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IDD-Net: A Deep Learning Approach for Early Detection of Dental Diseases Using X-Ray Imaging

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Abstract: Early detection of dental diseases such as cavities, periodontitis, and periapical infections is crucial for effective management and prevention, as these conditions can lead to severe complications if left untreated. However, traditional diagnostic methods are often manual, time-consuming, and heavily reliant on expert judgment, which can introduce variability and delay in diagnosis. To address these critical challenges, we propose IDD-Net (Identification of Dental Disease Network), a novel deep learning-based model designed for the automatic detection of dental diseases using panoramic X-ray images. The proposed framework leverages Convolutional Neural Networks (CNN) to enhance the accuracy and efficiency of dental condition classification, thereby significantly improving the diagnostic process. In our comprehensive evaluation, IDD-Net's performance is rigorously compared to four state-of-the-art deep learning models: AlexNet, InceptionResNet-V2, Xception, and MobileNet-V2. To tackle the issue of class imbalance, we employ the Synthetic Minority Over-sampling Technique with Tomek links (SMOTE Tomek), ensuring a balanced sample distribution that enhances model training. Experimental results showcase IDD-Net's exceptional performance, achieving a 99.97% AUC, 98.99% accuracy, 98.24% recall, 98.99% precision, and a 98.97% F1-score, thus outperforming benchmark classifiers. These findings underscore the transformative potential of IDD-Net as a reliable and efficient tool for assisting dental and medical professionals in the early detection of dental diseases. By streamlining the diagnostic process, IDD-Net not only improves patient outcomes but also has the potential to reshape standard practices in dental care, paving the way for more proactive and preventive approaches in oral health management.

Keywords: Dental Diseases; Dentistry; Dental Caries; Medical Imaging; CNN; Deep Learning.

1. Introduction

Dental cavities are an infectious condition that results in tooth damage caused by oral bacteria that produce lactic acids, which negatively impact the enamel layer of teeth. This may ultimately occur in the creation of a tiny hole among the teeth, which, if treated improperly, can lead to infection, discomfort, and even the loss of teeth [1,2,3]. It is predicted that dental disorders will affect almost fifty percent of the world's population, with 2.3 billion people dealing with chronic dental caries infection alone [4]. Dental informatics is an emerging field of research inside dentistry that attempts to reduce complexity and enhance the methods for diagnosis that are employed in the dental profession, minimize the duration of time that patients spend in treatment, and lessen the level of anxiety that patients suffer on every single day [5]. Dental diseases are ailments that can have an adverse effect on a person's gums, teeth, and various other components that are found in the dental cavity and the tissues immediately around it. The dental structure of an individual's tooth can be classified into two fundamental parts: the crown, which is the portion of the tooth that is shown to the naked eye, and the root, which is the portion of the tooth that is not seen but resides inside the mouth [6]. It's possible for a little hole to grow in a tooth almost undetected, and then for that hole to travel to the bone that supports the tooth, which can cause irreversible damage.

In nearly all of nations with a high income level, dentistry procedures represent roughly of 5 percent of the overall expenditure on health care and 20 percent of individual medical costs [7,8]. A significant number of problems of dentistry can be eliminated, while those that happen can usually be dealt with effectively if found ahead of time. Proper identification of tooth disorders may assist minimize further treatment, which could result in financial savings in the years to come. The decay of the tooth that happens by oral bacteria which manufacture lactic acids and, in turn, erode the outermost layer of enamel on teeth. The diagnosis of issues relating to teeth falls under the responsibility of dentists. They are able to discover significant dental issues by examining the teeth and moving them in a very careful manner. Very little advancement has been achieved with automated identification of issues with teeth. For the classification of diseases and recognition, performing a manual evaluation of dental issues demands time and skill. Errors made by humans may result to wrong assumptions in manual evaluation. The identification and categorization procedure for oral health issues can assist in early identification of disease and possibly avert the loss of teeth. It will help in preventing tedious, time-consuming, and demanding of labor manual medical tests. Furthermore, dental conditions are avoidable and manageable by performing appropriate oral hygiene procedures, such as brushing their teeth, flossing, and tooth evaluations, and also by choosing healthy dietary and lifestyle selections.

Dental diseases such as cavities [10], periodontitis [12], and periapical infections [11] are continuous conditions which influence the majority of the world's young and older population. These disorders usually cause patients to have discomfort in the teeth as well as the absence of teeth, both of which can result in significant difficulties for the patients [13].

The development of dental caries, sometimes referred to as a "cavity," is triggered by the disintegration of pulp and enamel carried on by the presence of lactic acid in the mouth. The decomposition of nutrients by microorganisms results in the production of an element known as lactic acid [14]. The process of creating enamel may result in a recovery of a carious lesion when calcium and saliva hold acid-neutralizing qualities. Caries have a tendency to grow in spots on the teeth where there is contact between the teeth, and these sites might be difficult to see visually. As a consequence of this, radiographs are necessary for the accurate identification of caries. The phrase "head" refers to a bigger demineralized portion in the inner dentin, whereas the phrase "stalk" refers to a little hole close to the darker dentin at the tooth's peripheral [15]. If the cavities grow severe enough, they have the possibility to propagate into the pulp chamber, which can affect teeth with either a single cavity or several cavities. When this takes place, an ulcer or lesion will develop on the surface of the tooth, and the tooth will become increasingly nonvital.

In addition to the symptoms of cavities are foul breath or an unpleasant taste in the mouth, tooth enamel that bleed rapidly, and other signs of gum disease, a facial enlargement, oral discomfort in the mouth, or molars that are susceptible to cold or warm foods or liquids. In every part of the globe, dental disorders are the most widespread kind of long-term illness, and almost ninety percent of the population are affected by tooth decay [16]. Caries can affect any and all of the layers which make up the enamel of a tooth. There are five primary phases associated with tooth decay, which are as follows: (1) At this point in the process, we can observe that particular parts of our teeth have formed a white coating that resembles chalk. This is a result of the amount of minerals of the dental enamel depleting over time. (2) In case that we fail to treat our dental cavities, they are going to worsen, and as a result, our tooth enamel will continue to deteriorate. At this time, cavities, which are also referred to as holes, could become noticeable. There is a chance that the extremely fine white particles will take on a tint of light brown. (3) The dentin layer can be found inside the hard outer layer of the tooth. When contrasted with enamel, it has a substantially softer consistency. When microbes and plaque enter this layer, the rate of hole formation quickens. It's possible that we've become aware of sensibility in our teeth. In addition to this, the brown spots that are currently on our teeth can develop even darker. (4) The pulp makes up the most superficial layer of a tooth's anatomy. It consists of the muscles and arteries that carry vitamins and minerals and ensure the tooth's continued wellness. It's probable that we'll feel discomfort if the holes reach the pulp. Additionally, the gums that wrap the damaged tooth may become red and retain water. This is another symptom of tooth decay. There is a chance that the white spots on the surfaces of your teeth may become more intense and there is also a chance that they might develop into entirely black [17,81]. The procedure used for dental cavities might be very different from one patient to the next, depending on the severity of the problem.

The therapies using fluoride may be able to cure broken teeth through a method known as remineralization in the beginning phases of tooth decay. It is possible for this to reverse the early indications of the presence of cavities. It's potential we'll need to use fluoride drugs in addition to mouthwash and toothbrush that have been recommended by a dentist. When a hole appears in a tooth, a dental expert employs drilling to extract the tissue that is infected and fill the space left behind by the removal of the tissue. Dental fillings can be made of hybrid material, which is a substance that is silver mercury, or tooth-colored [18].

Root canal therapy minimizes discomfort carried on by severe tooth decay. Typically, dental professionals (specialists in root-related issues) undertake the tooth extraction. A dental specialist takes the pulp from a cavity during the process of root canal therapy and then fills the canals and nerve chamber with gutta-percha, a specific healing material. Because of the severity of the damage to the tooth, it is possible that we will recommend that you get a crown in addition to the other dental work that needs to be done. Dentist might advise having the tooth retrieved (which is additionally referred to as "removing the tooth") in the instance that a root canal procedure is not an appropriate choice for treating the affected tooth [19]. When restoring a fixed tooth that has been taken out, it is possible that we will need a crown for the tooth or an implant. Dentist will be equipped to provide us with information regarding the specific remedies that are available to us.

If you have any of the following symptoms, including bleeding gums, problems chewing, evidence of spread of infection, swelling in the face, and headache or tooth pain, we need to make a visit to a dentist as soon as possible. Plaque, acidic substances and microbes which trigger cavities can be removed from the mouth by practicing good oral hygiene, which entails cleaning and brushing the teeth on a regular basis. To properly care for our teeth and gums, we need to reduce our consumption of sugary and carbohydrate foods and beverages, floss our teeth every day to remove food particles and plaque from among our teeth, and visit your dentist a minimum of twice per year (we may require a regular visit to the dentist if we have a tendency to cavities, gum disease, or other tooth-related issues), sealants for dentistry to preserve the highest chewing areas of our teeth, and brushing our teeth with a toothbrush that has soft bristles and a toothpaste containing fluoride a minimum of twice daily, and particularly after each intake of food.

In the most popular type of periapical abscess, bacteria invade the pulp of the decaying tooth and produce an infection. If the dental cavity is serious or remains there for an extended period of time, it may have occurred to the pulp of the molar. The pulp is where the neurovascular and other components of the oral cavity are situated. This disease leads to pulpitis, which is an inflammation of the pulp that can either be curable or irreversible depending on how severe it is [17].

In lack of therapy, the continuous inflammation that develops causes an increase in pressure behind the nerve of the molar, which ultimately results in a breakdown of pulp tissue, devitalization of the molar, and a propagation of infection throughout the pulp zone and the canals in the root. Germs can manage to travel via the root canals and exit through the apical foramen located at the highest point of the root, where they can then release harmful substances. This contributes to the development of a condition referred to as apical periodontitis, which is characterized by the aggregation of neutrophils, lymphocytes, and macrophages in a confined area surrounding the apex of the tooth [20]. This periapical lesion that consists of tissue that has the granulation and platelets that are injurious, demonstrates that there is an optimal balance within the patient's immunity and the microbes that are there. In a chronic state, preserving this state of balance helps to prevent the further development of disease. Someone who have periapical condition could or might not have discomfort in their teeth, swelling in the gums, or an increase in their sensitivity. Symptoms of a periapical infection include an extreme level of pain in the tooth, likely enlargement of the tooth that is infected, and possibly larger alerts such as a high temperature and lymphadenopathy. If the nasal or oral cortical portion of the jawbone or the surface of the maxilla has fractured, a periapical infection can propagate into the soft tissues that surround it and cause an infection there as well. Patients like this usually show up with symptoms related to infection, including cheek water retention, jaw mass, soreness in the face, and other facial pain and discomfort [13][77].

After confirming the diagnosis with tests that examine the existence of the pulp, possible treatments for periapical infectious conditions comprise surgical operations, dental root canal processes or the surgical removal of teeth [21,22]. However, it is very normal to find periapical radiation proceed to be present even after the procedure for root canals has been completed. The surgical removal of nonvital teeth and inadequate periapical infections often only requires one session of root canal therapy [23]. In this step, a hole is drilled into the tooth in order to provide access to the area identified as the pulp chamber for the dental expert. After the infection is eradicated, the insides of the root canals are transformed with the aid of sophisticated dental instruments.

The root canals are subsequently sealed with a solution of gutta percha and a solution of zinc oxide, a radiopaque secure substance with antiviral qualities. On a radiograph, the canals in the root of a treated tooth are obvious rather than radiopaque. In the months adhering to therapies, it is common for the periapical radiation area to begin growing with the formation of scar tissue or connective tissue [24-25][78]. A devitalized canal in the root can sometimes have a tube of metal inserted in it, and then it will be capped with a crown, so that the tooth will have improved stability. In the end, nonvital teeth will begin to fade their hue and become delicate, necessitating the insertion of a synthetic crown as the final part of the therapy for root canals. The base tooth is given additional support and its appearance is enhanced by the crown. It may be essential to lower the size of the patient's natural crown or, alternatively, to stuff it with silver or a resin mixture in order to make space for an artificial crown. After that, an ingredient such as polymeric silicon is used to make inspections of the teeth, which are then transmitted to a laboratory.

A preliminary estimate is employed to make an unfavorable mold, also known as an imprint, of the individual's teeth. This allows for the creation of an impression, which can then be used in the future as a pattern to produce a crown for the patient. Crowns can be crafted from a diverse assortment of materials, such as ceramics, metal, enamel that has been fused with metal, and many others [17]. Due to radiologists aren't spending enough time evaluating images in bone sections and investigating enamel surfaces for suspected periapical radiolucency, they often fail to identify the true infection site.

When plaque bacteria have an adverse influence on a patient's gums, a condition known as periodontitis can be detected. Periodontitis is a chronic gum disease and it is another name for gum disease, is an advanced infection of the gums that consumes away at the fragile connective tissues that wrap around the teeth [26]. If periodontitis fails to be addressed by a trained medical expert, it may ultimately contribute to the destruction of the bone that provides nourishment to the root surfaces of the tooth enamel. This might end up in the complete loss of teeth or in the enamel of the mouth becoming fractured. When the ligament that binds the periodontal tissue separates from the root of the tooth, a periodontal pocket is formed. This periodontal pocket is recognizable as a little empty area. The pocket grows soiled very shortly and is tough to maintain its clean appearance. If the periodontal pocket is allowed to become infected with a sufficient number of germs, an abscess will develop. After undergoing dental work that resulted in the formation of periodontal pockets unintentionally, a patient continues the risk of developing periodontal infections [27,80]. Furthermore, the intake of antibiotics during the course of uncontrolled periodontitis that is capable of covering up the manifestations of an abscess, may end up in a periodontal abscess. This is in case an abscess is triggered by an illness of the periodontium. Periodontal abscesses can happen as a consequence of gum destruction even in a lack of periodontitis diseases. Gums that are strong are sturdy and tightly link themselves to the teeth [28].

Periodontitis symptoms can consist of swollen or expanded gums, gums that are dark in color red or broad purple, gums that are adaptive if squeezed, tooth enamel that bleed with ease, expelling blood while cleaning your teeth, having chronic foul breath, pus behind the enamel and the gums, cracked or chipped teeth or tooth decay, painful eating and swallowing, spaces that grow around your teeth that approximate black forms, the condition known as receding gums happens when the gums push away from the teeth, providing an appearance that the teeth are larger than they actually are and altering the method by which the teeth come together when you chew down [29].

