the efficient net model is considered for the classification. However, the efficient net encounters two primary problems. (i) The efficient net finds it hard to select the target features from the segmented images, and (ii) The efficient net struggles with the overfitting issues. Therefore, resolving these two primary issues is highly important for obtaining promising solutions in the dental caries classification. Although the efficient net is relatively effective in feature extraction, the model can't properly focus on the related and target features from the segmented images while processing large amounts of images. In order to focus on the target features from the segmented images, the region attention is included with the efficient net model (ENet-RA). The region attention [31], in the ENet-RA technique helps to concentrate on the highly significant regions from the input images, enabling it to draw out highly related data and resulting in highly effective and accurate classification. Moreover, the region attention model helps to handle the complex inputs where not entire parts are equally significant. By concentrating on the highly significant areas, the efficient net model can accurately make the classifications. Moreover, by selectively attending to particular image regions, efficient attention can prevent unwanted computations on the unwanted sections of the images. It results in faster processing times. The region's attention also highlights the significant areas of the efficient net, which offers detailed insights into how the model makes its decisions. Thus, the ENet-RA technique helps in focusing on the highly significant features and regions thus improving the efficiency and minimizing the inference time in the classification. Further, the efficient net model also encounters overfitting during the training phase since the model utilizes more parameters. Therefore, for properly handling the efficient net parameters, the AUWGO is implemented. The AUWGO introduces the adaptive mechanism in the ENet-RA thus constructing the model named AdaENet-RA. In the AdaENet-RA, the AUWGO optimally selects the parameters of efficient net thus preventing the overfitting problems during the training. Moreover, the AUWGO improves the CSI and accuracy of the classification. Eq. (9) illustrates the fitness function of the parameter tuning operation.

$$ob = \arg \min_{\{af, hn, ep\}} \left[\frac{1}{Ac} + \frac{1}{CSI} \right] \tag{3.9}$$

In this, the optimized activation function, hidden neuron count, and the number of epochs are specified as af, hn, ep. Also, the optimized ranges of these parameters are specified as [1 - 5], [5 - 255], and [5 - 50] respectively. The maximized measures such as accuracy and CSI are explained below.

Accuracy: It helps to validate the effectiveness of the developed model and analyzes the outcomes with its original outcome. It is measured in Eq. (10).

$$Ac = \frac{ww + hh}{ww + hh + dd + bb} \tag{3.10}$$

CSI: It concentrates on the model's capacity to properly recognize the positive events, considering both false alarms and true positives, making it highly significant in situations where properly recognizing the positive events is vital. It is measured in Eq. (11).

$$CSI = \frac{ww}{(ww + dd)} \tag{3.11}$$

Here, the "true negative, true positive, false negative, and false positive rates" are explained as $hh, bb, ww,\ and\ dd$. Thus, the classification of the dental caries is performed with the help of the AdaENet-RA approach and the pictorial illustration of the implemented AdaENet-RA-aided classification framework for dental caries is provided in Figure 3.5.

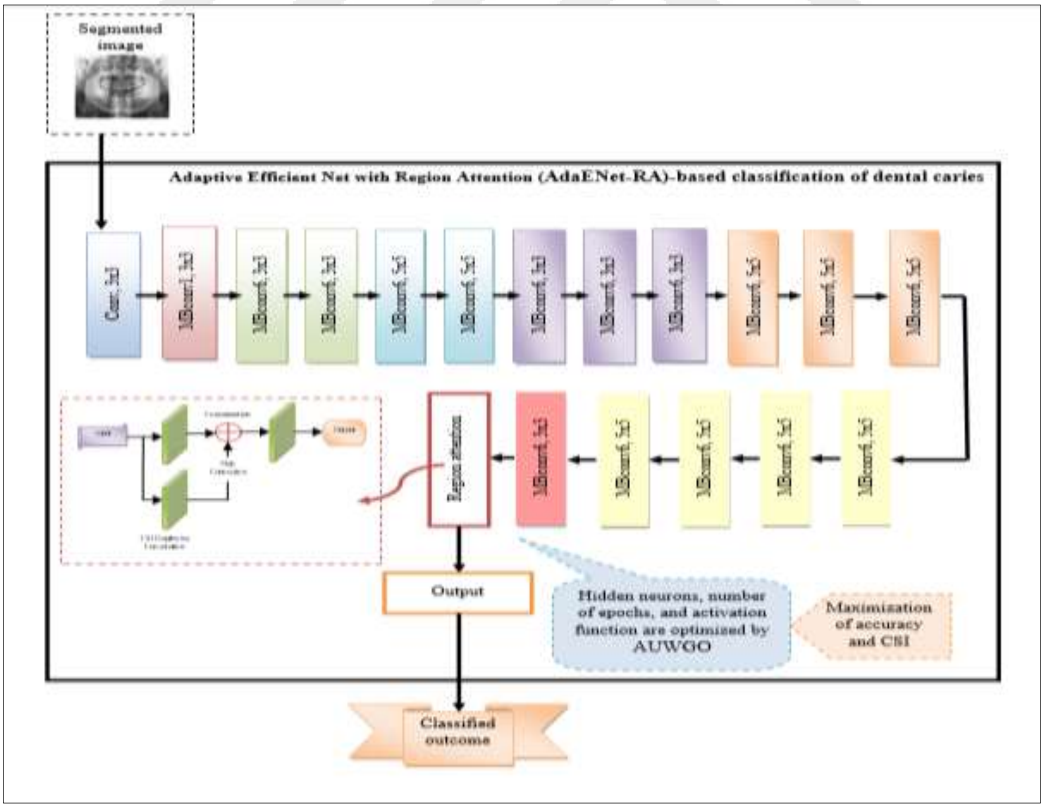


Figure 3.5: Pictorial Illustration of Implemented AdaENet-RA-Aided Classification Framework for Dental Caries.

4. EXPERIMENTAL RESULTS AND ANALYSIS

4.1 EXPERIMENTAL SETUP

The Python platform was exploited for validating the implemented classification system of dental caries. The Python platform has simple syntax and it is designed to be easy to write and read. It is a dynamically typed language that means that it is more forgiving and flexible than statistically typed languages. Moreover, it can run on distinct operating systems such as Linux, MacOS, Windows, and so on. Therefore, the Python platform was considered for classifying dental caries. The implemented AUWGO was designed for parameter tuning. This algorithm utilized the 10 highest numbers of populations, 50 utmost iterations, and 3 chromosome lengths. Further, experimental research was carried out for the implemented system. Here, the models and algorithms such as Unet [32], ResUnet [33], DenseUnet [34], Trans-Unet [35], Cheetah Optimizer (CO) [36], Gold Rush Optimizer (GRO) [37], Addax Optimization Algorithm (AOA) [38], GOA [26], CNN-AM [3], YoloV4 and CNN [4], CNN [6], and ENet-RA [30][31], are helped for analyzing the designed segmentation as well as classification of dental caries.

