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REVOLUTIONIZING DENTAL DIAGNOSIS: A CUTTING-EDGE DEEP LEARNING APPROACH FOR DISEASE CLASSIFICATION

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Abstract
Dental problems now affect a sizable section of the population and are a common global health problem. It is essential to get an early and precise diagnosis of dental disorders in order to treat them effectively and avoid subsequent consequences. Deep learning algorithms have recently demonstrated astounding effectiveness in a variety of health imaging claims. Through the use of dental radiographs, this study intends to investigate the potential of deep learning for the classification of dental illnesses.
A dataset with a variety of dental radiographs was gathered, including both healthy teeth and those with effected dental. Utilizing dental radiographs as a source, convolutional neural networks (CNNs) were used to extract distinguishing features. To assess how well different CNN architectures performed in classifying dental diseases, popular models like VGGNet19, ResNet50, and DenseNet169 were used.
The outcomes showed that deep learning models were effective at classifying dental diseases. The top-performing model outperformed on conventional machine learning methods and had a classification accuracy of over 99.90%. The models were effective at distinguishing between various dental disorders, such as Healthy and effected teeth. The models also demonstrated good specificity and sensitivity, recall, precision, f1score and training testing accuracy highlighting their potential as trustworthy diagnostic tools.

Keywords: Deep Learning, Dental Disease, Tooth Decay, Disease Detection, Computer Vision

Introduction
Dental disease states to a range of conditions that affect the teeth, gums, and surrounding structures in the oral cavity. These diseases can vary in severity and encompass various issues, including different dental caries, periodontal diseases/gum diseases, dental anomalies/structural abnormalities, oral infections, and oral cancer [1]. The effects of dental diseases can have significant consequences

on an individual's oral strength and complete health. Some common effects of dental diseases include, Tooth Loss: Dental diseases, particularly advanced tooth decay and severe periodontal diseases, can lead to tooth loss. This not only affects a person's ability to chew food properly but also impacts speech and aesthetics. Pain and Discomfort: Dental diseases can cause pain and discomfort, ranging from toothaches and gum sensitivity to persistent oral pain. This can meaningfully impact an entity's quality of life, heartwarming their skill to eat, speak, and carry out daily activities comfortably. Infections: Untreated dental diseases can result in oral infections. These infections can feast to other portions of the physique, leading to more serious health complications. For example, periodontal diseases have remained related to an improved risk of cardiac disease, respiratory infections, and preterm birth in pregnant women. Impaired Nutrition: Dental diseases, especially when associated with tooth loss, can affect an individual's capability to eat a balanced food. Difficulty in chewing or avoiding certain foods due to oral pain or missing teeth can result in nutritional deficiencies and related health issues [2].

Psychological and Social Impact: Dental diseases can impact an individual's self-esteem and social interactions. Visible signs of dental disease, such as tooth decay, missing teeth, or bad breath, can lead to embarrassment, self-consciousness, and social isolation. Systemic Health Concerns: Research has established links between oral health and overall systemic health. Poor oral hygiene and untreated dental diseases have been related with an improved risk of universal conditions such as cardiac disease, diabetes, breathing infections, and hostile pregnancy outcomes. Financial Burden: The treatment of dental diseases can often require extensive dental procedures, including fillings, root canals, extractions, and periodontal treatments [3]. The costs associated with dental treatments can impose a financial burden on individuals and their families, particularly in cases where dental insurance coverage is limited or unavailable. Given the significant impact of dental diseases on oral health, overall well-being, and systemic health, preventive measures, regular dental check-ups, and early interference are crucial in upholding optimal oral fitness and preventing the headway of dental illnesses.

“Dental diseases, such as dental caries, periodontal diseases, and dental anomalies, are a significant global health concern affecting a large portion of the population. Timely and accurate diagnosis of these diseases is crucial for effective treatment and prevention of further complications. Recent advancements in deep learning techniques have” demonstrated remarkable success in various medical imaging applications. Study aims to discover the possible of DL for the grouping of dental diseases using dental radiographs, providing a detailed analysis of the methodology and results. To create a comprehensive dataset, a large number of dental radiographs were collected, encompassing various types of dental diseases as well as healthy teeth. Convolutional neural network (CNN), a type of DL model, were employed to learn discriminative features from the dental radiographs. Multiple CNN architectures, including popular models such as VGGNet19, ResNet50, and DenseNet169, were implemented to evaluate their performance in dental disease classification. To ensure robust evaluation, the dataset stayed divided “into training, validation, and testing sets”. Augmentation techniques were extensively applied to rise the variety and generalizability of the training dataset. The models were trained using a large number of epochs and various hyperparameters were optimized through systematic experimentation.