Plaque is the primary factor behind the beginning of periodontitis in the vast majority of instances. Plaque is the outermost layer that forms on teeth and mainly consists of bacteria. In case the plaque is not eliminated, it has the possibility of trigger periodontitis, which can be classified as follows: (1) Plaque grows on your teeth as part of a link involving the glucose and calories in the foodstuffs you consume and the microbes that typically reside in your mouth. It can be extracted from teeth by cleaning them on a daily basis and flossing one time a day, but it will shortly return if these procedures are ignored. (2) If plaque is permitted to stay on the teeth, it will eventually harden into tartar and build on the surface of the gums.

The removal of tartar is a significantly more difficult task. It is necessary to have a specialized dental removal performed in order to get rid of it because cleaning and flossing your teeth will not be enough. Although dental plaque and tartar both happen to be composed of microbes, the more time they are let accumulate on the outermost layer of your teeth, the more damage they are able to cause to your teeth and gums [30]. (3) Plaque, the most prevalent trigger of gingivitis, is the least severe form of gum disease. Gingivitis is a condition characterized by inflammation and irritation of the gingival tissue that covers the tooth roots. Alternative term for the tissue of periodontal disease is gingiva. Gingivitis is preventable with appropriate therapy and good dental hygiene, but only when it is detected and addressed early, preceding to the bone loss that can occur from the disease [31]. (4) Inflammation, which can be an indicator of periodontitis, is represented by the gums obtaining swollen and discolored on a frequent basis. In final analysis, this contributes to the formation of cavities that are especially extensive among the tissues of the mouth and the teeth, which can cause significant discomfort. Tartar, dental plaque, and microbes are found within these pockets, and as time passes, these pockets will become deeper. In the unfortunate situation that they are not treated in the correct way, these dangerous infections might lead to the destruction of the cells and bone. Periodontitis is a disease that can lead to the loss of teeth as a consequence. It can happen for the microbes that trigger periodontitis to make their way into the circulatory system through the gums and jaw tissue, which means they can then move to other regions of the body and cause additional issues [32]. Cavities are areas of decay that can form on the surface of teeth and are known as the outermost layers.

This research chose to focus on panoramic X-ray images rather than other types of intra-oral and extra-oral radiographs because of the numerous benefits they have over more traditional X-ray techniques for imaging. They are able to observe (i) the entire thing that is in the interior of the mouth, (ii) each individual tooth in the two separate bottom and the upper levels jaws, and (iii) the placements of each of the completely formed teeth and teeth that are still in the process of erupting in a single X-ray. It is also ideal for usage in dentistry due to the fact that it reduces the amount of time spent in treatment, improves the accuracy of diagnosis, exposing patients to less radiation, receives more positive feedback from patients, and requires fewer measures to prevent infection [38]. Dental x-rays reveal significant details regarding the underside of teeth as well as the connective tissue that related to them. This enables dental experts to find difficulties with teeth that may not be seen right away. Bitewing and Periapical x-ray images are employed in Intraoral X-rays. Bitewings reveal both the front and back teeth in a single part of the mouth. This x-ray images typically do not reveal the roots of the enamel on your teeth. On the other hand, a periapical X-ray reveals every part of the tooth, from top to root edge. This form of X-ray enables a dental professional to recognize cavities, periodontal disease, loss of bone, and additional changes of the tooth or nearby bone. A panoramic dental X-ray is a type of extraoral X-ray that depicts all of the tissues in your mouth, such as your top and bottom teeth, jawbone muscles, nerves, alveoli, and surrounding bone, on a single image. Intraoral radiographs, such as bitewing and periapical X-rays, have the ability to reveal certain regions of the mouth, but multiple examinations are required to obtain the full image. As a consequence of this, it takes more time, the patient experiences more discomfort, and there is a possibility that they will receive a heavier radiation dose [39].

Dental experts are able to turn to several computer programs that can provide them with assistance when decision making regarding therapy, avoidance, and detection measures [35]. Throughout all of the years, a large number of researchers from all around the world have developed a variety of Machine Learning (ML) [33] and DL [34] techniques for the identification and categorization of dental diseases. Using the DL techniques, multiple groups of researchers have been able to produce remarkable outcomes. In addition to this, there is still scope for improvement for the purposes of accuracy, robustness, and the accessibility of data. A learning model is employed to implement DL so that it is capable of tasks like as a recognition of pictures, texts, and sound. By applying labeled datasets and a collection of various stages of the neural network, the model is trained to execute the intended task [36]. The medical industry is currently making use of DL as one of the AI approaches available to them.

The rapid advancement of CNNs has made them an increasingly popular option for the analysis of medical images. CNNs have been deployed successfully for mammography examinations, professional skin screenings, and eye evaluations for retinopathy due to diabetes. Thus, CNNs have been especially effective in the domain of cancer diagnosis [37]. The implementation of CNNs on panoramic scans could generate a greater detection outcome in the forms of better reliability, clarity, and time savings for analysis because of the difficulties associated with diagnostic tasks. Due to the fact that CNN employs features acquired through incoming data and leverages 2D layers of convolution, this approach is most suited for use with 2D data, like as photos. The primary objectives of the research are to present a novel model that is capable of identifying dental diseases in an accurate and efficient manner based on dental x-ray images. This proposed model is referred to as the Identification of Dental Disease Network (IDD_Net), which depends on CNN. This model is able to differentiate between the three distinct forms of dental disease, which include periodontitis, cavities, and periapical infections. The following is an outline that provides a summary of the most important contributions made by the study:

- The novel proposed IDD_Net is built for detecting dental diseases with a relatively minimal number of parameters, and the proposed approach is appropriate for training with a reduced dataset.
- We deployed the SMOTETOMEK oversampling strategy, which integrates new images to equalize the category samples, so that we could fix the issue of imbalance in the dental dataset.
- In our proposed model, the Grad-CAM heat-map approach is implemented for displaying the class activation map, illustrating the infected part of the teeth.
- The suggested model acquired improved outcomes in contrast with four well-known baseline classifiers, such as AlexNet, InceptionResNet-V2, Xception, andMobileNet-V2, on the basis of numerous assessment measures, such as accuracy, recall, loss, AUC, precision, and F1 score.
- In addition to this, the model that was proposed provided far greater significance outcomes than the models that are now considered to be state-of-the-art.

The remaining parts of the paper are organized as described below. The previous study on dental conditions is discussed in Section 2, the research methodology and structure of the suggested strategy are covered in Section 3, and Section 4 discusses the findings and experimental setup. The final portion describe the conclusion of this study.

2. Literature Review

The research on the detection of dental diseases has been carried out in a great number of studies in order to support dentists in identifying the disease at an initial stage. On the contrary, the majority of the latest study has been aimed at the development of various artificial intelligence techniques that can automate the identification of several different dental diseases. Table 1 presents a quick overview of the latest studies published in the field of dental disease diagnostics via ML and DL architectures.

In the study that was conducted by Oztekin et al. [40], the researchers examined three popular algorithms that had been developed for the caries identification task. These models comprised DenseNet-121, ResNet-50, and EfficientNet-B0. These algorithms took panoramic photos as their source of data and generated an identification of caries and non-caries, in addition to a heat map that displayed parts of relevance on the outermost part of the tooth. In the execution of this study, an average of 13,870 tooth images was put to use for the objective of validating and training data. The outcomes that had been produced by each of the three approaches were extremely comparable to the outcomes that were generated by each of the other. The performance of the ResNet-50 model was slightly higher than to that of the DenseNet-121 and EfficientNetB0 architectures. This model got an accuracy score of 92.00%, an overall sensitivity score of 87.33%, and an F1-score of 91.61%. Ali et al. [82] proposed a deep learning-based approach using a Multi-Layer Perceptron (MLP), which can also be effectively applied to medical imaging tasks, such as disease detection in X-ray images, when integrated with appropriate image feature extraction techniques. Rimi et al. [41] employed the approach that has been referred to as ML in order to forecast the rate of oral disease in the general population of an entire nation depending on the activities that individuals engage in on each day. After the collection of data and its subsequent the preprocessing phase, they produced the most of a total of nine different ML techniques. These comprised k-nearest neighbors, multidimensional perception, logistic regression, SVM, naive Bayes, classification and regression analysis trees, random forest, adaptive optimization, and discriminant evaluation using a linear relationship. Therefore, to conclude the process of assessments, they investigated the effectiveness of each predictor through examining its accuracy in addition to specific important performance procedures. The success rate of the logistic regression predictor is around 95.89%, which is a greater percentage than that of any other predictor that was utilized.

Hasnain et al. [42] were able to identify diseases by analyzing images captured on X-rays by making use of DL, a sort of artificial intelligence. The collection of images contains 126 photos, all of which have been annotated by dental professionals to indicate whether they are infected or normal. The dataset was enlarged making use of data augmentation with the aim to improve the effectiveness of DL architectures while they were being trained. The extraction of X-rays that are unclear due to noise demands the use of manual filtering, and this was carried out by the specialist. In order to conduct an evaluation of the overall quality of medical care, the CNN model must first be trained with the enhanced dataset.

Haghanifar et al. [43] presented the use of a computerized method of detection for identifying dental disease in panoramic photos. This system makes use of transfer learning to determine the relevant attributes, and a capsule network is utilized in order produce findings for predictive purposes. Through the implementation of a database that included 470 panoramic photographs, the model they developed was capable to achieve an accuracy of 86.05% on the set that was tested. Their algorithm acquired recall values of 90.52% and 69.44%, respectively, for seriously harmed samples and mildly impacted samples, which verifies their assumption that substantial cavity areas are quicker to recognize, whereas efficiently identifying mild cavity spots requires a larger database.

Deep CNNs were utilized by Sonavane et al. [44] in order to determine teeth that contained caries or not having cavities simply based on the outer appear of the molars. They developed the algorithm from sixty photographs that were retrieved via the Kaggle database, and after applying certain alterations to it, they were successful in getting an accuracy of 71.43%. It was selected to use 45 photographs of caries and 15 photographs of teeth without cavities for the sake of training.

Using the LIME approach, Bhattacharjee et al. [45] created an artificial intelligence system for the purpose of recognition. This method investigates the occurrence of holes in photographs and explains the thought process that went into each diagnosis. After the LIME module has been integrated into the system, it was now equipped to detect any indication of cavities and deliver the patient a description of its cavity analysis that is simple to understand. They studied a CNN that had been hand-designed and was composed of an overall of 12 stages. Additionally, they made a number of alterations to previously learnt detectors for photos using ResNet-27, and ResNet-18. With the effective implementation of curriculum learning, which resulted in a sensitivity score of 1.0, and an accuracy level of 82.8%, which is it was concluded that a ResNet-27 architecture would be the most suitable option.

Abdalla-Aslan et al. [46] implemented an AI-based computer vision approach to automatically determine and assemble various kinds of tooth restorations employing panoramic treatment with radiation. A collection of 738 restorations to the jaws were analyzed, and the images of those restorations were discovered in a collection of 83 unidentified panoramic photos. The photos were automatically cropped in order to obtain the points that were significant among them, such as the dental lines for the molar and maxillary regions of the mouth. Multi-classification of the restorations that depended on these attributes was accomplished by a method called cube SVM with correction for errors. When the process of classification came to a decision that discriminating between multiple types of genuine restoration, it had an average accuracy of 93.6%.

A CNN that was suitable of performing various categories was developed by Al-Ghamdi et al., [47]. In order accomplish this goal, the X-ray pictures were separated into the three distinct groups of cavity, implants, and filler material. To prepare for the CNN method to be used as the basis for the NASNet's design, an altered version of the method has to be constructed. As an immediate outcome of this, the total amount of the database, which was 83 preceding to the augmentation, has now grown to 245. A multi-categorization model was established after the procedures of data enhancement and preprocessing had been completed to a successful outcome. On a number of different classes, the accuracy of the architecture had the capability to reach or even surpass 96%.

Lee et al. [48] designed a technique for a CNN by deploying a U-shaped neural network (U-Net) with the aim to differentiate dental caries from bitewing photos. 304 pictures of bitewings were put to use in order to learn the CNN model, and then 50 radiographs were employed to determine the extent to which the model worked. For the reason that to make the photos suitable for use as network input, the resolution of each image was increased to 572 pixels by 572 pixels. The diagnostic success rate of the CNN model was as follows in all of the test dataset: 65.02% recall, 63.29% precision, and 64.14% F1-score show adequate effectiveness. The lightweight approach was employed by Lin et al. [49], and a number of renowned lightweight DL strategies were developed on a database comprising panoramic dental enamel X-ray photos. Within the database that was employed in their study to validate and evaluate their procedures, there were a total of fifteen hundred panoramic molars X-ray pictures available. Before performing the evaluations, they only standardized and scaled the images for the aim of their experimentation. The lightweight approach recommended to learn an architecture takes primarily 7.5 megabytes. In the studies they performed, the effectiveness of these techniques were assessed using five distinct error metrics. In contrast to other lightweight strategies, their performance was the highest conceivable, as evaluated by 0.89 ± 0.038 chucks and 0.80 ± 0.058 IoU.

In the experiment that was undertaken by Megalan Leo et al. [50], the researchers employed a DL approach that was centered on CNN with the aim to determine whether or not the teeth depicted in the image had an oral cavity. Elsevier's database is the origin of these 480 biteviewing x-ray photos, this database was used as the foundation for these images. Each image entered was resized to suit within a 128x128 pixel frame. The amount of noise in the photo is reduced by the use of a selective filter referred to as the median when the preprocessing step is being carried out. The CNN that makes employ of the GoogleNet Inception-V3 structural approach had been developed using the DL framework. This framework obtains its inputs only after the data have been preprocessed. As implemented to the database that was utilized for the evaluation, this method acquired a success rate of 86.7%.

From the radiography database of a hospital, Fukuda et al. [51] selected 300 panoramic photos including a total of 330 VRF tooth decays with obvious fracture lines. The aim of their study was to evaluate the efficacy of a CNN system for recognizing vertical root fracture (VRF) on radiographs with panoramic views. In order confirm the VRF lines, we needed the assistance of three doctors. These specialists included two professionals in the field of radiography and an endodontist. The total number of 300 photographs were separated as follows: 80% means 240 photos were assigned to the training class, and 20% means 60 photos were assigned to the testing photos. There was still a desire for an automated system that is adept at accurately and effectively detecting the critical components contained within oral X-ray pictures. They were able to get an F1 score of 0.83, a recall score of 0.75, and a precision score of 0.93.