4.2 PERFORMANCE MEASURES

The below performance metrics are leveraged for validating the designed framework. Intersection over Union (IoU) is measured in Eq. (4.1).

$$IoU\left(Y_b, Y_b^{seg}\right) = \frac{\left(Y_b \cap Y_b^{seg}\right)}{\left(Y_b \cup Y_b^{seg}\right)} \tag{4.1}$$

Dice coefficient is measured in Eq. (4.2).

$$Dc\left(Y_b, Y_b^{seg}\right) = \frac{2\left(Y_b \cap Y_b^{seg}\right)}{\left(Y_b + Y_b^{seg}\right)} \tag{4.2}$$

Balanced Accuracy (BA) is measured in Eq. (4.3).

$$BA = \frac{bb + hh}{2} \tag{4.3}$$

Book Maker (BM) is measured in Eq. (4.4).

$$BM = ww + hh - 1 \tag{4.4}$$

F1 score is measured in Eq. (4.5).

$$F1 - Score = 2 \times \frac{hh \times dd}{hh + dd} \tag{4.5}$$

FDR is measured in Eq. (4.6).

$$FDR = \frac{dd}{ww + dd} \tag{4.6}$$

Fowlkes–Mallows index (FM) is measured in Eq. (4.7).

$$FM = \sqrt{\Pr \times ww} \tag{4.7}$$

FNR is measured in Eq. (4.8).

$$FNR = \frac{bb}{ww + bb} \tag{4.8}$$

False Omission Rate (FOR) is measured in Eq. (4.9).

$$FOR = 1 - \frac{ww}{(ww + bb)} \tag{4.9}$$

FPR is measured in Eq. (4.10).

$$FPR = \frac{dd}{dd + ww} \tag{4.10}$$

MCC is measured in Eq. (4.11).

$$MCC = \frac{bb \times hh - bb \times ww}{\sqrt{(bb + ww)(bb + hh)(ww + dd)(ww + bb)}} \tag{4.11}$$

Markedness (MK) is measured in Eq. (4.12).

$$MK = \Pr + \frac{hh}{(hh + bb)} - 1 \tag{4.12}$$

NPV is measured in Eq. (4.13).

$$NPV = \frac{ww}{ww + bb} \tag{4.13}$$

Precision is measured in Eq. (4.14).

$$\Pr = \frac{ww}{ww + dd} \tag{4.14}$$

Prevalence Threshold (PT) is measured in Eq. (4.15).

$$PT = \frac{\sqrt{ww \times dd} - dd}{ww - dd} \tag{4.15}$$

Sensitivity is measured in Eq. (4.16).

$$Sy = \frac{ww}{ww + hh} \tag{4.16}$$

Specificity is measured in Eq. (4.17).

$$Sp = \frac{dd}{dd + bb} \tag{4.17}$$

4.3 RESULTANT IMAGES

The NDT-R2Unet model is supported for segmenting the abnormal regions from the CBCT images. This technique efficiently segmented the abnormal areas thus improving the classification. Figure 4.1 displays the resultant images of NDT-R2Unet-assisted segmentation operation over traditional segmentation mechanisms.

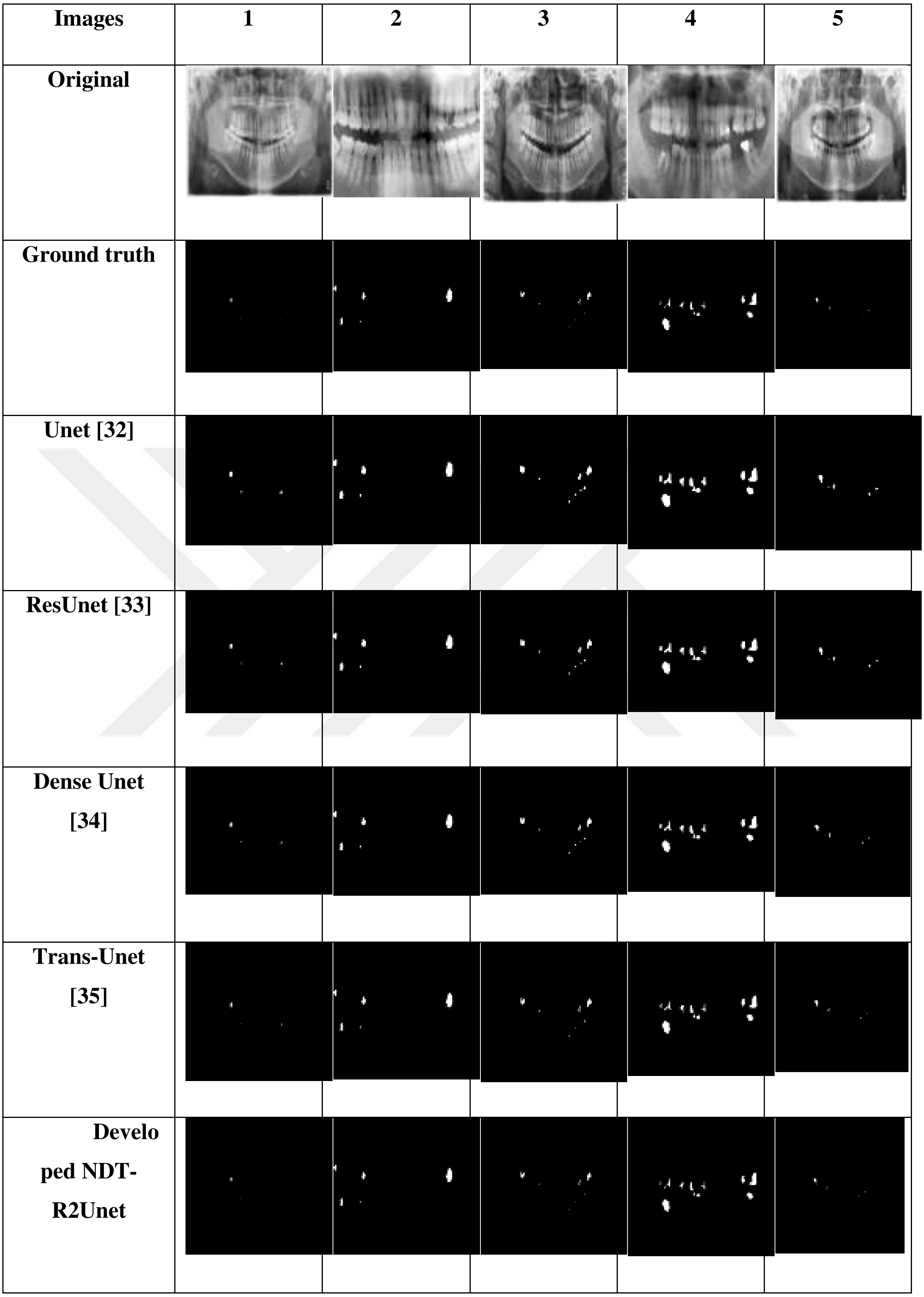


Figure 4.1: Resultant Images of NDT-R2Unet-Assisted Segmentation Operation Over Conventional Segmentation Mechanisms.

4.4 CONVERGENCE ANALYSIS

The convergence analysis provides an important role in the classification of disease, most importantly when employing the heuristic algorithms. The implemented work leverages the AUWGO for classification. It defines the experiment of how rapidly an AUWGO algorithm converges its ideal solution, which in this case is the accurate disease classification. The convergence validation supports the practitioners and researchers in understanding the character of the AUWGO algorithm, recognizing significant problems, and tuning its functionality. In the classification of dental caries, the convergence validation involves estimating the convergence rate of the AUWGO that is affected by the attributes including the learning rate, choice of optimizer, and the regularization approaches. A fast rate of convergence specifies that the AUWGO can rapidly adapt to the input data and make correct classifications, whereas a slow convergence value can result in underfitting and overfitting. By employing the convergence validation, the experts can implement highly effective and efficient dental caries disease classification models, resulting in enhanced patient outcomes and better decision-making in the healthcare sector. In addition, the convergence validation can also support the implementation of personalized medicine techniques, where the AUWGO can support to separate patient features and medical histories. In total, convergence validation is a significant component in disease categorization, allowing the implementation of accurate, effective, and robust deep learning techniques that can make a meaningful impact in the healthcare sector. Figure 4.2 presents the convergence examination of designed AUWGO over traditional algorithms. The cost function rates are varied with the distinct iteration rates. When the rate of iteration is 10, the suggested AUWGO's cost function rate is decreased by 10.25% of CO-AdaENet-RA, 6.5% of GRO-AdaENet-RA, 5.75% of AOA-AdaENet-RA, and 6.4% of GOA-AdaENet-RA respectively. The experiment proved that the AUWGO can explore the optimal outcomes for the AdaENet-RA technique than the conventional heuristic algorithms.