Results of the learning demonstrated the efficacy of DL models in dental disease classification. The best-performing model achieved a classification accuracy more than the previous studies that surpassing the performance of traditional ML algorithms. The models successfully differentiated between different types of dental diseases, accurately identifying cases of caries, periodontal diseases, and dental anomalies. Additionally, the models exhibited high sensitivity and specificity, indicating their potential as reliable diagnostic tools for dental practitioners. The study provides valuable visions into the potential of deep learning for dental illness classification, offering a promising avenue for the expansion of computer-aided analysis systems in dental healthcare. The proposed models have the potential to automate the process of dental disease diagnosis, assisting dentists in making accurate and timely decisions. Future research can focus on further refining the models by exploring more advanced deep learning architectures and techniques, expanding the dataset to encompass a wider range of dental diseases and patient demographics, and considering the integration of these models into clinical practice to enhance dental healthcare outcomes. The successful implementation of deep learning in dental disease classification has the possible to suggestively improve the competence and effectiveness of dental analysis and handling [4]. The models also demonstrated good specificity and sensitivity, recall, precision, f1score and training testing accuracy highlighting their potential as trustworthy diagnostic tools.

LITERATURE REVIEW / RELATED WORKS

The literature has employed a variety of terms to denote the different stages of dental caries. This multifactorial illness is branded by a limited and dynamic decay of the tooth's organic parts and the subsequent degradation of its natural part. AI technology is utilized in dentistry to give information that helps clinical decision-making rapidly and efficiently from large data sets. In order to improve oral healthcare outcomes and support dental doctors in making correct diagnoses and handling plans, it is essential that dental illnesses be classified. Traditional methods for classifying dental diseases frequently rely on subjective manual examination and visual interpretation, which can take a lot of time [1, 2]. DL algorithms have recently transformed medical image processing, opening up exciting new paths for the quick and accurate detection of dental problems. This study of the literature intends to investigate the current DL algorithms for classifying dental diseases [3]. This study aims to provide insights into the accomplishments, limitations, and potential future directions in employing deep learning for precise dental disease categorization by reviewing the existing studies, methodology, datasets, and performance measures [4, 5].

Yassir Edrees Almalki et al. [6] conduct a study to classify the dental images based on Orthopantomography X-ray OPG. In this study they explain that the human body's teeth present the greatest technical challenges. The difficulty of the experience procedure, low efficiency, and advanced level of operator involvement are the defining characteristics of existing systems for detecting dental issues. Older methods for finding oral diseases required a dentist to inspect and assess the condition, which was manual and inefficient. “They suggest a unique method based on a DL model for detecting and classifying the four most typical dental issues: cavities, root canals, dental crowns, and broken-down root canals, in order to allay these worries. They use YOLOv3 deep learning model to create an automated tool that can identify and categorize dental anomalies in images taken during dental panoramic X-rays (OPG). OPG dental panoramic X-rays were gathered from clinics and are included in the dataset”. Approximately OPGs were took with a DSLR camera, while others were received in soft form from clinics. High resolution photos are used throughout. There are some augmentation techniques to boost the number of photos. In the end, we had 1200 pictures. To enhance the image data generating function using the following settings, range of rotation, zoom level, bending range, flip horizontally and a vertical turn. There are 1200 photos of patients in the unique dataset, whose ages and dental issues range. They developed the Dental X-rays dataset to identify and categorize dental disorders because there aren't any datasets for them. After augmentation, the datasets used included a total of 1200 photos. The collection consists of panoramic dental photos with dental conditions such dental crowns, cavities, root canals, and BDR. 30% of the photos were used for testing, and 70% for training. After training, the YOLOv3 model was assessed using test photos. The trials showed that the suggested model performed well than the current prototypes in terms of correctness and universality condition we used our data on additional replicas, achieving a 99% accuracy rate.