Muramatsu et al. [52] executed a cross-validation strategy with one hundred distinct photos of molars that had been acquired via radiation therapy to be able to produce an object recognition system. On the basis of the outcome of the representation, a substantial amount of image data had been employed for the multiple input stages of a CNN. Their analysis was undertaken out with the aim of building an automated system that was capable of recognizing and sorting teeth in dental x-rays of panoramic views in order to assist the programmed, arranged filing of oral chart material. In addition to this, it has the potential to serve as a preprocessing step for the computerized image assessment of dental diseases and abnormalities. The detection of teeth has a sensitivity of 96.4%, and only a success rate of 93.2%. Karaoglu et al. [53] devised an architecture identified as Faster R-CNN that can understand, organize, and identify things that are present in an image. A total of 2702 radiographs with panoramic views were used in the creation of the dataset; 1747 of those were utilized for training, 471 for the purpose of testing, and 484 for validation. The database images that were used for the Mask R-CNN model were reduced to a dimension of 1024 x 1024 pixels so that the model would be suitable for usage with data of varying sizes. To be able to boost the accuracy of the predictions generated by the model, a technique comprised of three phases was devised. The findings of the research study reveal that the levels of precision, f1 scores, and recall were 96.08%, 95.87%, and 95.65%, respectively.

Jiang et al. [54] designed a two-phase DL method that was able to locate the dental pulp as well as important regions by making use of YOLO-v4 and UNet. This was accomplished to ensure a reliable determination could be made of the percentage of periodontal loss that had occurred in the alveolar bone. The studies they conducted included an overall of 640 panoramic pictures, and three highly skilled periodontists were in charge of highlighting those areas that were needed to figure out the severity of periodontal bone loss in the alveolar bone as well as that particular location and kind of the alveolar bone loss. It was determined that the model's categorization had an overall accuracy of 0.77, however the usefulness of the model varied according to the tooth placement and type that was being studied.

In order to help with the identification of periapical diseases, Fatima et al. [55] suggested a lightweight version of the Mask-RCNN framework. For the purpose of developing the suggested model, a lightweight, modified version of MobileNet-v2 and a region-based network (RPN) were provided for the periapical identification of diseases by making use of a constrained data set. The entire amount of 534 periapical radiographs were taken, and qualified radiologists and dental specialists were responsible for identifying 516 of those images. Their research consisted of the creation of a lighter M-RCNN technique with the intention of offering efficiency even when operating on systems that have little computational capacity such as memory and GPUs. Their effort was focused mostly on improving the effectiveness of the model in as many ways as it could. According to the findings, the model has an overall a precision of 85% and accuracy of 94% as it comes to determining the presence and type of periapical lesions.

Chen et al. [56] established AI methods by employing the YOLOv5 framework and the VIA tagging system in their research. The VGG-16 and U-Net architectures are also representations of these algorithms. They incorporated 27,964 different teeth in the framework and utilized an overall of 8,000 images taken within the periapical region. The goal of their research was to develop a DL ensemble approach that was founded on deep CNN methodologies. Their model was employed to forecast dental spot, determine construction, evaluate residual interproximal surface bone, and detect radiographic destruction of bone implementing bitewing and periapical x-rays. The DL-trained integrated approach that was suggested functions as a significant foundation for radiographic evaluation and a helpful adjunct to treatment of periodontal disease. When employed on periapical photos, the DL-trained integrated approach achieved an accuracy rate of around 90%.

CariesNet is a form of the DL model that Zhu et al. [57] created in order to recognize the severity of cavities according to panoramic X-rays. They proceed by compiling a high-resolution database of panoramic imaging encompassing 3127 caries regions, which may include from shallow caries to mild caries all leading to severe caries. After that, they came up with the concept for CariesNet, which was a U-shaped system that included an additional full-scale orthogonal emphasis element. This was done so that it could differentiate between the three different types of caries using dental radiographs with panoramic images. According to the results of their research, their approach has the possibility of accomplishing a success rate of 93.61% and a mean Dice score of 93.64% when employed for identifying each of the three distinct levels of caries. The study carried out by Singh et al. [58] provided a strategy that was proposed for recognizing and categorizing the images of the panoramic x-rays. The procedure that evolved had an overall of 4 stages: the initial processing phase, the division, the numbering stage, and the classifying step. The collection of images contained four hundred panoramic oral photos that were taken from various types of dental practices. By employing a variety of transformations in a broad range of combinations, the depiction of the dataset can be made more reliable. In addition, a global oral identification system is employed in order to allocate consecutive numbers to the panoramic photographs of the patient's teeth. In the last phases of the categorizing process, assistance from a CNN with six distinct levels was employed. This CNN was constructed from 3 other CNNs as well as 3 fully connected systems. By applying the method that was suggested, it was possible to accomplish an accuracy of 95% for the enlarged database, but for the first dataset, it was only possible to acquire an accuracy rate of 92%.

The CNN framework was designed by Casalegno et al. [59] with with the objective of implementing it on semantic categorization-related tasks after it was initially established. They incorporated a variety of strategies as a way to address difficulties involving limited training data, uneven categories, and overfitting in their algorithms. In order to assemble their data set, they used the DIAGNOcam technology to acquire 217 photographs in grayscale depicting the smallest and upper premolars together with the molars. They have incorporated all molars and premolars in their dataset. They grabbed each image and adjusted the dimension from 480 by 640 pixels to 256 by 320 images in order that they were able to develop the system more swiftly. An AUC of 83.6% was achieved by their model for occlusal lesions, and an AUC of 85.6% was achieved for proximal lesions.

A deep CNN that makes use of a Long Short-Term Memory (LSTM) algorithm was introduced by Singh et al. [60] for the goal of distinguishing and completing a diagnosis of decay in the teeth using periapical pictures. The model they have suggested employs the capabilities of a CNN for the intent of storing attributes and an LSTM for the aim of executing long as well as short term connections. When the performance of their suggested CNN-LSTM system was assessed in conjunction with that of the CNN framework, the 2-layer LSTM strategy, and the CNN-LSTM strategy with no modification of dragonflies, the efficiency of the model they suggested boosted even more. The optimum CNN-LSTM algorithm that was suggested indicates better performance, with a success rate of 96%, and supports in the categorization of dental photos as a different viewpoint for the medical expert.

Cantu et al. [61] made use of a CNN to ensure the reliability of its results by employing the intersection-over-union assessment. The efficacy of the developed neural network was examined in contrast to that of seven various algorithms making use of tooth-level dependability parameters when it was deployed on the test database. There was an aggregate of 3686 images of bitewings that were examined by the four highly qualified dentists. The neural network demonstrated a success rate of 0.80, while the mean accuracy of dental practitioners was substantially less at 0.71.

Chen et al. [62] suggested incorporating faster regions with CNN attributes (faster R-CNN) in the compiled version of the Tensor Flow program to be able to recognize and identify teeth in oral periapical photographs. In order to adjust the findings that deviate from certain intuitive norms, it was offered to make use of a rule-base component that was dependent on a tooth recognition mechanism to correlate with the descriptions of discovered dental boxes. The intersection-over-union (IOU) value that was produced among recognized and true boxes was implemented as a way to achieve precision and recall on an experimental database. A filtering method was devised in order to acquire eliminate of redundant boxes that had been discovered by a faster R-CNN and were associated with the same tooth.

Table 1. A recent evaluation of dental diseases that relies on ML and DL.

Ref	Year	Models	Diagnostic Technique	No. of Images	Accuracy
[40]	2023	EfficientNet-B0, DenseNet-121, ResNet-50	Panoramic Radiographs	13,870	92%
[45]	2022	ResNet-27 & ResNet-18	Dental Images	500	82.8%
[59]	2019	CNN	Transillumination Imaging	217	85%
[62]	2019	R-CNN	Periapical Radiographs	1250	90%
[61]	2020	CNN	Bitewing Radiographs	3686	80%
[57]	2022	CariesNet	Panoramic Radiographs	3127	93.61%
[47]	2022	NASNet	Panoramic Radiographs	245	96.57%
[48]	2021	U-Net	Bitewing Radiographs	354	65.02%
[50]	2020	GoogleNet Inception-V3	Bitewing Radiographs	480	86.7%
[53]	2023	Mask R-CNN	Panoramic Radiographs	2702	92.49%

[58]	2020	Deep CNN	Panoramic Radiographs	400	95%
[41]	2022	Logistic Regression	Dental Images	N/A	95.89%
[44]	2021	CNN	Dental Images	74	71.43%
[46]	2020	SVM	Panoramic Radiographs	83	93.6%
[56]	2023	YOLO-v5	Periapical & Bitewing Radiographs	8000	90%
[60]	2021	CNN	Periapical Radiographs	N/A	96%
[51]	2020	CNN	Panoramic Radiographs	300	93%
[52]	2021	CNN	Panoramic Radiographs	100	93.2%
[54]	2022	YOLO-v4 & UNet	Panoramic Radiographs	640	77%
[43]	2023	CNN	Panoramic Radiographs	470	86.05%
[55]	2023	Mask R-CNN	Periapical Radiographs	534	94%

According to the mentioned studies, there is a specific need for a technique that can categorize and recognize three different kinds of dental diseases with higher level of accuracy than existing techniques. Although [40,43, 45, 44] categorized dental issues into binary classes, only a few studies accomplished the multi-classification, and they were not capable of achieving improved results [47, 57, 53]. However, the most challenging aspect of this study is to develop such a system that might improve the accuracy for the categorization of three distinct types of dental diseases (such as cavities, periodontitis, and periapical infection).

3. Materials and Methods

The following subsection covers the experimental methods applied to evaluate the efficacy of the proposed model when contrasted with a few of the most well-known deep CNN classification techniques, such as AlexNet, InceptionResNet-V2, Xception, and MobileNet-V2.

3.1. Dataset Description

The dataset consists of dental panoramic X-rays obtained from the Nishtar Institute of Dentistry, which is situated in Multan, Pakistan. An overall of 670 images of patients suffering from dental diseases are appeared within the private collection. These are Periodontitis, cavities, and Periapical infections. The number of samples of dental disease that were split up prior to the up-sampling is shown in Figure 1, and the dental disease images is depicted in Figure 2.

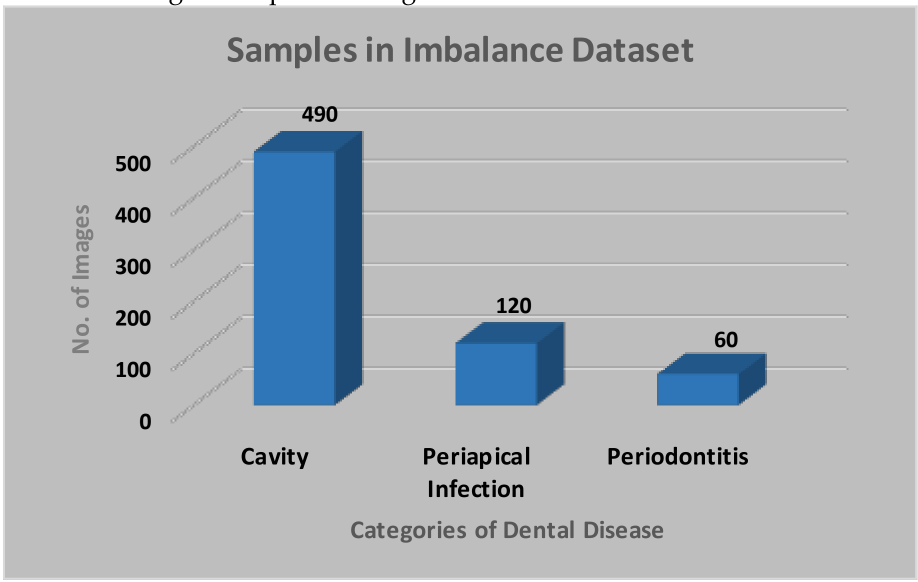


Figure 1. Dental dataset class distribution prior to SMOTE Tomek

3.2. Working with SMOTE Tomek Technique

Oversampling and under-sampling are two frequently used methods for resampling. Oversampling leads to an increase in the number of data points belonging to the minority class, whereas under-sampling results to a drop in the number of data points belonging to the majority class. In our proposed method, however, we utilize an up-sampling approach known as SMOTE Tomek [63] in order to equalize all categories and offer more precise and accurate results regarding dental disease classification. TOMEK is an arrangement of condensed closest

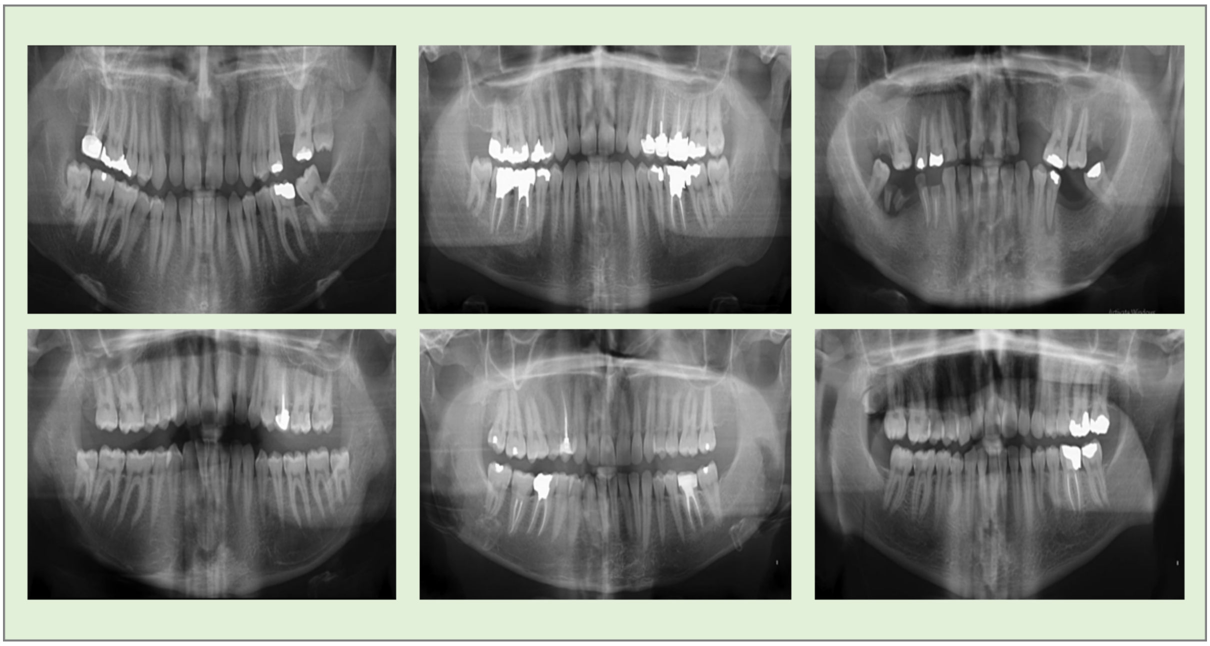


Figure 2. Different Samples of dataset of dental disease

neighbors, whereas SMOTE makes new data points based on category the closest neighbors. Both algorithms operate in sequence, and SMOTE takes a random example on a minority category and improves its proportion by combining additional samples. TOMEK then chooses an example at randomly and eliminates it when its closest neighbors are members of the minority category. As stated in Figure 3, SMOTETOMEK effectively resolves the dataset inequality issue by balancing the instances of every category. SMOTE Tomek employs the Nearest Neighbor technique to calculate new recreation samples for the minority categories that exist in the dataset.