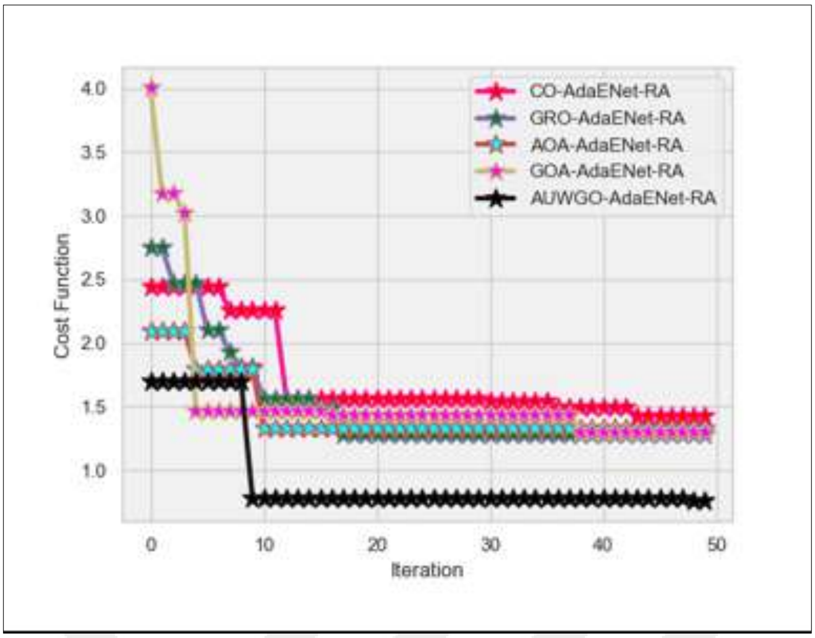


Figure 4.2: Convergence Examination of Implemented AUWGO Over Traditional Algorithms.

4.5 STATISTICAL ANALYSIS

The statistical experiment helps in the dental caries classification phase, allowing the practitioners and clinicians to recognize the patterns, relationships, and trends within the complex medical images. The important objective of this statistical validation in the categorization phase is to implement and estimate the deep learning approaches that can properly forecast the presence of the disease, and its progression. Table 2 presents the statistical examination of the AUWGO over conventional algorithms. The measures including the standard deviations, worst, median, best, and mean helps to describe the primary data features. This validation is significant in the disease categorization to understand the disease-oriented features and recognize the patterns. The best measure helps to recognize the optimal feature rates that result in the highest performance and accuracy in the classification of dental caries. The worst measure helps to recognize the feature values that lead to the lowest performance or accuracy in the categorization of dental caries. The mean measure estimates the feature's mean value in the data source. The median measure validates the feature's middle value in the data source when it is arranged in a descending or ascending order. The standard deviation validates the amount of dispersion in the feature from its value of mean. Overall, the worst and best validation support to improve the accuracy of the classification operation. The median, standard deviation, and mean measures can offer a deeper understanding of the input. Thus, these measures can enhance patient outcomes. When considering the mean factor, the performance of AUWGO is increased by 82.97% of CO-AdaENet-RA, 60.63% of GRO-AdaENet-RA, 53.19% of AOA-AdaENet-RA, and 65.95% of GOA-AdaENet-RA respectively. Therefore, the developed AUWGO is more suitable than the other heuristic algorithms for the AdaENet-RA-aided dental caries classification.

Table 4.1: Statistical Investigation of Implemented AUWGO Over Conventional Algorithms.

Algorithms	**CO-AdaENet-RA [36]**	**GRO-AdaENet-RA [37]**	**AOA-AdaENet-RA [38]**	**GOA-AdaENet-RA [26]**	**AUWGO-AdaENet-RA**
Best	1.4287579	1.2798889	1.3292439	1.3015408	0.7547586
Worst	2.438504	2.7488501	2.0915742	4.0021025	1.6975666
Mean	1.724014	1.513134	1.4461907	1.5644555	0.9459671
Median	1.5647184	1.2798889	1.3292439	1.4391204	0.7823267
Standard deviation	0.3637713	0.4162321	0.2427172	0.5393957	0.3521814

4.6 ROC ANALYSIS

The ROC validation is a statistical process utilized to estimate the functionality of the designed AUWGO-AdaENet-RA technique. It plots the True Positive Rate (TPR) over the False Positive Rate (FPR) at distinct thresholds. Figure 4.3 presents the ROC investigation of the implemented AUWGO-AdaENet-RA-aided classification system of dental caries over traditional classification models. The TPR estimates the proportion of the actual positives properly recognized by the technique. The FPR estimates the proportion of the actual negatives incorrectly recognized as positives. The cutoff value is referred to as the threshold that is supported to categorize the samples as negative or positive. The ROC estimation helps to recognize the optimal threshold value for the dental caries categorization. By employing the ROC validation, the experts and the practitioners can implement highly reliable and accurate predictive techniques, highly enhancing patient outcomes and improving personalized medicine. When the FOR value is 0.4, the suggested AUWGO-AdaENet-RA model's efficiency is enhanced by 12.85% of CNN-AM, 11.42% of YoloV4 and CNN, 4.28% of CNN, and 12.85% of ENet-RA respectively. Therefore, the designed AUWGO-AdaENet-RA model is effective and attained very low false negative rates than the traditional classifiers.

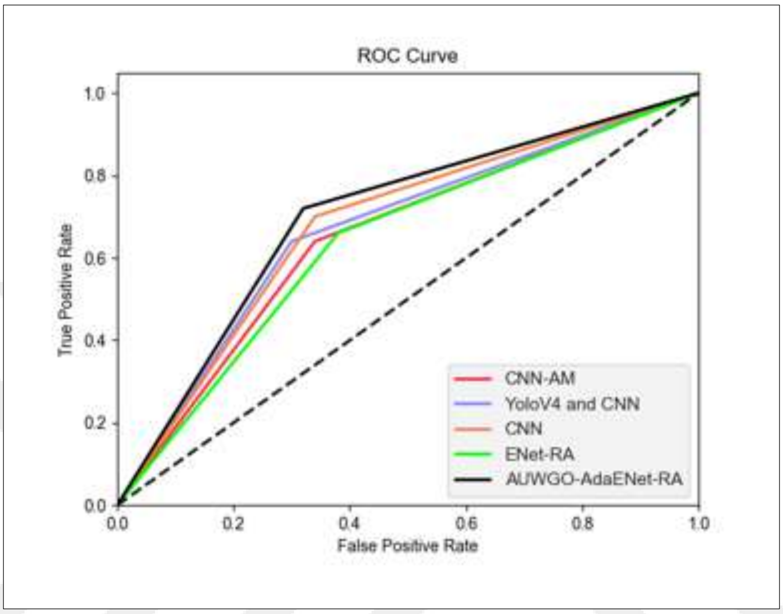


Figure 4.3: ROC Examination of Implemented AUWGO-AdaENet-RA Over Traditional Classifiers.

4.7 PERFORMANCE ANALYSIS FOR SEGMENTATION

The implemented work employs the NDT-R2Unet model for segmenting the abnormal regions from the input CBCT images. This model's performance is investigated over traditional segmentation models. Figure 4.4 displays this experiment and it is carried out by utilizing the various activation functions. The activation function plays an important part in dental caries segmentation, as these functions present a non-linearity in the neural networks, allowing them to understand complex relationships and patterns. Distinct activation functions can influence the accuracy of the segmentation. For instance, the ReLU has been displayed to perform well for tumor segmentation, whereas the sigmoid function is suitable for organ segmentation. The model's complexity is decided by the choice of the activation function. Moreover, the selection of the activation function also influences the training time of the approach. This activation functions-aided experiment supports improving the disease identification's accuracy which is crucial for the early disease treatment as well as the diagnosis. In addition, the analysis on the basis of the activation function for the segmentation enhances the NDT-R2Unet approach's robustness in terms of noise and other variations. When considering the activation function as Sigmoid in Figure 12 (a), the implemented NDT-R2Unet technique's accuracy in the segmentation operation is enhanced by 14.73% of Unet, 12.63% of ResUnet, 10.52% of DenseUnet, and 5.26% of Trans-Unet respectively. Therefore, the implemented NDT-R2Unet model accurately segments the abnormal regions than the conventional models.