A new research work is introduced by Abdullah et al. [7] and in explained that DL technique in the field of dentistry for classification and detection of dental disease. “Their study discussed that in routine clinical practice, the examination of dental radiographs remains a central step in the diagnosing process. This is due to the fact that, throughout the diagnosis procedure, the dentist must analyze a variety of dental disorders, including the tooth statistics and associated diseases. Abdullah’s research suggests a CNN for panoramic radiographs that can do multitask classification by dividing the X-ray pictures into three categories: cavity, filling, and implant. The convolutional neural networks used in this study are represented by a NASNet model with varying numbers of max-pooling layers, dropout layers, and activation functions. The dental picture collection was composed of 116 patients' anonymous, unidentifiable panoramic dental X-ray photos that were obtained from the Noor Medical Imaging Center in Qom, Iran. This dataset comprised a range of dental problems, from healthy teeth to cases where all of the teeth had fallen out. Two dentists manually segment all conditions of various cases. The dataset can be accessed from the publicly accessible Kaggle website at “https://www.kaggle.com/daverattan/dental-xrary-tfrecords.”. Different types of procedures, including scale, rotate, translate, gaussian blur, and gaussian noise, have been used to amplify the data. In order to apply augmentations like bounding box and image_aug, a function has been written. The dataset was therefore 83 bytes in size before the augmentation was done, and it was expanded to 245 by the augmentation”. The dataset has been augmented in order to expand its size and enable the production of more precise findings. In this study, the multiclass classification can carry out using dental X-ray pictures. There are three categories in this classification: "cavity," "filling," and "implant." The suggested effort will first preprocess the data after which it would be enhanced. The information is then divided into training and validation sets. The multioutput model, which is used to build and train the model, is produced in the end. The data first enhanced and preprocessed, and after that, a multioutput model built. Finally, the model is assembled and trained; loss and accuracy curves are utilized as evaluation criteria for the model analysis. The model has surpassed other current algorithms with an accuracy of better than 96%.

Iffat Firozy Rimi et al. [8] suggested a study to detect the dental disease using machine learning techniques. They explain that Worldwide, the prevalence of oral diseases is rising at a similar rate to that of infectious and non-communicable diseases. Periodontitis, gingivitis, and cancer are just a few of the dental illnesses that affect more than 80% of the general population. In this study, they applied machine learning to forecast dental illness based on a nation's populace's routine activity. They talked about the crucial aspects of oral illness with the concerned doctors and dentist. Their research began gathering information from the general public and dental disease patients keeping all these significant considerations in mind. “k-nearest neighbors, logistic regression, SVM, naive Bayes, classification and regression trees, random forest, multilayer perception, adaptive boosting, and linear discriminant analysis” are some of the most well-known machine learning methods we employed after data collection and preparation. The evaluation of each classifier's performance for the evaluation task using accuracy and a few notable performance measures. The accuracy of the logistic regression classifier approaches 95.89%, outperforming all other classifiers for all metrics. Based on this, AdaBoost exhibits several poor results in other metrics in addition to the deficient result of an accuracy close to 34.69%. In summary, this research work's primary contribution is:

- This is the first effort to use machine learning to address the issue of dental disease.
- The application of machine learning models can be applied in Bangladesh to predict dental illness.
- To extract the essential data from a large dataset, various features are discovered and new strategies are introduced.
- The suggested approach for the expert system can be utilized in conjunction with other models for treating dental disorders.

They were able to get 1012 data by combining the data of those with oral illness and those who are healthy. We created test sets using the remaining 15% of the collected data sets and used the remaining 85% for training sets. The following section will go into great length regarding data gathering and pre-processing techniques. The gathered information was in text format, making it unsuitable for training. The data is subsequently presented in a machine learning algorithm using the data cleaning technique. The accuracy of the nine techniques was gathered at three stages: prior to principal component analysis (PCA), following PCA, and using raw data sets. To evaluate the effectiveness of these algorithms, we employed metrics such as accuracy, sensitivity, specificity, recall, and F1-score.