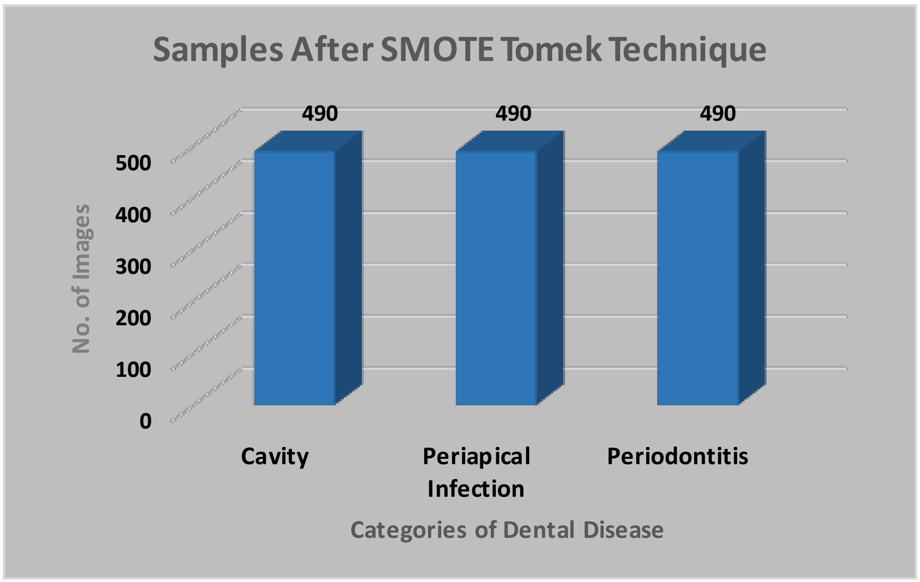


Figure 3. Dental dataset class distribution after SMOTE Tomek

3.3. The Proposed IDD_NET for Early Dental Disease Detection

Dental cavities are one of most significantly prevalent persistent illnesses affecting more than half of the population over the duration of their lives. Patients suffering from dental caries require treatment that is both quick and efficient if they are to experience the least amount of pain possible. If treatment does not occur, this might result up in an extremely tiny crack between the teeth, which could lead to discomfort, swollen gums, or even broken teeth. A significant amount of tooth decay is undetectable by either the sense of touch or visually even if it exists in the teeth. Consequently, imaging techniques are frequently employed in order to boost the detection rate. As a direct result of this, the success of both the examination and the treatment relies on the capabilities of the reader as well as modern technological developments. If tooth decay is identified in its initial phases, it may be effective to reduce the need for further treatment, which may ensue in decreased expenses over a longer period of time. Therefore, automatically analyzing dental X-rays might be of huge assistance to practicing dentists, enabling them to decrease the amount of work they perform while also improving the accuracy of their research [49].

In our study, we developed the system that is known as IDD_Net, which is an automated technique for recognizing dental issues. Caries, periodontitis, and periapical infections are three of the most prevalent dental ailments, and this method has been trained and examined through the process of interpreting X-ray images. In this suggested approach, the initial data are preprocessed by employing the normalization procedure, and the one-hot encoder is applied to present a basic conversion process for the categorical data variables. The dimensions of the samples are set on 150 by 150 pixels. The Synthetic Minority Oversampling Technique (SMOTE TOMEK) procedure is subsequently employed to cope with the uneven database issues by over-sampling the categories in order to even out the database. After that, the dataset is segmented into training, testing, and validation parts, each of which has rates of 80%, 10%, and 10%, respectively. Furthermore, the suggested workflow for dental conditions is shown in Figure 4. There were no more than forty epochs employed over the whole duration of the research. The IDD_Net that was proposed fulfilled the degree of accuracy that was estimated over the training phase and the validation phases after it had been assessed for all of the epochs. During the training process for the proposed IDD_Net, we implemented a batch size of 32 and a learning rate of 0.001. A comparison was established between the efficacy of the proposed IDD_Net and that of four well-known CNN baseline classification techniques by applying a variety of metrics, which include AUC, accuracy, precision, recall, F1-score, and loss. The Grad-CAM heat-map approach serves to express the category activated map, which focuses out the properties linked to the classification of the dental photo.

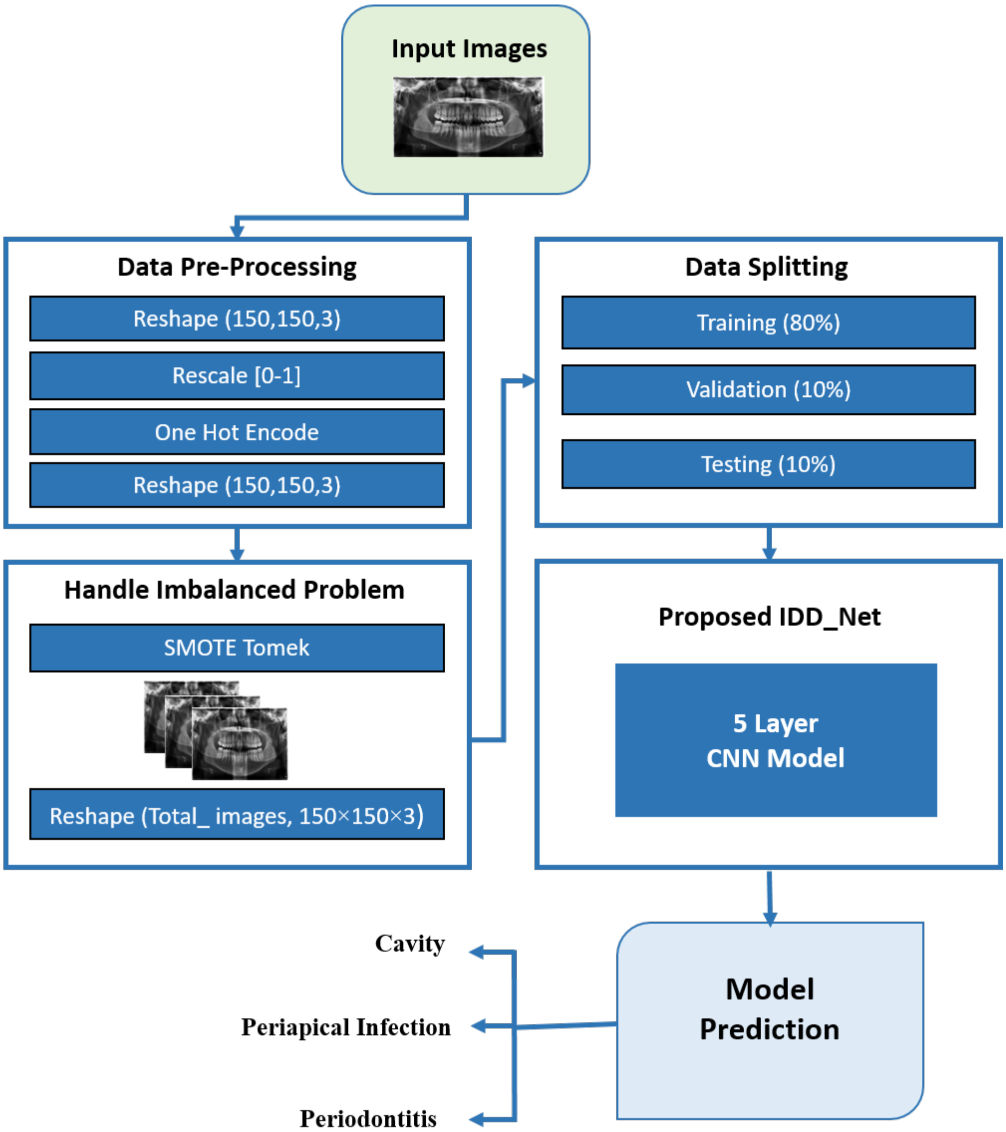


Figure 4. Methodology of the suggested IDD_Net for the detection of dental problems

3.4. Detailed Architecture of the IDD_Net

The design of CNN focuses on the structural biology of the mind of a person and is mostly applied in the areas of computer vision that deal with recognizing images, segmenting images, and determining the identities of objects. Due to the fact that this is translation-invariant, this was selected before the construction of the deep architectures [64]. Because of the invariance or translation, it is necessary for a CNN to be able to locate the same element regardless of where it is located in each of the individual pictures.

This paper describes a CNN architecture that is extremely innovative and is effective at detecting dental diseases. Figure 5 depicts that the suggested IDD_Net is composed of five blocks of convolutional, all of them encompasses an activation function that is Rectified Linear Unit (ReLU) and a MaxPool2D layer, two dense layers, 1 layer of dropout, and a categorization layer of SoftMax. Kernel initializer is also used to assign weights that is known as LecunUniform V2. An outline of the hyper-parameters that possess a vital part in the actual use of the IDD_Net architecture can be found in table 2.

Table 2. An outline of the hyper-parameters that are implemented in the IDD_Net Architecture

Parameter Name	Type
Epochs	40
Activation function of Hidden layer	ReLU
Activation function of Output layer	Softmax

Call back	ReduceLROnPlateau
Optimizer	RMSprop
Learning Rate	0.001
Batch size	32

All convolutional block comprised of a convolutional2D, a ReLU, and a MaxPool2D. The convolutional block is the core structural aspect of the suggested IDD_Net. The kernel initializer is responsible for determining the weights that will be used in the convolutional2D layer. The ReLU is implemented to circumvent the gradient vanishing difficulty, which in turn helps to accelerate the network's capability to gather information and carry out operations. convolutional layer is responsible for initiating the procedure through the use of filters, which are also identified as the kernel. As shown by Equation 1, the size of the kernel is determined by the product of two different values.

$$Filter\ Size(FS) = f_w \times f_h \tag{1}$$

Where the width of the kernal, indicated by f_w, and the height of the kernal, indicated by f_h, are presented. Due to the fact that the dimensions of the kernal was discovered to be 3 in our study, Equation (1) was rewritten as FS = 3 × 3. The convolutional 2D approach concurrently declines both the resolution of the photo as well as its spatial dimensions. This is accomplished by picking the maximum value that can be obtained by an input window for any given input channel. The size of this window is determined by the size of the pool. Asymmetrical work is done by the convolutional layers, and the characteristics are constructed gradually. The earliest layers comprise of the gathering of local patterns such as corners, contours, and arcs, and the ones that follow include of the extraction of local properties according to these patterns. The model reliably extracts high-level characteristics that enables the deep model to effectively recognize a picture by providing it with more information to work.

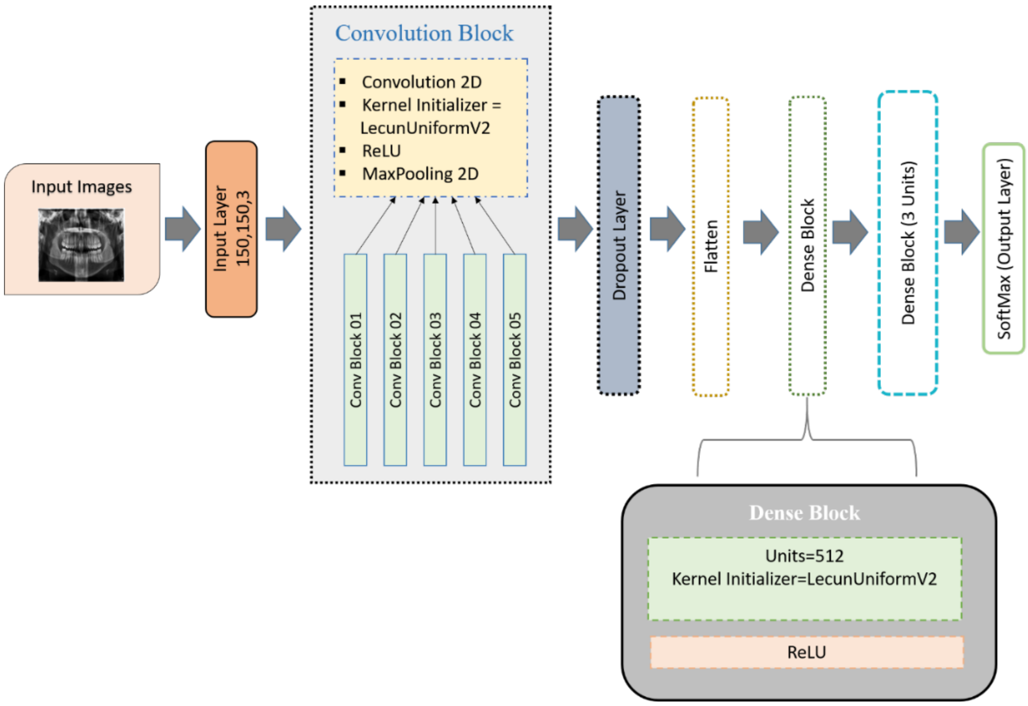


Figure 5. The proposed IDD_Net architecture used for recognizing dental conditions

CNN employs the phrase "dropout" to describe the process of randomly disregarding part of the units in a layer once the architecture is being learned. By ensuring that no two units are reliant on one another, the regularization approach defined as a dropout eliminates the possibility of overfitting occurring. Because of this, the model takes on all of the relevant characteristics and thoroughly combines a broad range of elements with every new iteration. Among the convolution and the dense layers is where resides the flatten layer. The initial data types that are employed by the layers of convolution are tensors, whilst the layers that are dense demand the information to be delivered in a 1D structure. The mapping of features is vectorized due to the flatten layer so that it can be provided to the dense layers. The input data, which typically consist of multiple dimensions, are to be collapsed into one dimension for the purposes of this layer.

In order to decide whether or not the result of a perceptron should be passed on to the subsequent layer, that result is evaluated by means of a sequence of mathematical operations that are collectively referred to as activation functions. In short, their responsibility entails switching off and on units in a deep architecture. In the output layer, the function known as activation serves to start analyzing the node, and then applies its label to the image after it has been analyzed by the architecture. There are multiple activating functions. We relied on ReLU function which were hidden as an outcome of the crucial and effective computation technique. In order for ReLU to be activated properly, every negative result must be changed to zero. This function of activation was implemented to begin operating the network determined by the findings of the convolutional layer.