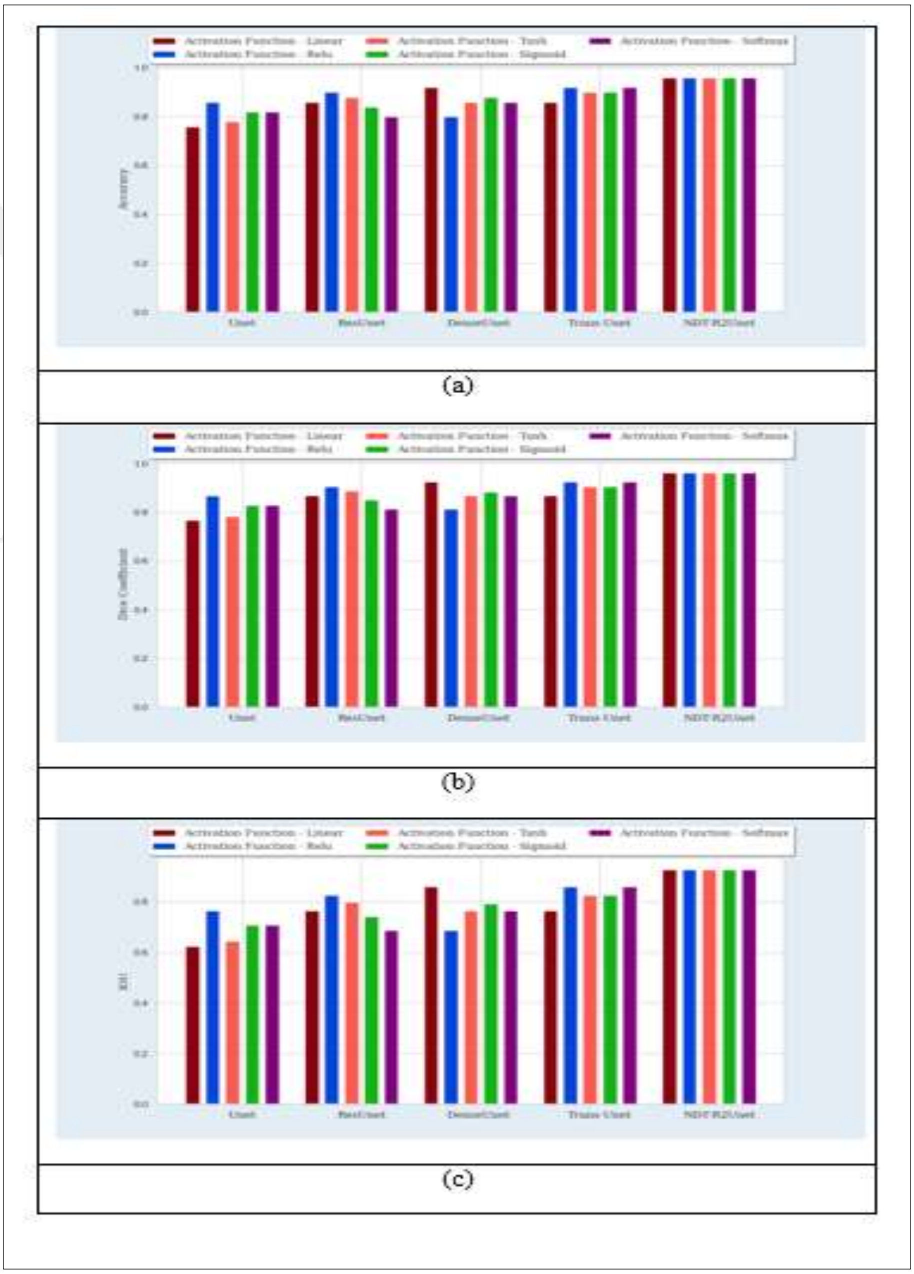


Figure 4.4: Performance Examination of Implemented NDT-R2Unet-Aided Segmentation Technique Over Existing Segmentation Approaches.

4.8 OVERALL COMPARATIVE ANALYSIS FOR SEGMENTATION

The overall comparative validation of the NDT-R2Unet-aided segmentation model over traditional segmentation approaches is performed and the findings are presented in Table 4.2. The statistical metrics are exploited in this examination. In dental caries segmentation, validating the distribution of voxel or pixel values is significant for proper segmentation. The worst and best measures represent the poorest and optimal performing segmentation techniques accordingly. The medians and mean metrics offer insights into the data's central tendency with the median offering highly robust validation and the mean being sensitive to the outliers. The data dispersion is validated by the standard deviation measure. By validating these measures, the experts can estimate the efficacy of the developed NDT-R2Unet technique over the other segmentation approaches, recognize the powerful biases, and tune the performance of the model. Overall, this experiment allows the implementation of highly reliable and accurate disease segmentation approaches, resulting in enhanced patient outcomes. When considering the best measure, the designed NDT-R2Unet technique's IoU is improved by 12.43% of Unet, 12.71% of ResUnet, 10.36% of DenseUnet, and 10.61% of Trans-Unet respectively. Hence, the suggested NDT-R2Unet model's potential in the abnormal region segmentation than the conventional segmentation approaches.

Table 4.2: Performance Investigation of Implemented NDT-R2Unet-Aided Segmentation Over Conventional Segmentation Models.

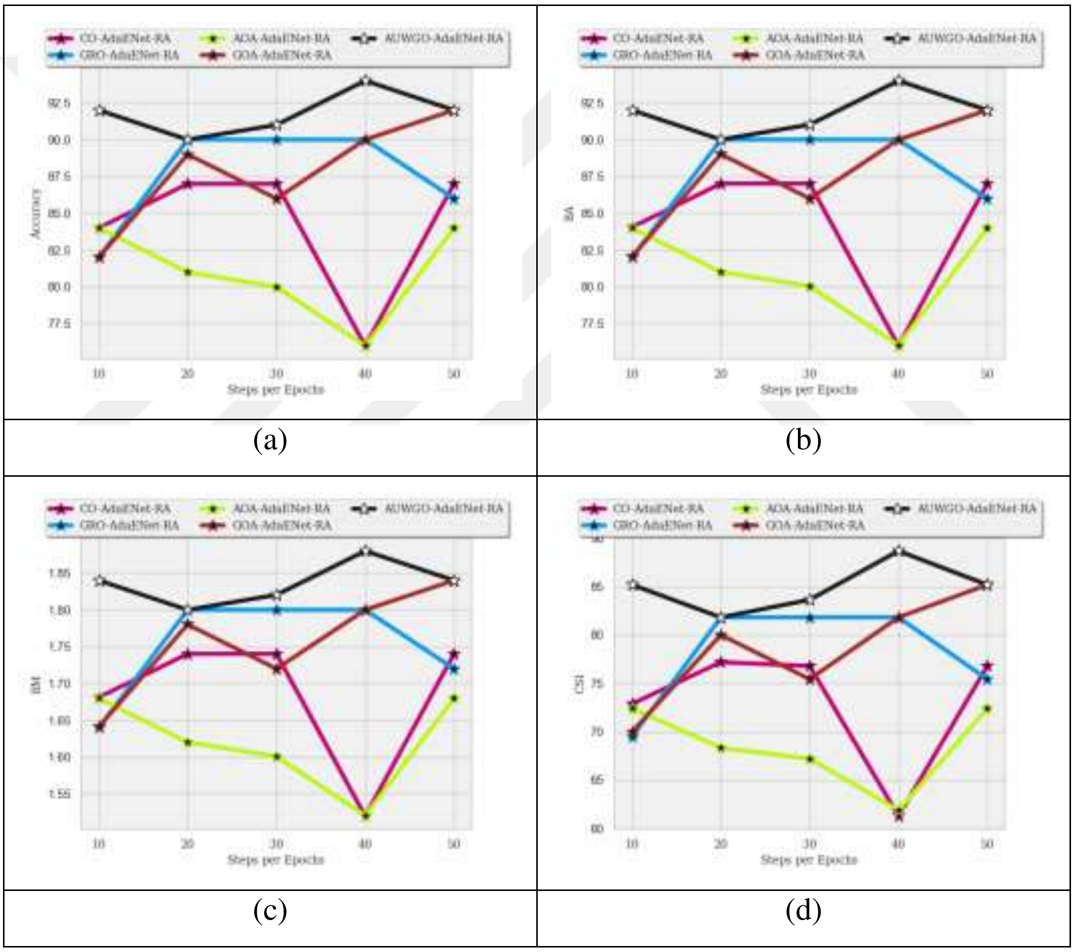
Algorithms	Unet [32]	ResUnet [33]	DenseUnet [34]	Trans-Unet [35]	NDT-R2Unet
Accuracy					
Best	88.711548	89.69574	90.483093	90.444946	95.733643
Worst	84.202576	85.858154	84.67865	86.457825	92.701721
Mean	86.207886	87.723846	87.749176	88.749084	94.398651
Median	85.871887	87.84256	87.360382	88.980103	94.769287
Standard deviation	1.4294009	1.2644934	1.9859794	1.4234946	0.9987845