Andac Imak et al. [10] provide a study that detect dental disease on the image’s dataset using deep learning method. In their paper firstly, they introduce that Dental professionals can diagnose the most prevalent dental disorders, like dental caries, with the aid of panoramic and periapical radiograph instruments. Tooth professionals typically use panoramic and periapical pictures to manually diagnose tooth caries. For a number of reasons, including negligence brought on by a tremendous “workload and inexperience, manual diagnosis may result in dental caries that is not readily apparent. To avoid these negative effects, computer-based intelligent vision systems supported by machine learning and image processing methods are required. Based on periapical pictures, this study offered a unique method for the automatic identification of dental caries. A multi-input deep convolutional neural network ensemble (MI-DCNNE) model was employed in the suggested technique. In particular, a score-based ensemble strategy was used to improve the suggested MI-DCNNE method's performance. Both unaltered and improved periapical pictures served as the inputs for the suggested method. In the Softmax layer of the suggested multi-input CNN architecture, the score fusion was done. For the performance assessment of the suggested method in the experimental studies, a periapical image dataset (340 photos) including both caries and non-caries images was used. The findings showed that the suggested approach is extremely successful at identifying dental caries”. 99.13% is the reported accuracy rating. This outcome demonstrates how well the suggested MI-DCNNE model may help classify dental caries. The following are the suggested model's main contributions:

- The deteriorated area in the unprocessed dental photos is further highlighted by the study's usage of the sharpening filter and intensity colormap techniques.
- “Despite studies on dental caries existing in the literature, no publicly accessible data set exists. In this study, a brand-new dataset with 340 photos (caries and non-caries) was introduced and made openly available to researchers”.
- “In order to detect dental cavities, pre-trained AlexNet architecture based on the transfer learning approach was modified. The learnt weights of the pre-trained architecture were employed in this work rather than beginning the training process with random weights using a data set containing a small number of images. According to the experimental findings, the AlexNet model based on transfer learning that was employed for the suggested model boosted success by about 10% when compared to the Training from scratch method”.
- “With an accuracy score of 99.13%, the suggested score-based multi-input CNN model has demonstrated considerable performance in identifying dental caries. This outcome demonstrated the suggested model's suitability for use in real-time applications”.

Prerna Singh and Priti Sehgal [12] conduct a study related to dental caries classification using deep learning techniques. In this study both authors stated that one of the oral disorders that is a serious health issue for many people worldwide is dental caries. It may result in suffering, discomfort, disfigurement, and in extreme cases, even death. The calcified tissue of the teeth becomes infected, which results in dental caries. By receiving early diagnosis and treatment, they are easily avoidable. The creation of an accurate classification and diagnosis model for dental caries can result in prompt and efficient care. One of the systems that is commonly used internationally is the G.V. Black Classification system for dental caries. Based on where the caries is, it divides them into six classes. In order to detect and diagnose dental caries on periapical dental pictures, “this research suggests a unique CNN with an LSTM model. Convolutional neural networks are used in the proposed model to extract the features, and long short-term memories (LSTM) are used to handle short-term and long-term dependencies. This study's primary goal is to identify dental cavities and classify them according to the G.V. Black Classification [15]. Deep convolutional neural networks receive pre-processed periapical dental pictures as input. The input is divided into different classifications using the deep convolutional neural network. The Dragonfly optimization technique was used to optimize the suggested algorithm, which provided accuracy of 96%. Examining and contrasting the suggested model with current state-of-the-art deep learning models is done through experiments”. This study supports the claim that one of the most effective methods for identifying and categorizing dental caries into different G.V. black classes is a deep convolutional neural network. The proposed CNN-LSTM model's achieved accuracy for classifying G.V. blacks is evidence of its effectiveness when compared to the classification accuracy attained by two commonly used pre-trained CNN models, Alexnet (accuracy: 93%) and GoogleNet (accuracy: 94%) on the same database. By contrasting the outcomes with the CNN model, the 2-layer LSTM model, and the CNN-LSTM model without dragonfly optimization, the performance of the proposed CNN-LSTM model is further reinforced. With 96% accuracy, the suggested ideal CNN-LSTM model performs best and aids in the classification of dental images as a second opinion for the medical professional.