The dense layer is often known as the FCL. This layer gathers data from a single direction of input at a time and creates outcomes determined by the parameters that were assigned to it. Images can be differentiated from one another and categorized with the help of these layers. The back-propagation strategy is applied to provide assistance with the classifier's understanding, which takes place over layers that are completely interconnected. A model's number of trainable parameters can be estimated by the amount of values implemented within a single dense layer.

After a couple of layers, an approach referred to as SoftMax is put into implementation, and the amount of neurons is scaled up to be equal to the total amount of various classes [65]. The output layer implements the probability-based activation process known as SoftMax because our model was developed with the purpose of classifying a number of different classes. For the classification of a number of different classes, the labels make use of a process known as one-hot encoding, and the loss term only includes the positive type. Table 3 includes an analysis of the detailed outline of the architecture, as well as a model summary of the suggested IDD_Net, which is applied for the diagnosis of dental illnesses. There are a total of 1,149,011 parameters, and these parameters have been split up into two separate sets: there are 1,149,011 trainable parameters, and non-trainable parameter are zero.

Table 3. Model description and parameter list for the proposed IDD_Net

Model Summary		
Layer Name	**Output Shape**	**Params**
Input	(None, 150, 150, 3)	0
Convolution_Block1	(None, 150, 150, 8)	224
Convolution_Block2	(None, 75, 75, 16)	1168
Convolution_Block3	(None, 37, 37, 32)	4640
Convolution_Block4	(None, 18, 18, 64)	18496
Convolution_Block5	(None, 9, 9, 128)	73856
Dropout_Layer	(None, 4, 4, 512)	0
Flatten_Layer	(None, 2048)	0
Dense_Layer1	(None, 512)	1049088
ReLu	(None, 512)	0
Dense_Layer2	(None, 3)	1539
SoftMax (Output Layer)	(None, 3)	0
Total Params		1,149,011
Trainable Params		1,149,011
Non-Trainable Params		0

3.5. DL Classifiers

This section provides an explanation of the four well-known CNN baseline classification techniques that were applied in order to achieve the goal of categorization of dental disease. AlexNet, InceptionResNet-V2, Xception, and MobileNet-V2 are some of the classifiers that are included in this category.

MobileNet-V1 is a convolutional framework that was developed specifically for portable or cost-effective devices; it decreases both expenditures and the size of the systems that it is used in. The MobileNet-V1 model served as the basis for the construction of the MobileNet-V2 model. The MobileNetV2 structure eliminated problems driven on by the irregularities of the MobileNet-V1 design's small layers, that featured development blocks [66]. The MobileNet-V2 model is able to carry out categorizing, the process of segmentation and recognizing objects, and it extends two characteristics to its predecessor. The first potential is that bottlenecks will arise among layers in a sequential manner. The other potential outcome is that methods will be created to circumvent bottlenecks [67].

MobileNet-V2 architecture includes depth-independent filters in along with combined sections. This architecture employs a convolution filter that has a pixel resolution of 1 x 1 for each layer of incoming data that it processes. Depth-wise independent conv filters are those that assess inputs by depth-wise separating the results into two separate stages. This declines both the progress and cost of the architecture. During the combining sections, the properties derived from filter separation are incorporated to produce a new layer [68]. The linearity of the ReLU as well as the Batchnorm were implemented throughout the process of developing the MobilNetV2 architecture.

The architecture known as Inception is merged using residual connections to create Inception-ResNet. Both ResNet and Inception have been essential to the most significant improvements in image recognition efficiency that have been made in the past few years, at an extremely low computational expense. InceptionResNet-v2 is a CNN architecture that consists of 164 layers and has the capacity of categorizing images into 1000 object categories. Batch normalization is only implemented on the highest of the traditional layers in Inception-ResNet; it does not take place during the summations. Various sizes of convolutional filters are paired using residual connections in the InceptionResnet-V2 block. Not only provides the implementation of residual connections eliminate the degradation issue that is associated with deep constructs, it additionally decreases the duration of training [69].

AlexNet model frequently won the ImageNet competition by an extensive margin in 2012, and Alex Krizhevsky and his team proposed this model [70]. The AlexNet comprises 8 layers using achievable parameters. AlexNet is the CNN architecture consisting of 5 convolutional and 3 layers that are fully integrated with each other. Each convolutional layer in the initial two layers of convolution is succeeded by an Overlapping max-pooling layer. The 3rd, 4th and 5th layers of convolution are connected directly. After the 5th layer of convolution is the Overlapping max-pooling layer, which links to the layers in full connection.

Francois Chollet proposes the Xception (Extreme Inception) model, which is a version of the Inception architecture. The main difference between both of them is that the Xception model uses depthwise-separable convolutions instead of typical Inception modules [71]. The Xception model is able to categorize photos into one thousand different object sections due to its pre-trained network. This architecture has an overall of 36 layers of convolution, which serve as the network's primary source for the extraction of elements. The data passes first via the entering flow, then across the middle flow a total of eight times, and lastly by the exit flow to complete the entire process. Batch normalization follows all the layers of Convolution and Separable Convolution.

3.6. Evaluation of the Proposed IDD_Net

In the present study, a confusion matrix was implemented to ensure the usefulness of the model could be evaluated. Before creating the model, the dataset was first partitioned into test samples and training samples. After that, the model was checked for accuracy using the test data. We examined a number of distinct metrics in order to determine the efficacy of the model. The evaluation measures listed below (see Equations (2)–(9)) are often employed for evaluating the efficiency of the suggested IDD_Net for dental disease detection:

3.6.1. Accuracy

Accuracy is often defined as the total quantity of valid predictions that can be produced from accurate forecasts through the utilization of the following expressions:

$$Accuracy = \frac{TP + TF}{TP+FN+FP+TN} \quad (2)$$

In this, TP, FN, TN, and FP correspond to True Positive, False Negative, True Negative, and False Positive, respectively.

3.6.2. Recall

The actual positive rate and sensitivity score are both other names for recall. It is the proportion between the accurate positive forecasts to the exact number of accurate positives. The recall percentage can be calculated by using the following formula

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

3.6.3. Precision

The percentage of the number of real positive estimations to the overall amount of positive estimates is the measure of is referred to by precision, and it is calculated based on the following formula:

$$Precision = \frac{TP}{TP+FP} \quad (4)$$

3.6.4. F1-score

When a classification model's values for both precision and recall are equal to one, the model is considered to be at its "optimal" state. The F1-score is calculated by taking the harmonic average of the recall and precision scores. The F1-score is distinctive in that its graph displays each class mention as a single line. The following equation will tell us how to calculate the F1 score

$$F1 - score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (5)$$

3.6.5. Receiver Operating Characteristics (ROC) Curve

A ROC curve is a graphic representation that is utilized to clarify the probable relationship that is present among sensitivity and specificity for each and every possible threshold for a set of tests.

$$FPR = \frac{FP}{FP + TN} \quad (6)$$

$$TPR = \frac{FP}{FP + FN} \quad (7)$$

3.6.6. Loss Function

The mathematical distinction that exists between the value that was anticipated and the value that actually occurred is the basis for loss functions computation.

$$Loss = y - \overline{y} \quad (8)$$

$$L_{CE} = -\sum_{n=1}^{k} (L_i \ \log(p_i)) \quad (9)$$

4. Results and Discussion

In the remaining section, we contrast the suggested model with the most earlier classifiers produced. In this section, we will describe the distinctions among the model that is suggested and four well-known deeper classifiers.

4.1. Experimental System

Research experiments were conducted out by employing a personal computer that had been installed with an NVIDIA GPU that was 11 GB in size and had a total of 32 GB of RAM. The model was validated deploying the test set that was produced by splitting the database prior to the initial execution of the model. Multiple distinct measurements can be employed to produce a reliable assessment of a model's performance from all relevant perspective points. In addition, Python language has enabled the implementation of techniques and the keras library has been utilized to carry out a total of six different classifiers. These six classifiers comprise four baseline classifiers, the suggested model without using up-sampling, and the suggested strategy using up-sampling.

The optimization strategy known as RMSprop is applied throughout the procedure of training [72]. This strategy is based on gradients and seeks to improve performance. The concept of back-propagation was firstly invented by Geoffrey Hinton, who has been referred to as the "father" of back-propagation. Gradients of incredibly complex functions, like neural networks, have a disposition to either vanish entirely or grow as input data passes over the challenging function. This algorithm for stochastic learning was designed particularly to be employed via mini-batch input. It normalizes the gradient by determining the standard variation in squared gradients and using that value to solve the issue that was mentioned above. The total amount of repetitions that are performed when the weights are being raised throughout the training phase is referred to as the "Learning Rate" [73]. To put it more simply, the learning rate is a hyperparameter that can be adjusted and used during the process of training a neural network [83]. It has an extremely tiny value that is positive and usually lies among 0.0 and 1.0.

4.2. Assessment with Other Classification Methods Using Accuracy

The term "accuracy" refers to a metric that establishes the consistency at which the classifier creates reliable estimations. In the basic terms, it shows the complete accuracy of the representation. Through the use of the private dataset, we verified our suggested model using up-sampling and without up-sampling through SMOTE Tomek and four baseline classification methods, which involves AlexNet, InceptionResNet-V2, MobileNet-V2, and Xception.

According to the results presented in Table 4, the proposed IDD_Net via up-sampling, the IDD_Net without up-sampling, AlexNet, InceptionResNet-V2, MobileNet-V2, and Xception all gained accuracies of 98.99%, 79.69%, 87.22%, 91.73%, 81.20%, and 90.20% respectively. Figure 6 exhibits the enhanced efficiency that obtained by employing SMOTE Tomek utilizing the proposed IDD_Net model.

Table 4. The outcomes of the suggested IDD_Net and the baseline classification techniques.

Classifiers	Accuracy	Loss
AlexNet	87.22%	0.4558
InceptionResNet-V2	91.73%	0.2533
MobileNet-V2	81.20%	0.5818
Xception	90.20%	0.3021
Proposed IDD_Net using up-sampling	98.99%	0.2327
Proposed IDD_Net without up-sampling	79.69%	0.4965

4.3. Loss of Proposed IDD_Net with Other Classification Methods

Loss functions are created to compute the amount of computation that is necessary to distinguish between the value that was estimated and the real value. In order to compute the amount of loss that occurred as a result of our research, we decided to implement a categorical cross-entropy technique. Cross entropy loss is the metric employed by DL to determine the performance of a model used for classification. The phrase "categorical cross-entropy" describes a method of cross-entropy because a function of loss for the purpose of solving a categorization problem involving more than one class. In order to perform optimization functions, backtracking procedures are utilized. The biases and weights of the different layers are modified by these procedures so that they are in accordance with the loss value. The results, on the other hand, are considerably more affecting when the system is trained implementing the SMOTE Tomek approach.

According to the Figure 7, the proposed IDD_Net via up-sampling, the IDD_Net without up-sampling, AlexNet, InceptionResNet-V2, MobileNet-V2, and Xception all gained loss values of 0.2327, 0.4965, 0.4558, 0.2533, 0.5818, 0.3021 respectively. Figure 7 depicts this significant reduction in the loss of the suggested IDD_Net via the up-sampling approach.

4.4. Analysis of IDD_Net to Other Classification Methods Using AUC

The AUC operates independently of both the threshold and the scale used to classify the data. AUC (area under the curve) is the level or assessment of division. The capacity of a model to distinguish between multiple categories is quantified by the AUC. As previously stated earlier than in this research, the design that was suggested is a deep CNN structure that is made up of a variety of distinct blocks. This model performs quite well in terms of its effectiveness when it comes to identifying the three types of dental disease. In order to illustrate the efficacy of the proposed IDD_Net, we analyzed its results to those of four classification algorithms that serve as a baseline. The AUC values of the four baseline classification techniques, such as AlexNet, InceptionResNet-V2, MobileNet-V2, and Xception were successively 96.48%, 97.78%, 92.90%, 97.87%. According to Table 5, the suggested IDD_Net using up-sampling gained an AUC of 99.97%, whereas the suggested IDD_Net without up-sampling acquired an AUC of 93.55%. After analyzing the results of the previous evaluation, we've reached the conclusion that the AUC values produced through the proposed IDD_Net are better to those created by various other models.

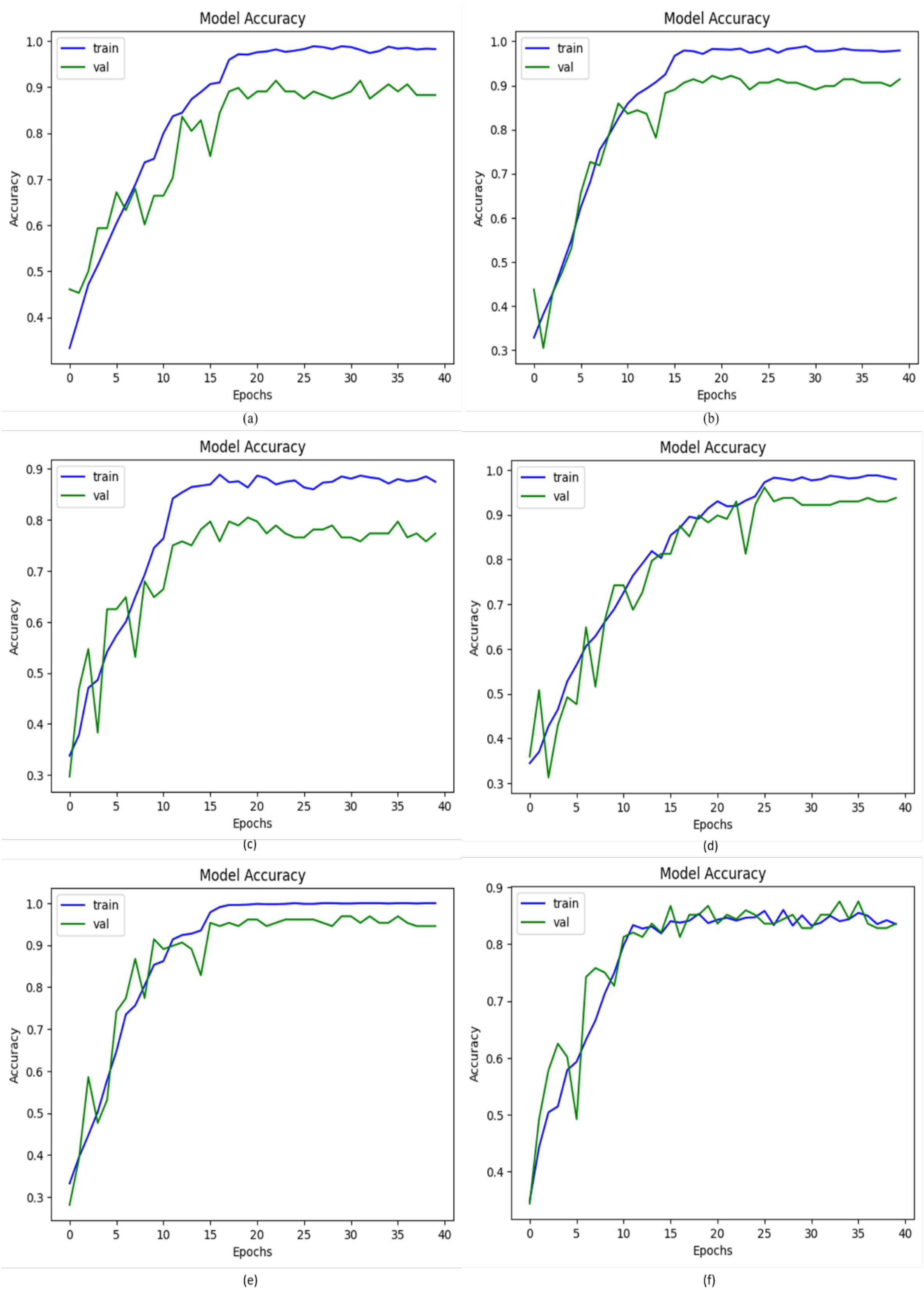


Figure 6. Accuracy improvement of the proposed IDD_Net with four baseline classification methods; (a) AlexNet, (b) InceptionResNet-V2, (c) MobileNet-V2, (d) Xception, (e) Suggested IDD_Net using up-sampling, and (h) Suggested IDD_Net without up-sampling