Table 4.3: Performance Investigation of Implemented NDT-R2Unet-Aided Segmentation Over Conventional Segmentation Models.

Dice coefficient					
Best	89.072711	88.908921	90.227661	90.088067	95.665381
Worst	83.550217	85.718248	85.176929	86.074797	92.715615
Mean	86.038404	87.587066	87.599861	88.709077	94.322313
Median	85.86293	87.842826	87.018195	89.174247	94.785805
Standard deviation	1.7005879	1.0438826	1.9582771	1.3243595	1.0615306
IoU					
Best	80.298286	80.032458	82.195261	81.963863	91.690929
Worst	71.747851	75.006068	74.181023	75.55378	86.420419
Mean	75.537077	77.930745	77.989947	79.734395	89.273744
Median	75.227911	78.321308	77.025201	80.464488	90.088474
Standard deviation	2.6378983	1.6450236	3.1124605	2.1193558	1.8949971

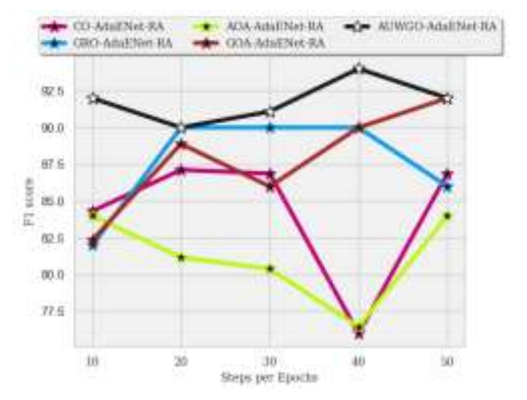
4.9 PERFORMANCE ANALYSIS FOR CLASSIFICATION

The implemented work develops the AUWGO-AdaENet-RA technique for classifying dental caries and its performance is investigated over traditional algorithms and classifiers. Figures 4.5 and 4.6 display the AUWGO-AdaENet-RA technique's validation with the support of steps per epoch. The steps per epoch-aided validation are an important aspect of training deep learning techniques for classifying dental caries. It includes validating the functionality of the implemented AUWGO-AdaENet-RA model during each epoch, where an epoch specifies one entire pass via the training data source. The AUWGO-AdaENet-RA model sees each sample in the data source once during an epoch. A term step indicates a single iteration of the training operation, where the AUWGO-AdaENet-RA model executes the operations of a batch of samples from the training data source. The steps per epoch validate the training accuracy at each step within epochs. This supports recognizing if the AUWGO-AdaENet-RA model is learning effectively during each epoch. The training loss at each step is monitored by this analysis within epochs. Moreover, the model's functionality on the validation data source is estimated by this analysis at each epoch. This support recognizes if the AUWGO-AdaENet-RA model is generalizing well to the unseen data. Also, the learning rate is adjusted on the basis of the AUWGO-AdaENet-RA model's functionality at each epoch. This enhances the convergence rate of the AUWGO-AdaENet-RA model. When the steps per epoch are 40 in Figure 4.4 (d), the designed AUWGO-AdaENet-RA model's CSI is enhanced by 29.54% of CO-AdaENet-RA, 6.81% of GRO-AdaENet-RA, 28.4% of AOA-AdaENet-RA, and 30.68% of GOA-AdaENet-RA respectively. Therefore, the effectiveness of the AUWGO-AdaENet-RA model in the caries classification is higher than the traditional classifiers.



(a) (b) (c) (d)

Figure 4.5: Performance Examination of Implemented AUWGO-AdaENet-RA-Aided Dental Caries Classification Technique Over Existing Optimization Algorithms in Terms of (a) Accuracy, (b) BA, (c) BM, (d) CSI, (e) F1-Score, (f) FDR, (g) FM, (h) FNR, (i) FOR, (j) FPR, (k) MCC, (l) MK, (m) NPV, (n) Precision, (o) PT, (p) Sensitivity, and (q) Specificity.



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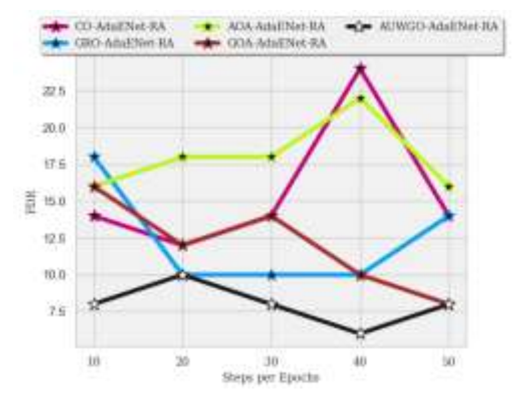

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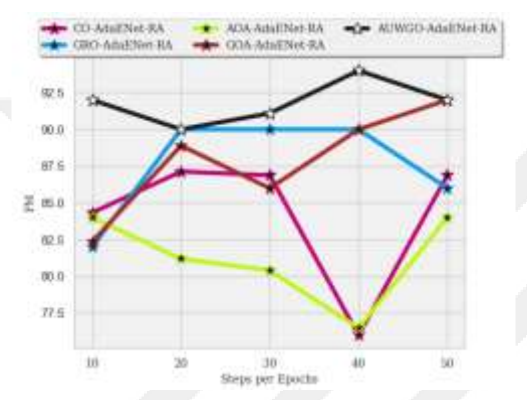

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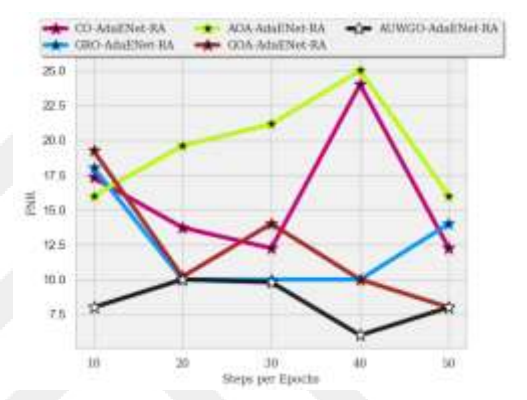