“Michael G. Endres et al. [18] introduced a study based on deep learning to detect dental disease using radiograph images. in this study they stated that one of the most frequent radiographic findings in dentistry is periapical radiolucencies, which can be seen on panoramic radiographs and have a variety of differential diagnoses, including infections, granulomas, cysts, and tumors. In this study, we examine how well 24 oral and maxillofacial (OMF) surgeons are able to detect periapical lucencies on panoramic radiographs and compare their performance to that of a predictive deep learning algorithm we developed using a curated data set of 2902 de-identified panoramic radiographs [13]. Based on their evaluation of panoramic radiography images, OMF surgeons' mean diagnostic positive predictive value (PPV) was 0.69 (0.13), indicating that on average, dentists incorrectly identify 31% of cases as radiolucencies. The average diagnostic true positive rate (TPR) was 0.51 (0.14), which means that 49% of all radiolucencies were missed on average. We show that the deep learning method outperforms 14 of the 24 OMF surgeons in the cohort, with average precision of 0.60 (0.04), F1 score of 0.58 (0.04), and PPV and TPR of 0.67 (0.05) and 0.51 (0.05), respectively. The system has the potential to help OMF surgeons identify periapical lucencies on panoramic radiographs. It was trained on sparse data and assessed using clinically proven ground truth. Four OMF surgeons from the same outpatient department of the Department of Oral and Maxillofacial Surgery, Charité, Berlin, with experience ranging from five to twenty years, visually evaluated the images and then produced contour labels around any visible and treatable periapical radiolucencies that they had identified. The training data set, which included 3240 radiographic images, was labeled. Notably, thanks to the training in dentistry school, doctors who started the OMF surgery residency program in Germany had at least two years of experience reading dental radiographs and treating patients. Furthermore, the OMF surgery residency program in Germany includes training in dent maxillofacial radiology. In Germany, there isn't a single specialist in OMF radiology”.

Guan-Hua Li et al. [17] conduct a study to train and validate DL models for classification of dental images. In their study they stated that one of the most common dental conditions is gum disease (also known as gingivitis and periodontitis), which is brought on by dental plaque (a bacterial biofilm). It has a strong link to systemic illnesses like cancer, atherosclerosis, hypertension, and stroke as well as respiratory and cardiovascular conditions like aspiration pneumonia and poor pregnancy outcomes. As gum inflammation is characterized by an increase in redness (color), an increase in volume (oedema), and a loss of surface features (stippling; gum fiber attachment), these symptoms are all signs of the condition. These diseased sites are site-specific, meaning that an individual may have both healthy and diseased sites in their mouth. Dentists can identify these diseased sites by visual inspection. Additionally, intraoral photography, a clinical practice of routine dental examinations, can identify these inflammatory alterations of the gums. The purpose of this work is to use a DL approach to teach the computer to recognize inflamed disease locations at the pixel level. We randomly selected 110 patients' standard intraoral photos, and we then gathered 337 and 110 images for training and validation, respectively. They are classified into four categories of health status (healthy, doubtful healthy, questionable diseased, and sick), and a dental professional with more than 15 years of clinical experience verifies each category [14]. The DeepLabv3+ network, with Xception and MobileNetV2 serving as the backbone, forms the foundation of the suggested semantic segmentation architecture. The effectiveness of the suggested approach has been demonstrated through experimental data, which suggests potential applications for dental self-checkups utilizing mobile apps, particularly during pandemics where seeing a dentist is challenging or even impossible.

Table 1. Comparison of Different research work in the domain of dental disease classification

Authors	Year	Dataset Size	Results
Yassir Edrees Almalki et al. [6]	2022	1200 Images	99.33
Abdullah S. AL-Malaise AL-Ghamdi et al. [7]	2022	245 Images	96
Iffat Firozy Rimi et al. [8]	2022	1012 Images	95.89
Andac Imak et al. [9]	2022	240 Images	99.13
Andac Imak et al. [10]	2022	340 images	99.13
Prerna Singh and Priti Sehgal [12]	2021	1500 images	96
Guan-Hua Li et al. [17]	2021	447	95
Michael G. Endres et al. [18]	2020	2902	72

MATERIALS AND METHODS

Our proposed methodology used three different variants of Convolutional Neural Network (CNN), DenseNet169, ResNet50 and VGG19 that depicted in the figure1. First of all, the raw dental X-ray images dataset is collected from the online Kaggle repository and then processed and annotated by using different image processing techniques to improve the quality of images. The processed dataset is evaluated by building and applying three deep learning neural networks (DenseNet169, ResNet50 and VGG19). Finally, the builded models are compared and evaluated on the basis of training accuracy, testing accuracy, training loss, testing loss, precision, recall, f1-score, specificity and sensitivity.