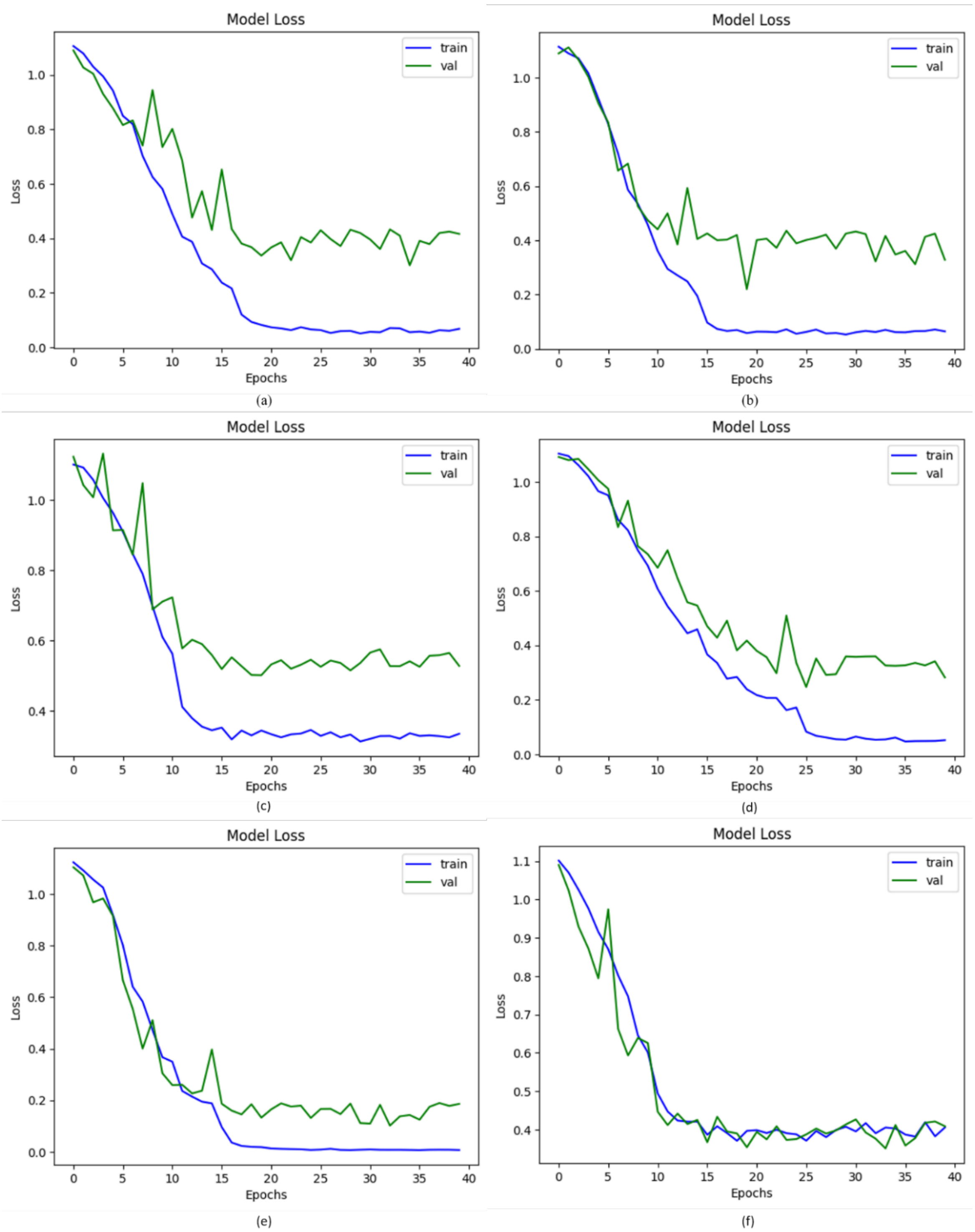


Figure 7. Loss values of the proposed IDD_Net with four baseline classification methods; (a) AlexNet, (b) InceptionResNet-V2, (c) MobileNet-V2, (d) Xception, (e) Suggested IDD_Net using up-sampling, and (h) Suggested IDD_Net without up-sampling

4.5. Evaluation of IDD_Net to Other Classification Methods Using Precision

The concept of "precision" describes the degree of exact positive estimation in contrast to the entire amount of positive assessments. As was clarified prior in the present research, the model that we propose is a CNN-based IDD_Net that is composed of independent blocks. When it comes to determining the various dental disease classifications, this model performs really well due to its efficiency. On the private dataset, we tested both our suggested and existing classifiers, such as AlexNet, InceptionResNet-V2, MobileNet-V2, and Xception. Additionally, we made use of SMOTE Tomek to verify that the dataset had been separated in an even manner.

According to Table 5, the suggested IDD_Net using up-sampling gained a precision of 98.99% whereas the suggested IDD_Net without up-sampling acquired a precision of 84.55%. The precision values of the four baseline classification techniques, such as AlexNet, InceptionResNet-V2, MobileNet-V2, and Xception were successively 88.55%, 91.72%, 82.03%, and 90.15%. Table 5 exhibits the enhanced efficiency that obtained by employing SMOTE Tomek utilizing the proposed IDD_Net model.

Table 5. The F1-score, precision, AUC, and recall of the proposed IDD_Net

Classifiers	F1-score	Precision	AUC	Recall
AlexNet	86.71%	88.55%	96.48%	87.22%
InceptionResNet-V2	91.28%	91.72%	97.78%	91.73%
MobileNet-V2	80.99%	82.03%	92.90%	78.95%
Xception	89.59%	90.15%	97.87%	89.47%
Proposed IDD_Net using up-sampling	98.97%	98.99%	99.97%	98.24%
Proposed IDD_Net without up-sampling	78.85%	84.55%	93.55%	78.19%

4.6. Assessment of the Proposed IDD_Net Using Recall

The actual positive rate and sensitivity score are both other names for recall. It is the proportion between the accurate positive forecasts to the exact number of accurate positives. High recall values suggest that a higher proportion of positive samples were identified. As can be seen in Table5, the proposed IDD_Net is assessed by comparing it to already existing classifiers by means of a recall curve. These classifiers include AlexNet, InceptionResNet-V2, MobileNet-V2, and Xception.

The suggested IDD_Net using up-sampling gained a recall of 98.24%, whereas the suggested IDD_Net without up-sampling acquired a recall of 78.19%. The Recall values of the four baseline classification techniques, such as AlexNet, InceptionResNet-V2, MobileNet-V2, and Xception were successively 87.22%, 91.73%, 78.95%, and 89.47%. After analyzing the results of the previous evaluation, we've reached the conclusion that the recall values produced through the proposed IDD_Net are better to those created by various other baseline models.

4.7. Analysis with Other Classification Methods Using F1-score

In order to determine the F1-score, the harmonic average of the precision score and the recall score is utilized. When a classification model's values for both precision and recall are equal to one, the model is considered to be at its "optimal" state. The F1-score is distinctive in that its graph displays each class mention as a single line. In this suggested approach, the initial data are preprocessed by employing the normalization procedure, and the one-hot encoder is applied to present a basic conversion process for the categorical data variables.

The F1-score values of the four baseline classification techniques, such as AlexNet, InceptionResNet-V2, MobileNet-V2, and Xception were successively 86.71%, 91.28%, 80.99%, and 89.59%. According to Table 5, the suggested IDD_Net using up-sampling gained a f1-score of 98.97% whereas the suggested IDD_Net without up-sampling acquired a f1-score of 78.85%. After analyzing the results of the previous evaluation, we've reached the conclusion that the f1-score values produced through the proposed IDD_Net are better to those created by various other models.

4.8. Evaluation of Proposed IDD_Net Using ROC & Extension of ROC

In order to illustrate the efficacy of the proposed IDD_Net, we analyzed its results to those of four classification algorithms that serve as a baseline. The ROC values of the four baseline classification techniques, such as AlexNet, InceptionResNet-V2, MobileNet-V2, and Xception were successively 0.9584, 0.79680, 0.8813, 0.9654. According to Figure 8, the suggested IDD_Net using up-sampling gained an ROC value of 0.9840%, whereas the suggested IDD_Net before up-sampling acquired an ROC value of 0.9215%. Figure 8 illustrates the improved efficiency that was accomplished by implementing SMOTE Tomek when used with the suggested IDD_Net model.

On the basis of the even and uneven dental dataset, the suggested IDD_Net has been tested by the Extension of the ROC curve to contrast with AlexNet, InceptionResNet-V2, MobileNet-V2, and Xception. The results of this evaluation are shown in Figure 9.

4.9. Confusion Matrix of IDD_Net with Other Classification Methods

Evaluating and generating various categorizing model measurements can both be done with the use of a confusion matrix. Figure 10 is a representation of the significant modifications that were made to the suggested IDD_Net as an immediate consequence of utilizing up-sampling technique.

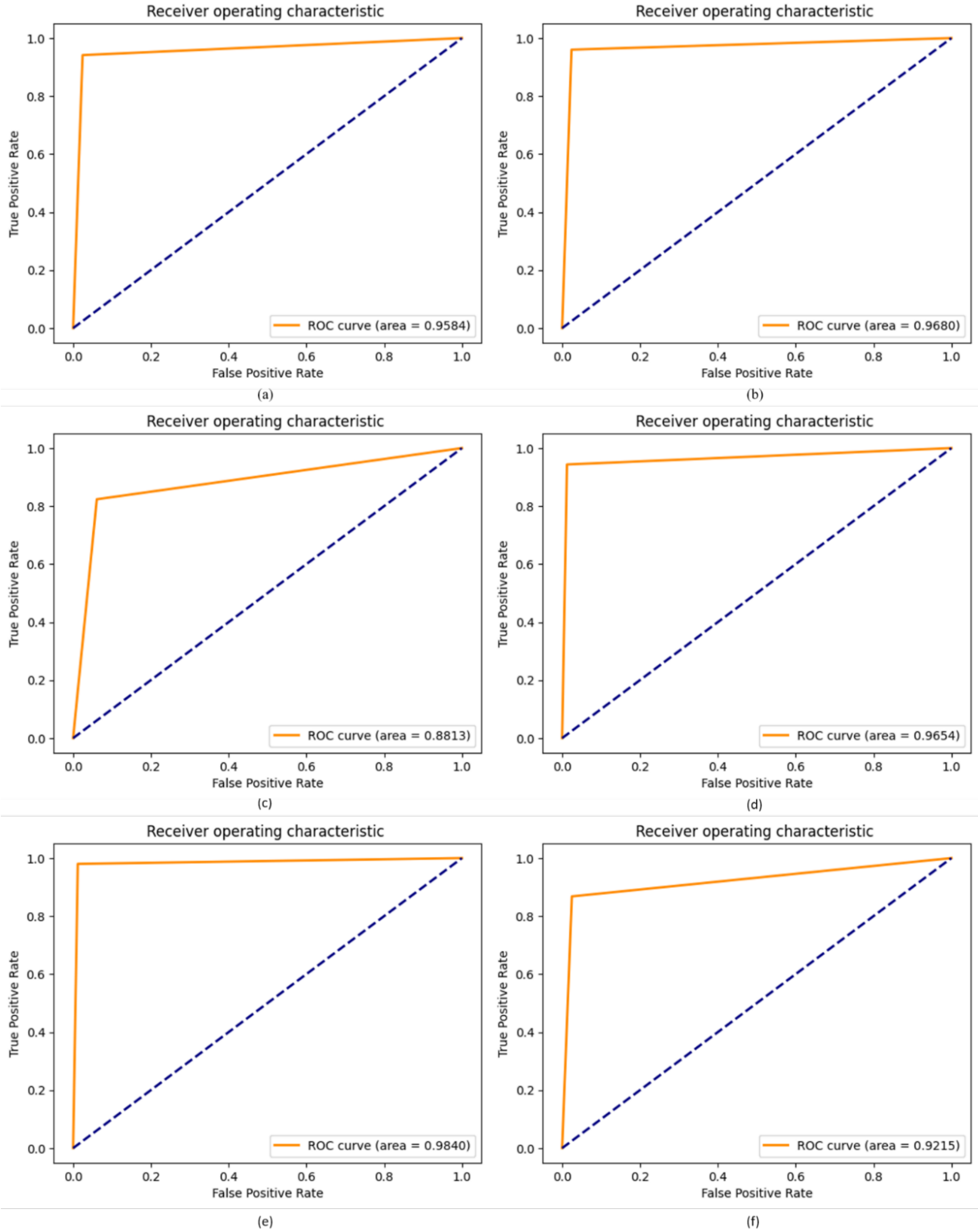


Figure 8. ROC values of the proposed IDD_Net with four baseline classification methods; (a) AlexNet, (b) InceptionResNet-V2, (c) MobileNet-V2, (d) Xception, (e) Suggested IDD_Net using up-sampling, and (h) Suggested IDD_Net without up-sampling