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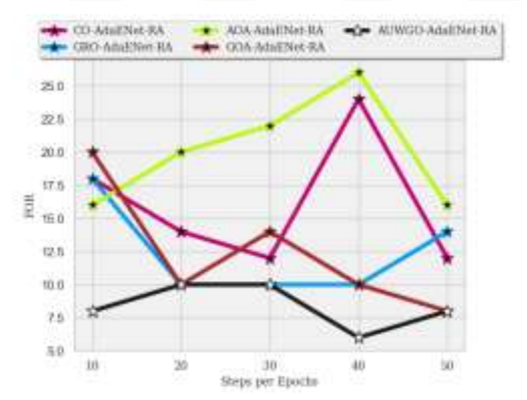

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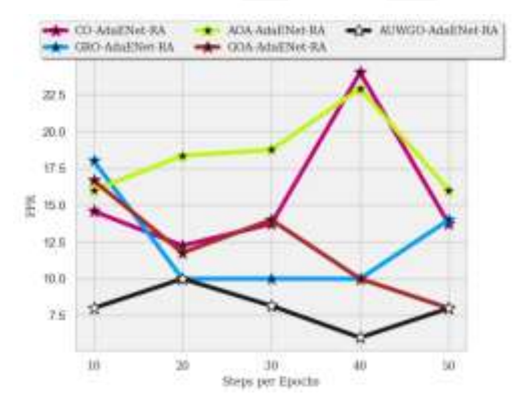
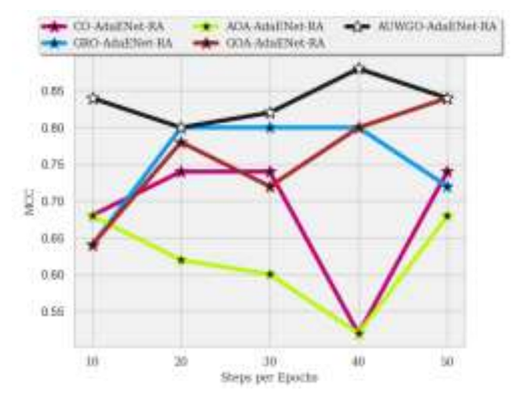


(j)

Figure 4.5: Performance Examination of Implemented AUWGO-AdaENet-RA-Aided Dental Caries Classification Technique Over Existing Optimization Algorithms in Terms of (a) Accuracy, (b) BA, (c) BM, (d) CSI, (e) F1-Score, (f) FDR, (g) FM, (h) FNR, (i) FOR, (j) FPR, (k) MCC, (l) MK, (m) NPV, (n) Precision, (o) PT, (p) Sensitivity, and (q) Specificity (Figure Continued).



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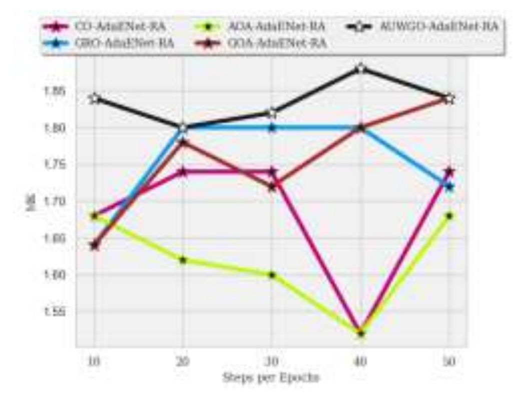

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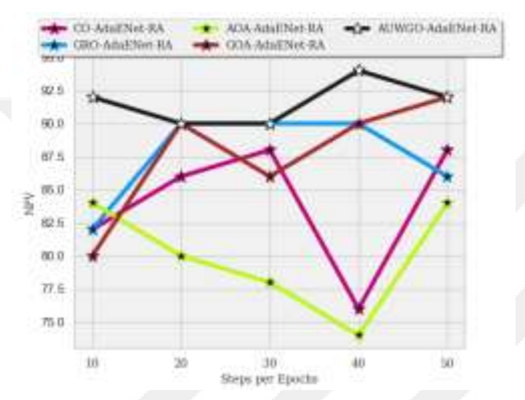

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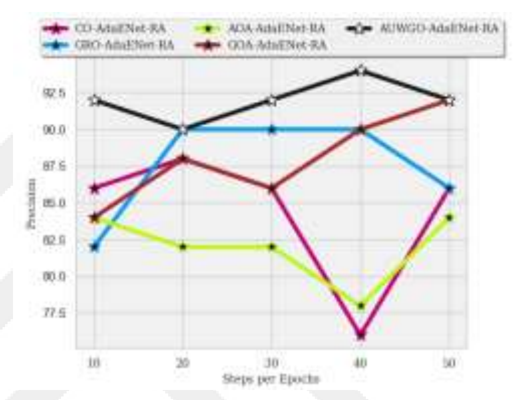

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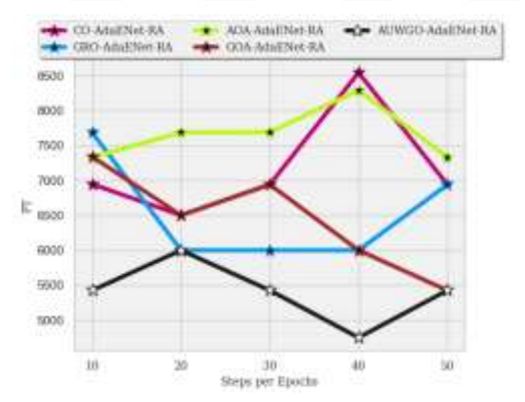

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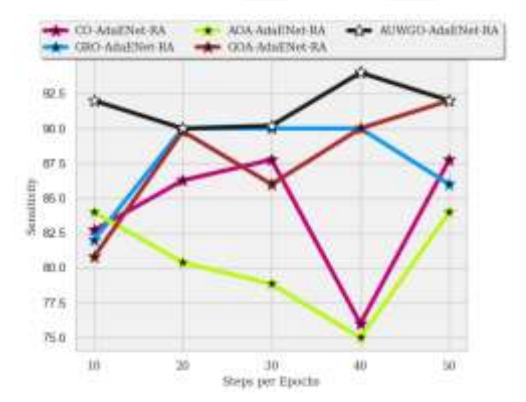
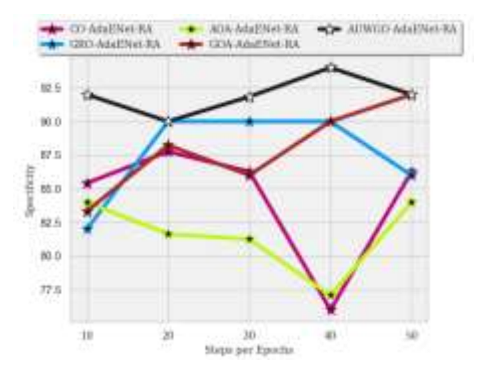


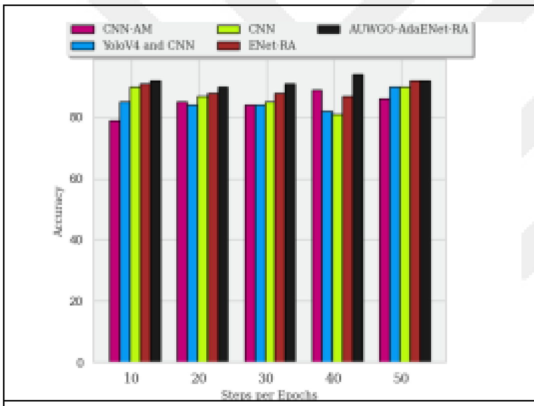
(p)

Figure 4.5: Performance Examination of Implemented AUWGO-AdaENet-RA-Aided Dental Caries Classification Technique Over Existing Optimization Algorithms in Terms of (a) Accuracy, (b) BA, (c) BM, (d) CSI, (e) F1-Score, (f) FDR, (g) FM, (h) FNR, (i) FOR, (j) FPR, (k) MCC, (l) MK, (m) NPV, (n) Precision, (o) PT, (p) Sensitivity, and (q) Specificity (Figure Continued).