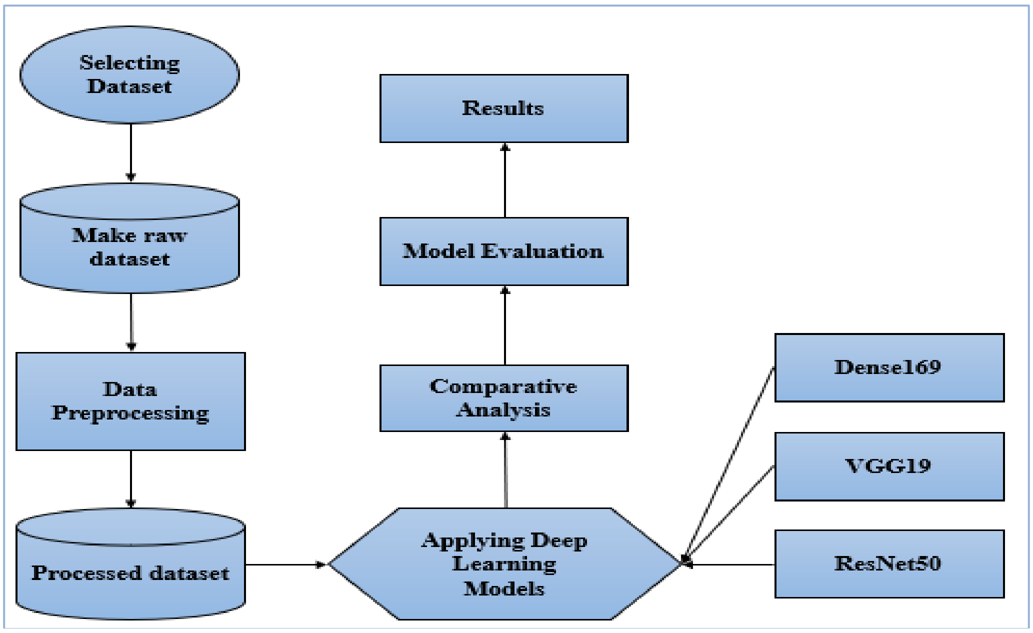

Figure 1. Proposed Methodology

The steps of our methodology are explained in the following section:

- Dataset collection and selection
- Data Preprocessing
- Construction of Dee learning models
- Comparison of results and evaluation

Dataset collection and selection

The selected dataset is collected from the well online Kaggle repository. The dataset named as Dental-Panoramic-Xrays dataset and it contains 232 images in the two different folders. We select this dataset because it suits to our research and according our need and it is a benchmark dataset that is used by many other researchers. The dataset contains 116 images in segmentation folder one and

116 images in segmentation folder two.

Data Preprocessing
The collected dataset is need to be process before applying any deep learning model so we firstly apply different preprocessing techniques on the dataset to improve the quality of images. following preprocessing steps are applied on the dataset.