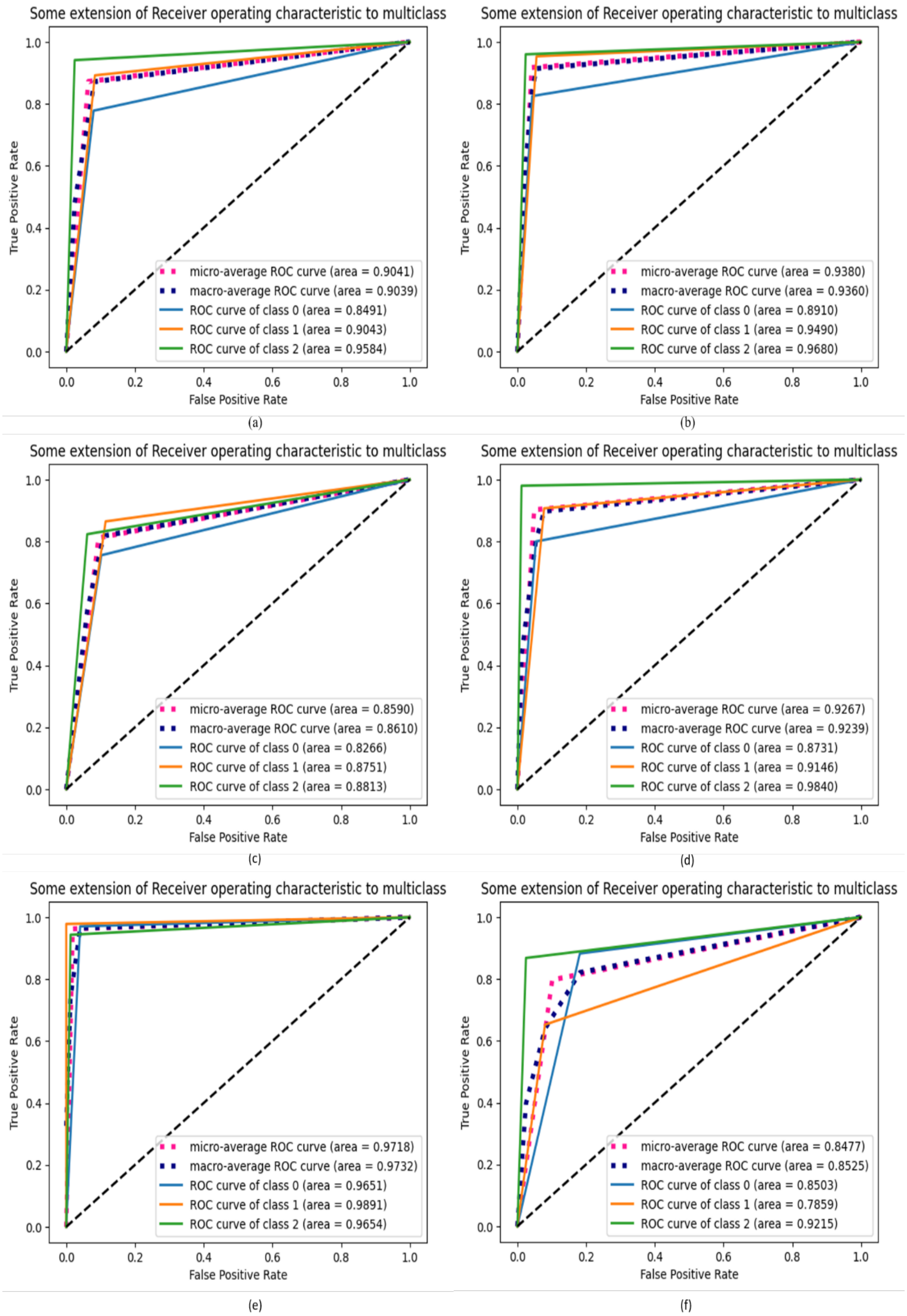
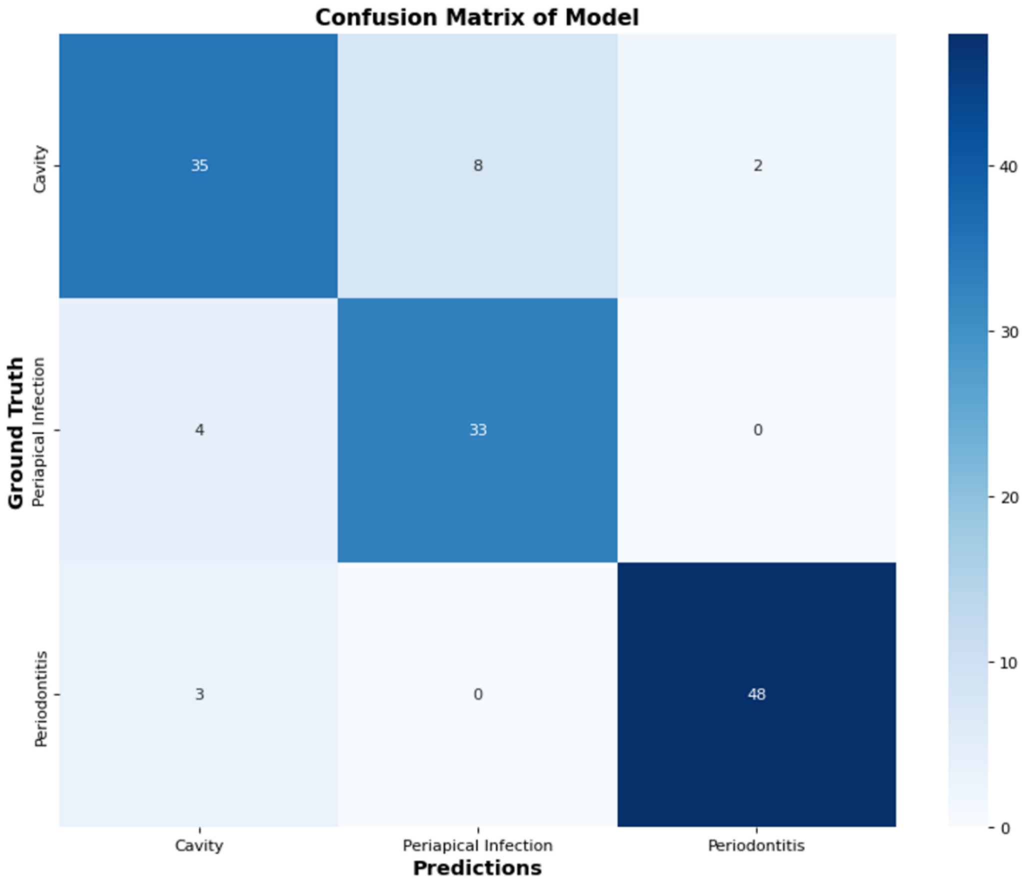
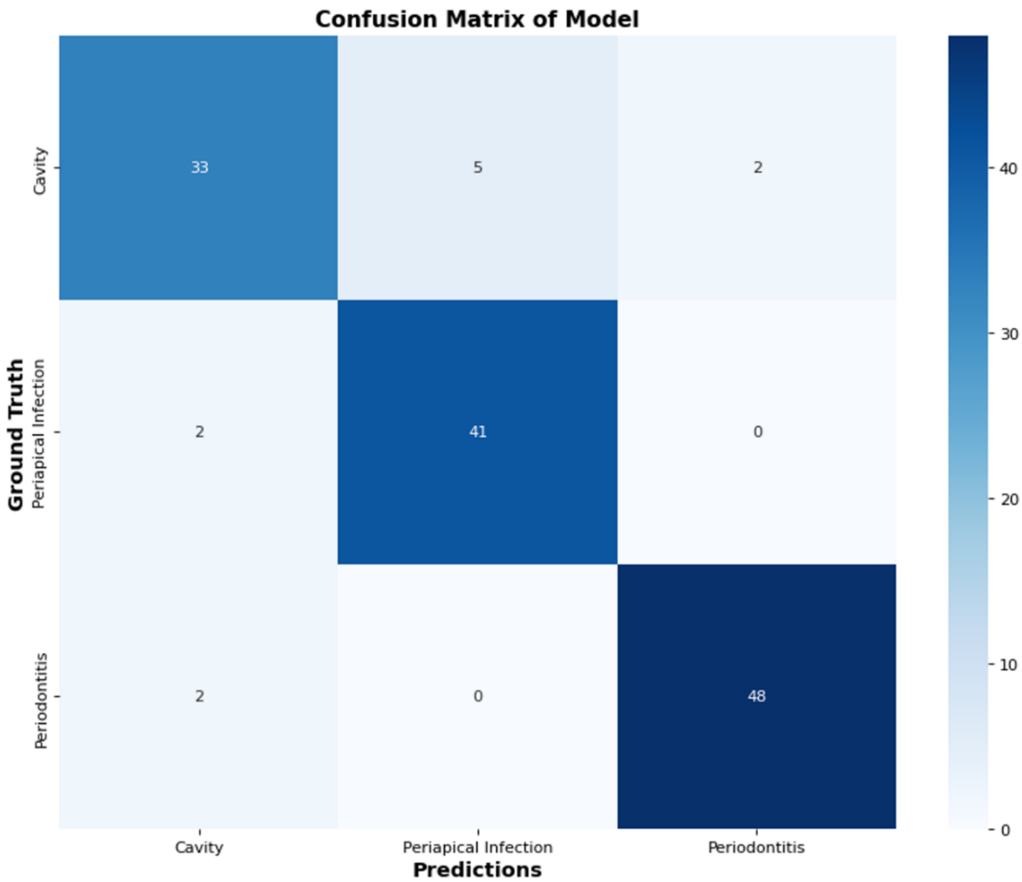


Figure 9. ROC extension of the proposed IDD_Net with four baseline classification methods; (a) AlexNet, (b) InceptionResNet-V2, (c) MobileNet-V2, (d) Xception, (e) Suggested IDD_Net using up-sampling, and (h) Suggested IDD_Net without up-sampling


Confusion Matrix of Model
Ground Truth
Cavity
Periapical Infection
Periodontitis
35
8
2
4
33
0
3
0
48
Predictions
Cavity
Periapical Infection
Periodontitis
40
30
20
10
0

(a)


Confusion Matrix of Model
Ground Truth
Cavity
Periapical Infection
Periodontitis
33
5
2
2
41
0
2
0
48
Predictions
Cavity
Periapical Infection
Periodontitis
40
30
20
10
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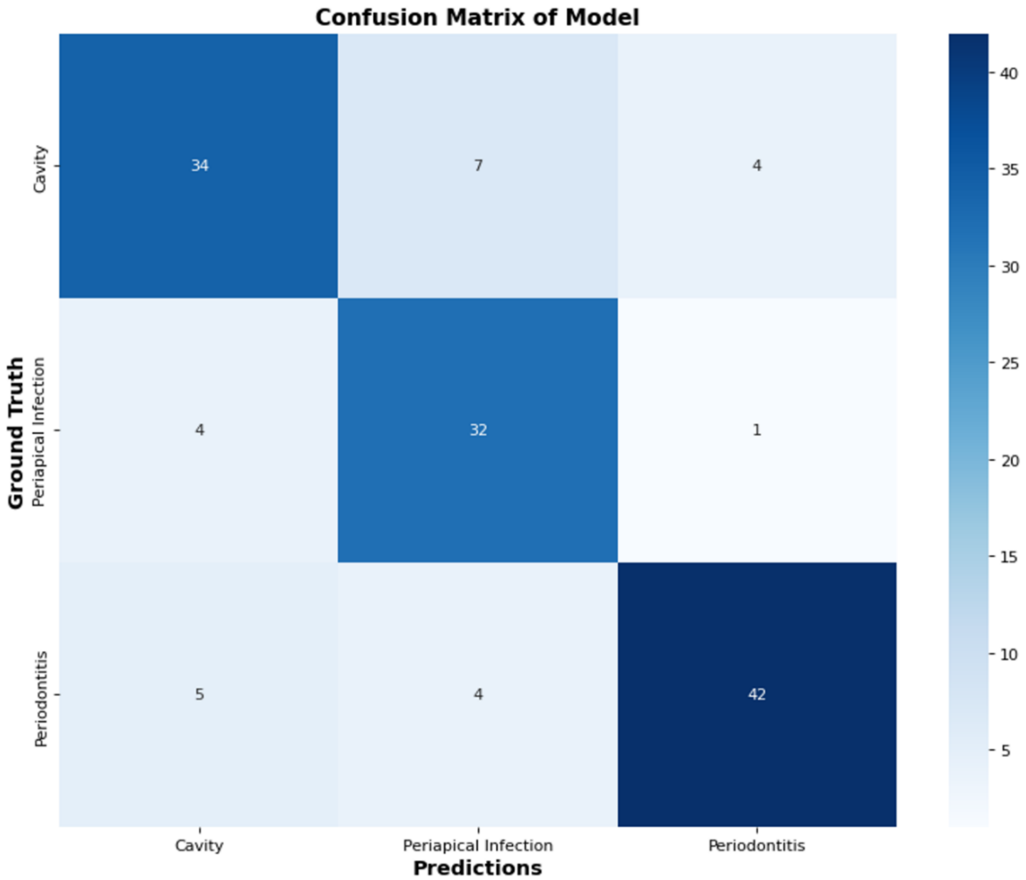
(b)


Confusion Matrix of Model
Ground Truth
Predictions
Cavity
Periapical Infection
Periodontitis
34
7
4
4
32
1
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42
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35
30
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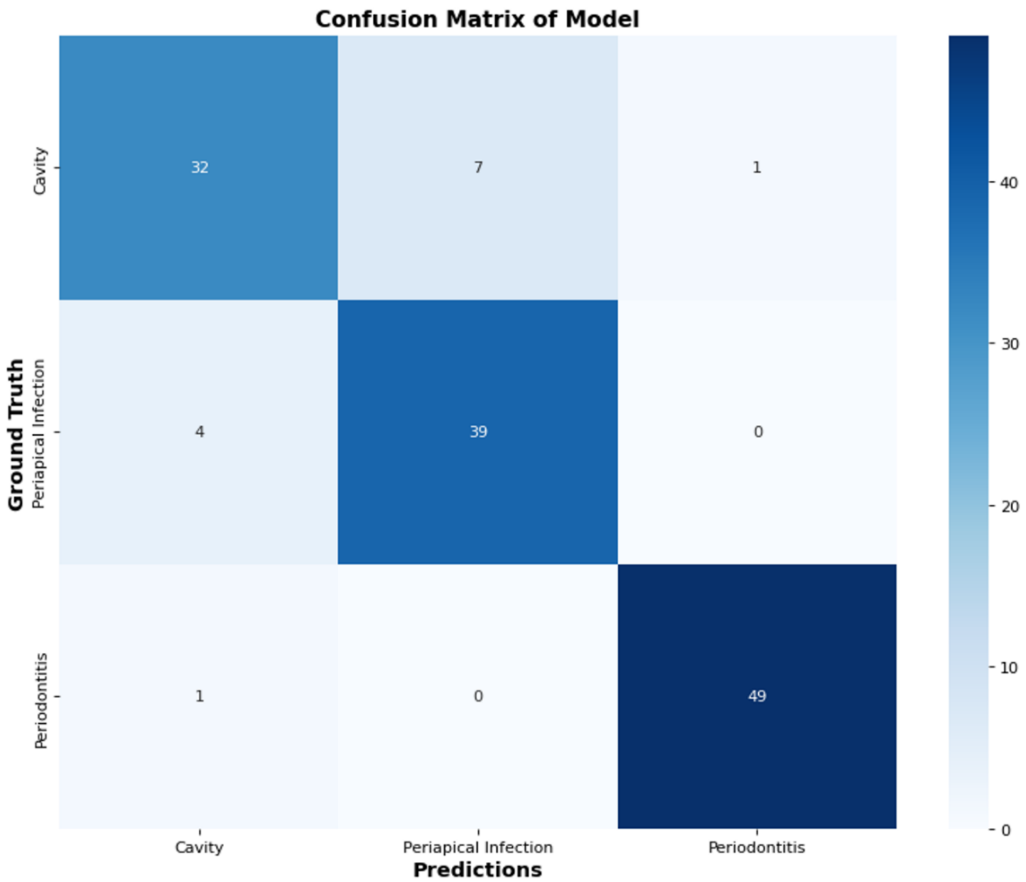
15
10
5