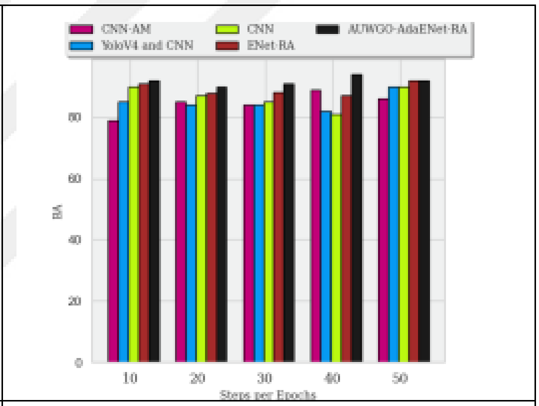


(q)

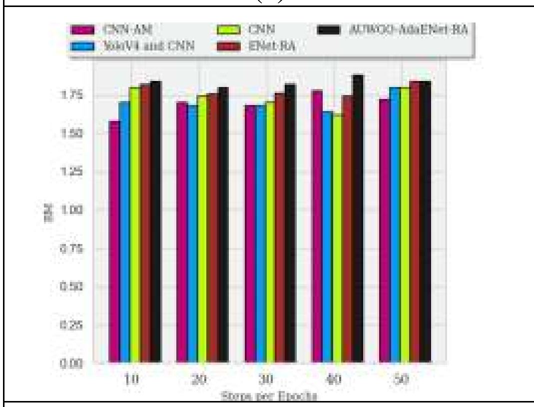
Figure 4.5: Performance Examination of Implemented AUWGO-AdaENet-RA-Aided Dental Caries Classification Technique Over Existing Optimization Algorithms in Terms of (a) Accuracy, (b) BA, (c) BM, (d) CSI, (e) F1-Score, (f) FDR, (g) FM, (h) FNR, (i) FOR, (j) FPR, (k) MCC, (l) MK, (m) NPV, (n) Precision, (o) PT, (p) Sensitivity, and (q) Specificity (Figure Continued).



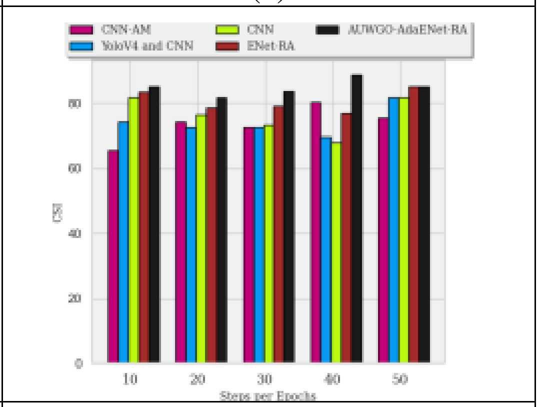
(a)



(b)

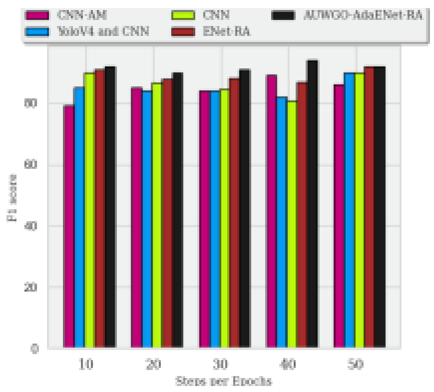


(c)



(d)

Figure 4.6: Performance Examination of Implemented AUWGO-AdaENet-RA-Aided Dental Caries Classification Technique Over Existing Classifiers in Terms of (a) Accuracy, (b) BA, (c) BM, (d) CSI, (e) F1-score, (f) FDR, (g) FM, (h) FNR, (i) FOR, (j) FPR, (k) MCC, (l) MK, (m) NPV, (n) Precision, (o) PT, (p) Sensitivity, and (q) Specificity.



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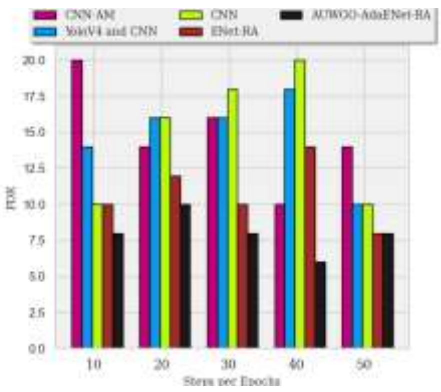
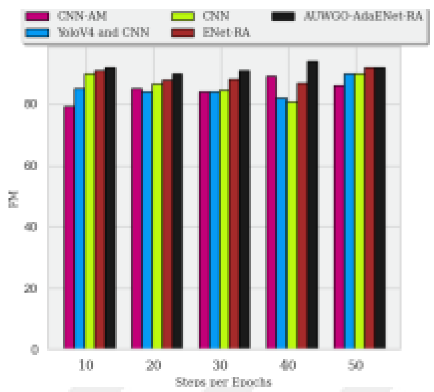


(f)



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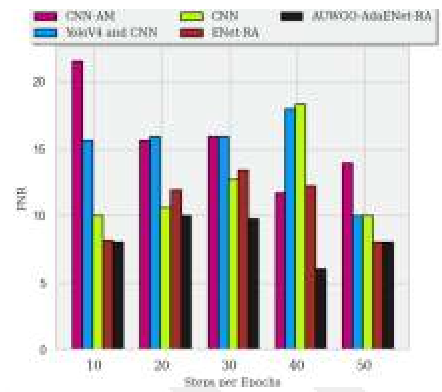

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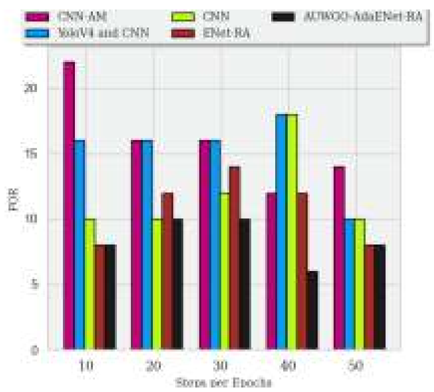
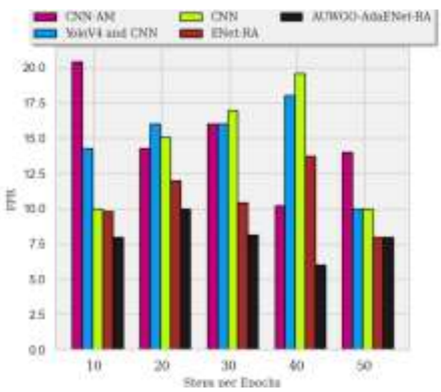


(i)



(j)

Figure 4.6: Performance Examination of Implemented AUWGO-AdaENet-RA-Aided Dental Caries Classification Technique Over Existing Classifiers in Terms of (a) Accuracy, (b) BA, (c) BM, (d) CSI, (e) F1-score, (f) FDR, (g) FM, (h) FNR, (i) FOR, (j) FPR, (k) MCC, (l) MK, (m) NPV, (n) Precision, (o) PT, (p) Sensitivity, and (q) Specificity (Figure Continued).