- Labeling and annotating
- Gray-Scaling
- Normalization
- Augmentation

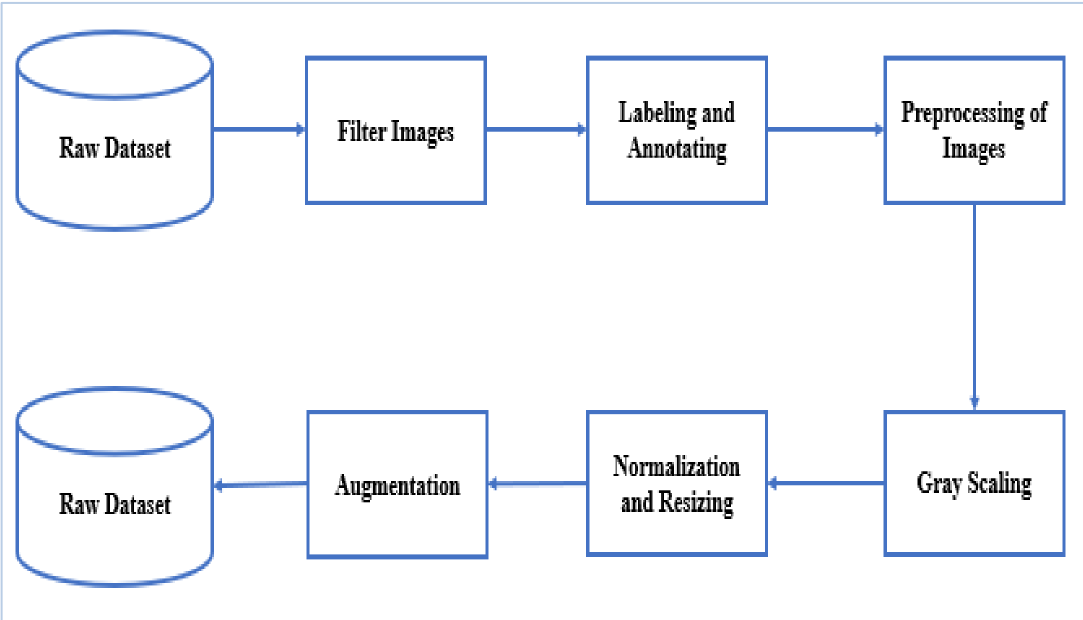

Figure 2. Preprocessing Steps

Labelling and annotating: Our selected dataset is not labelled we need to categorize the images into Healthy and Effected images. In order to make images easier to comprehend and more useful for a variety of applications, labeling and annotating are crucial processes in image processing and computer vision. In order to train machine learning models for tasks like object identification, picture classification, and segmentation, both labeling and annotating are essential processes. We classify our selected dataset into two classes Healthy and Effected by communicate with expert dentists. We labelled all of our 232 images by the help dental doctors. There are 120 images are labelled as Healthy and 112 images are labelled as Effected.

Table 2 Class Distribution

Class	**Images**
Healthy	120
Effected	112

Gray-Scaling: A full-color (RGB) image can be turned into a grayscale image using the image processing technique known as grayscaling, sometimes known as grayscale conversion. Red, green, and blue (RGB) channels with a color range of 0 to 255 are used to represent each pixel in a full-color image. Grayscaling reduces the complexity of the image by replacing the color information with a single intensity value, ranging from 0 (black) to 255 (white), for each pixel. Grayscaling is the process of converting RGB data into a single grayscale value by first determining the luminance or brightness of each pixel using its RGB value.
Normalization: Normalization in image processing refers to the process of adjusting the pixel

values of an image to a specific range or scale. The primary goal of normalization is to enhance the image's features, making it more suitable for various image analysis and computer vision tasks. Normalization is a common preprocessing step before feeding images into machine learning algorithms or performing certain image processing operations. There are different methods of normalization, but the most common one involves rescaling the pixel values to a range between 0 and 1. This is often referred to as "min-max normalization" and can be expressed using the following formula:

$$\text{Normalized Pixel Value} = (\text{Pixel Value} - \text{Minimum Pixel Value}) / (\text{Maximum Pixel Value} - \text{Minimum Pixel Value}) \quad (1)$$

where "Pixel Value" is the original value of a pixel, "Minimum Pixel Value" is the minimum pixel value in the entire image, and "Maximum Pixel Value" is the maximum pixel value in the image. After applying this normalization, the pixel values in the image will lie between 0 and 1.

Augmentation: By applying various alterations to the original images, image augmentation is a data augmentation technique used in image processing and computer vision to artificially expand the size of a training dataset. In order to simulate real-world settings and add diversity to the training data, image augmentation aims to provide additional versions of the original photos. To enhance the functionality and generalization of image-based models, augmentation is frequently employed in machine learning, particularly in deep learning. The enhanced dataset exposes the model to a wider range of variations it can encounter during inference, such as changes in lighting, rotation, scale, and perspective, by applying various transformations to the photos. This makes the model more resilient and able to handle many real-world situations. Following techniques are used to augment the images:

- Horizontal Flipping
- Vertical Flipping
- Zoom in
- Zoom out
- Rotation

Construction of Deep learning models

We use different variants of CNN model to classify the healthy and effected X-ray images. we use following three CNN models:

- DenseNet169
- ResNet50
- VGG19

DenseNet169

The first model that we used is pretrained DenseNet169 neural network to classify the disease images and healthy images. The "169" in its name alludes to the network's layer count, thus DenseNet-169 is a specific variation of the DenseNet architecture. Convolutional layers, pooling layers, thick blocks, and transition layers make up its 169 total layers. Compared to its predecessor, DenseNet-121, which has 121 layers, DenseNet-169 is deeper and has more parameters. DenseNet-169 may thus capture more intricate patterns and characteristics, thus making it more effective for jobs requiring higher-level representations. The vanishing gradient problem and the requirement for many parameters are two issues with typical deep neural networks that the DenseNet architecture is intended to overcome. DenseNets establish dense connections between layers, allowing each layer to acquire feature maps from all levels before it, resulting in a dense network with a high degree of connectivity.