(c)


Confusion Matrix of Model
Ground Truth
Predictions
Cavity
Periapical Infection
Periodontitis
32
7
1
4
39
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(d)

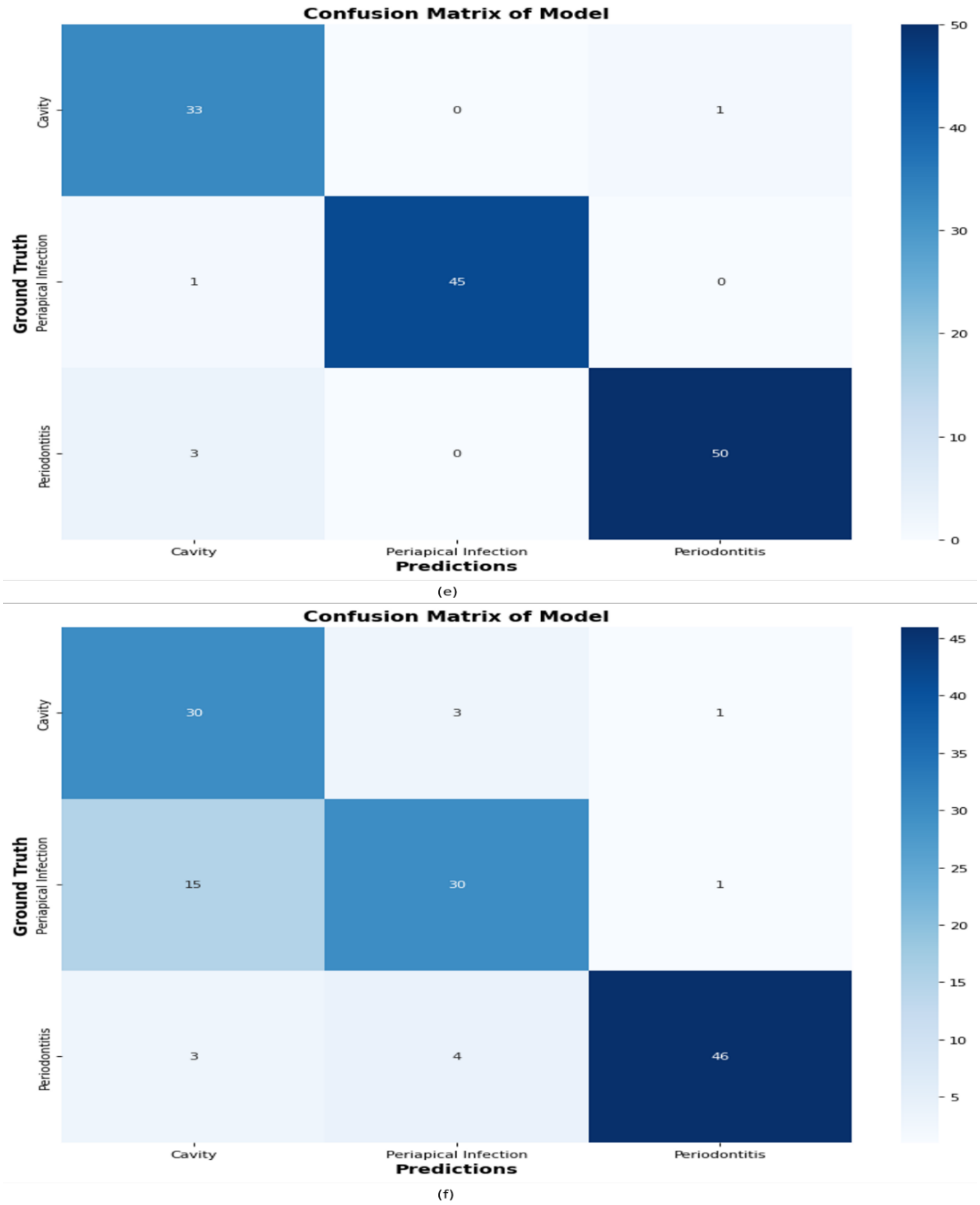

Figure 10. Confusion Matrix of the proposed IDD_Net; (a) AlexNet, (b) InceptionResNet-V2, (c) MobileNet-V2, (d) Xception, (e) Suggested IDD_Net using up-sampling, and (h) Suggested IDD_Net without up-sampling

The proposed IDD_Net correctly recognizes 33 out of 34 images in the cases of cavity, while wrongly identifying a single photo as periodontitis. In the categorization of periapical infections, with a total of 46 images, 45 were correctly identified as periapical infections, whereas a single picture had been misidentified as a cavity [79]. Figure 10 demonstrates that during the periodontitis categorization procedure, 50 of the total of 53 images had been properly categorized, while 3 images were incorrectly labeled as cavities. In addition, we implemented the Grad-CAM heat-map strategy that gives a visual illustration of the findings derived from our suggested IDD_Net. The primary goal of the heat-map is to explain the section of the mouth that is significant to the classification process. The heat map for the IDD_Net model can be found depicted in Figure 11.

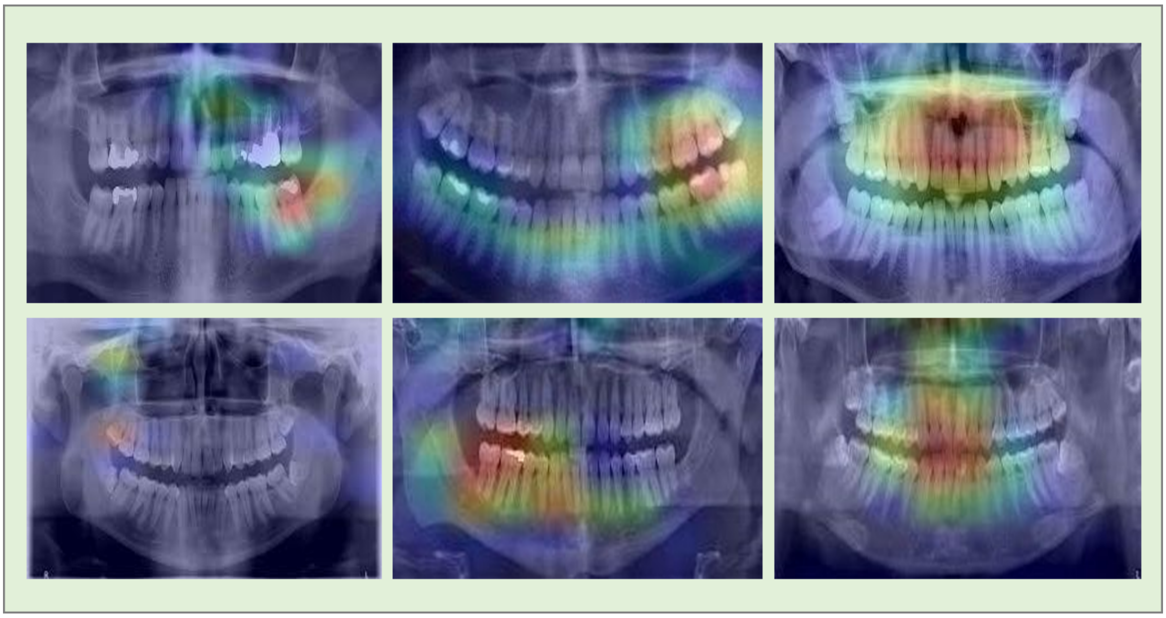

Figure 11. Evaluation of the suggested IDD_Net for dental problems by applying Grad-CAM

4.10. Analysis of the Suggested IDD_Net Using SOTA

In this part, we analyze our suggested IDD_Net approach to recent prior research [53, 54,40,43,74,75,52]. In addition, the suggested approach correlates directly with the outcomes of these studies [53,61,49,52,62,60,83,84]. Table 8 examines the findings of the suggested IDD_Net model's evaluation criteria to the most recent research that represents the SOTA in this field, including measures such as precision, recall, and F1-score.

Table 6. Compared the proposed IDD_Net using SOTA.

Ref	Year	Model	Diagnostic Technique	Accuracy	Precision	F1-score	Recall
[53]	2023	Mask R-CNN	Panoramic Radiographs	92.49%	96.08%	95.87%	95.65%
[54]	2022	YOLO-v4 & UNet	Panoramic Radiographs	77%	77%	77%	77%
[43]	2023	CNN	Panoramic Radiographs	86.05%	-	-	90.52%
[40]	2023	EfficientNet-B0, DenseNet-121, ResNet-50	Panoramic Radiographs	92%	-	91.61%	87.33%
[74]	2021	Mask R-CNN	Panoramic Radiographs	96%	-	-	-
[75]	2020	CNN	Panoramic Radiographs	89%	98%	93%	91%
[52]	2021	CNN	Panoramic Radiographs	93.2%	-	-	96.4%
Ours	-	Suggested IDD_Net using SMOTE Tomek	Panoramic Radiographs	98.99%	98.99%	98.97%	98.24%

5. Discussion

Dental informatics is an emerging field of research inside dentistry that attempts to reduce complexity and enhance the methods for diagnosis that are employed in the dental profession, minimize the duration of time that patients spend in treatment, and lessen the level of anxiety that patients suffer on every single day [5]. It is predicted that dental disorders will affect almost fifty percent of the world's population, with 2.3 billion people dealing with chronic dental caries infection alone [4]. The dental structure of an individual's tooth can be classified into two fundamental parts: the crown, which is the portion of the tooth that is shown to the naked eye, and the root, which is the portion of the tooth that is not seen but resides inside the mouth.

By applying panoramic x-ray images, Suryani et al. [74] designed the Mask R-CNN for recognizing the dental condition. Visual Object Tagging Tool (VoTT), which is accessible for freely on the internet, was employed to annotate the data utilized by their study. The training part includes 110 images and the evaluation part includes six images. One of the classes was assigned with providing an explanation of the restoration. In the panoramic image of the jaw, the results of object detection reveal degrees of assurance that vary from 0.91 to 0.96. Muresan et al. [75] created a CNN approach for performing automatic dental recognition and oral illness categorization. This system utilized panoramic X-rays as its primary imaging modality. This approach may help healthcare providers in determining the correct diagnosis. A CNN was built by making use [77] of the data that had been annotated for the goal of acquiring information that was connected to segmentation. After this, a series of processing steps for images were executed to segment and then to refine the dental detection bounding boxes. In the final stages, each dental case acquired a designation, and the issue affecting it was identified using a histogram-based largest amount system of voting within the identified region of interest. The overall performance of the tooth detection was determined to be 89%, 98%, 93%, and 91%, respectively, when using the accuracy, precision, f1-score, and recall criteria for assessment.

Dental disorders (cavities, periodontitis, and periapical infections) usually cause patients to have discomfort in the teeth as well as the absence of teeth, both of which can result in significant difficulties for the patients [13]. The development of dental caries, sometimes referred to as a "cavity," is triggered by the disintegration of pulp and enamel carried on by the presence of lactic acid in the mouth. In addition to the symptoms of cavities are foul breath or an unpleasant taste in the mouth, tooth enamel that bleed rapidly, and other signs of gum disease, a facial enlargement, oral discomfort in the mouth, or molars that are susceptible to cold or warm foods or liquids. Periodontitis is a chronic gum disease and it is another name for gum disease, is an advanced infection of the gums that consumes away at the fragile connective tissues that wrap around the teeth. Using the DL techniques, multiple groups of researchers have been able to produce remarkable outcomes. As stated in Figure 3, SMOTETOMEK effectively resolves the dataset inequality issue by balancing the instances of every category.

As a results presented in Table 4, the proposed IDD_Net via up-sampling, the IDD_Net with no up-sampling, AlexNet, InceptionResNet-V2, MobileNet-V2, and Xception all gained accuracies of 98.99%, 79.69%, 87.22%, 91.73%, 81.20%, and 90.20% respectively. Table 8 examines the findings of the suggested IDD_Net model's evaluation criteria to the most recent research that represents the SOTA. Figure 6 exhibits the enhanced efficiency that obtained by employing SMOTE Tomek utilizing the proposed IDD_Net model.

6. Conclusion

Dental Cavities is the most prominent problem affecting people nowadays, and it has a significant negative influence on their usual way lifestyles and medical care. Because of a huge amount of cases, an immediate and efficient testing technique is required. This paper presents an approach for the categorization of dental diseases using X-ray images. Radiography of the teeth can be helpful in the diagnostic process, treatment, and quality assurance in the medical field. The present research introduces an IDD_Net that can perform multi-categorization of dental disease. In this study, the X-ray images have been separated down into three categories: cavities, periodontitis, and periapical infections. In order to produce samples, the SMOTE Tomek approach was applied, and these samples were employed to resolve database imbalance conflicts and maintain a balance in the total amount of instances for each of the categories. The results of our suggested IDD_Net model showed an accuracy of 98.99%, precision of 98.99%, AUC of 99.97%, f1-score of 98.97%, and recall of 98.24%. In addition, CNN-based baseline classification techniques such as AlexNet, InceptionResNet-V2, MobileNet-V2, and Xception achieved accuracies of 87.22%, 91.73%, 81.20%, and 90.20%, respectively. The findings showed that our proposed IDD_Net model much better than four baseline approaches. As a result, it has been determined that the IDD_Net that has been presented is capable of playing a crucial part in assisting medical professionals.

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