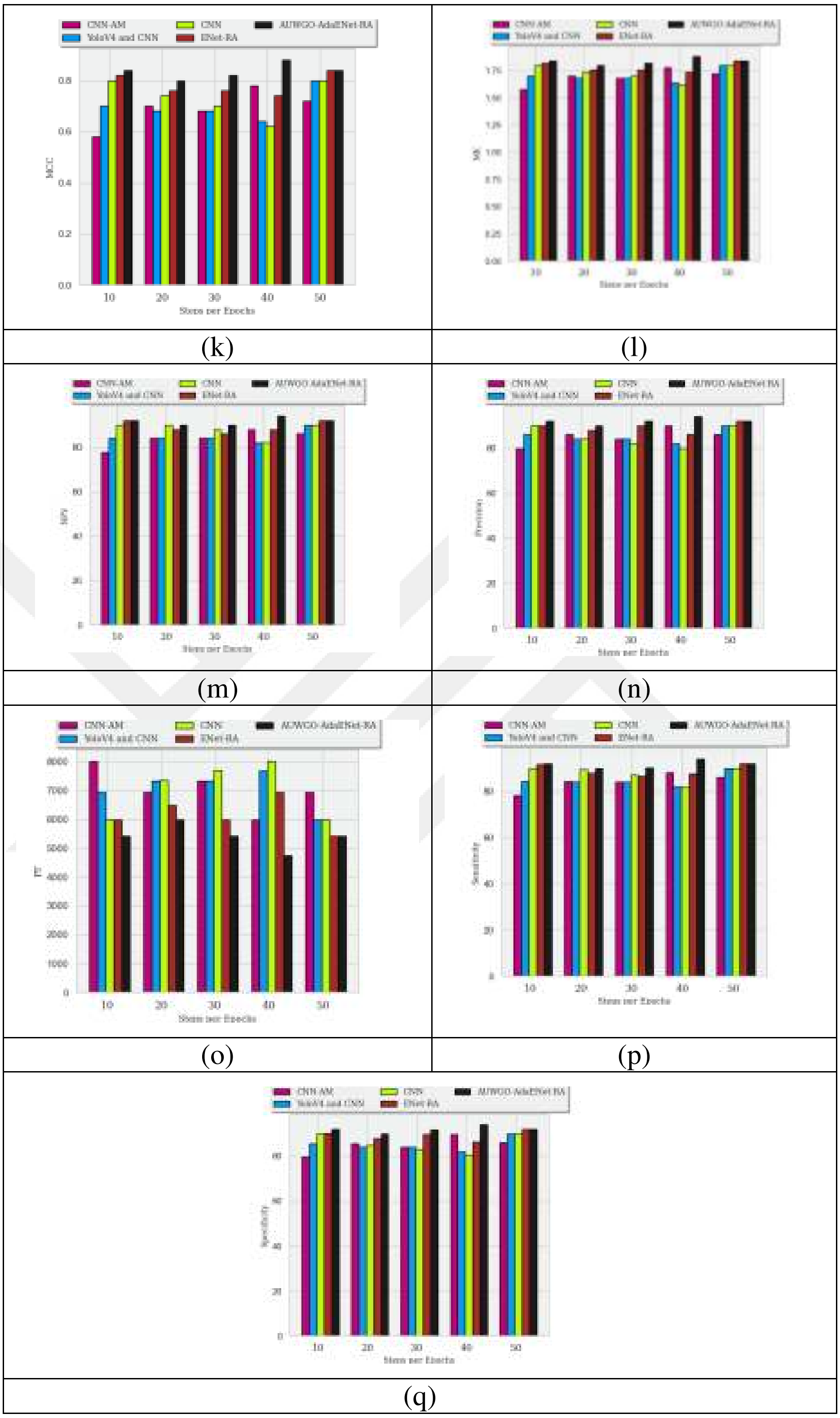


Figure 4.6: Performance Examination of Implemented AUWGO-AdaENet-RA-Aided Dental Caries Classification Technique Over Existing Classifiers in Terms of (a) Accuracy, (b) BA, (c) BM, (d) CSI, (e) F1-score, (f) FDR, (g) FM, (h) FNR, (i) FOR, (j) FPR, (k) MCC, (l) MK, (m) NPV, (n) Precision, (o) PT, (p) Sensitivity, and (q) Specificity (Figure Continued).

4.10 ACCURACY ANALYSIS FOR CLASSIFICATION

The accuracy examination of AUWGO-AdaENet-RA-aided dental caries classification technique over conventional heuristic algorithms and classifiers is provided in Table 4. The batch size values are supported in this experiment. The batch size-aided validation highly impacts the efficiency and performance of the deep learning strategies. The batch size defines the number of training samples executed together as a single module before the AUWGO-AdaENet-RA model's weights are upgraded. A huge batch size value can result in faster training periods. On the other hand, the smaller batch size can enhance the generalizability of the AUWGO-AdaENet-RA model. By validating the impact of distinct batch sizes on the dental caries categorization approach, the experts can recognize the optimal batch size that trade-off the model functionality and the training efficiency. This validation also discloses insights into the AUWGO-AdaENet-RA model's robustness to distinct batch sizes that is crucial for real-world applications where the batch size values may change. When the batch size is 32, the accuracy of the AUWGO-AdaENet-RA-aided dental caries classification model is improved by 11.95% of CNN-AM, 1.08% of YoloV4 and CNN, 3.26% of CNN, and 2.17% of ENet-RA respectively. Hence, the developed AUWGO-AdaENet-RA model illustrates its efficacy over other conventional classifiers.

Table 4.4: Accuracy Investigation of Implemented AUWGO-AdaENet-RA-Aided Dental Caries Classification Over Conventional Algorithms.

Analysis against algorithms					
Batch size	**CO-AdaENet-RA [36]**	**GRO-AdaENet-RA [37]**	**AOA-AdaENet-RA [38]**	**GOA-AdaENet-RA [26]**	**AUWGO-AdaENet-RA**
4	84	76	84	82	91
8	84	90	84	88	88
16	79	89	83	83	92
32	82	89	78	90	92
48	89	86	76	88	91

Table 4.5: Accuracy Investigation of Implemented AUWGO-AdaENet-RA-Aided Dental Caries Classification Over Conventional

Analysis against classifiers					
Batch size	**CNN-AM [3]**	**YoloV4 and CNN [4]**	**CNN [6]**	**ENet-RA [30] [31]**	**AUWGO-AdaENet-RA**
4	86	90	77	88	91
8	83	92	82	88	88
16	82	84	81	85	92
32	81	91	85	84	92
48	90	91	88	92	91

5. RESULT

5.1 THE RESULT

A new classification framework for dental caries has introduced in the recommended work. Here, the CBCT images were garnered from the available datasets in the beginning. Further, these images were subjected to the segmentation stage. Here, the NDT-R2Unet model was supported for segmenting the abnormal regions in the input images. The suggested NDT-R2Unet model was the integration of transformer-based R2Unet with nested dilated convolution, which increases the segmentation operation's effectiveness. Further, the segmented images were provided to the AdaENet-RA model for categorizing the dental caries. Here, the AUWGO was exploited for improving the CSI and accuracy of the classification task. Finally, the research calculations were conducted for the implemented framework. The accuracy of the developed AdaENet-RA model was enhanced by 10.52% of CNN-AM, 5.26% of YoloV4 and CNN, 5.78% of CNN, and 1.05% of ENet-RA respectively when the steps per epoch were 50. From the experiments, the implemented framework showed relatively more competitive solutions than the conventional mechanisms. Thus, the implemented dental caries categorization process provides satisfactory solutions and hence supports dentists in making timely diagnosis plans.

5.2 FUTURE SCOPE

The developed classification system accurately categorized the dental caries than the existing approaches. Therefore, dentists can make timely and effective treatment and diagnosis plans without any false alarms with the support of the implemented framework. Moreover, the developed framework relatively minimizes the intervention of manual analysis thus improving the patient outcomes. Nevertheless, the suggested classification framework is validated by employing a single dataset. This creates a concern in terms of generalization capability. Therefore, future work will be considered for this implemented framework by utilizing distinct datasets for ensuring its ability to generalization. Moreover, although the developed model works better than the existing algorithms, the model may produce limited outcomes when processing the raw input images directly without involving the image pre-processing. Hence, this issue also will be considered in future works for improving the model performance with high effectiveness.

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