The following are the primary elements of the DenseNet architecture:

- **DenseNets' building blocks:** are known as Dense Blocks. Several convolutional layers are piled on top of one another to create a dense block, with each layer getting feature mappings from all preceding layers. The network may effectively reuse features thanks to its dense interconnectedness.
- **Transition Layers:** To downsample the spatial dimensions of the feature maps and lower the number of feature maps, a transition layer is added after each dense block. Managing computational complexity and avoiding the network from getting too deep are both aided by this.
- **Global Average Pooling:** A global average pooling layer is often employed at the network's end to spatially combine the feature maps into a single vector, which is then fed into a fully connected layer for classification.

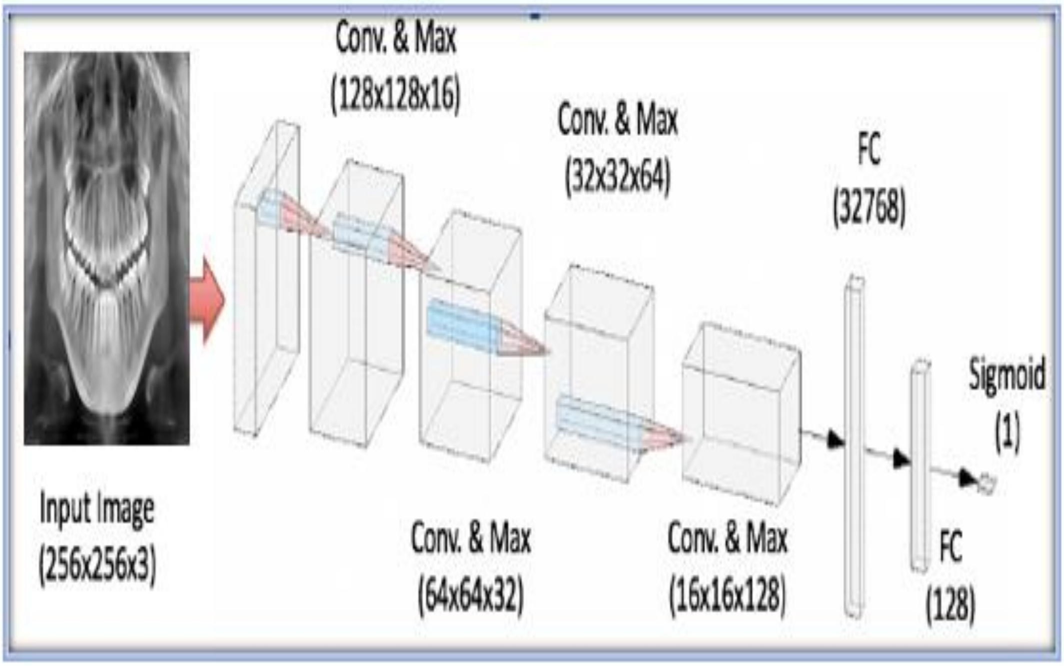

Figure 3. DesNet169

Figure 3 shows the architecture of DenseNet169 and it contains Conv layer, Max layer and sigmoid function. The input image size of the model is 256*256.

VGG19

Third model that we use in our proposed methodology is VGG19. Our proposed VGG19 contains different layers (conv1, conv2, conv3, conv4, conv5, max_pooling layers and fully connected layers) as shown in figure 4. The VGG architecture is known for its simplicity and uniformity, featuring a series of convolutional layers with small 3x3 filters and max-pooling layers. The number "19" in VGG-19 indicates the total number of layers in the network, which includes 16 convolutional layers and 3 fully connected layers. Blue color in the figure 4 indicate convolutional layers, pink color indicate max pooling layers and gree color indicate fully connected layers.

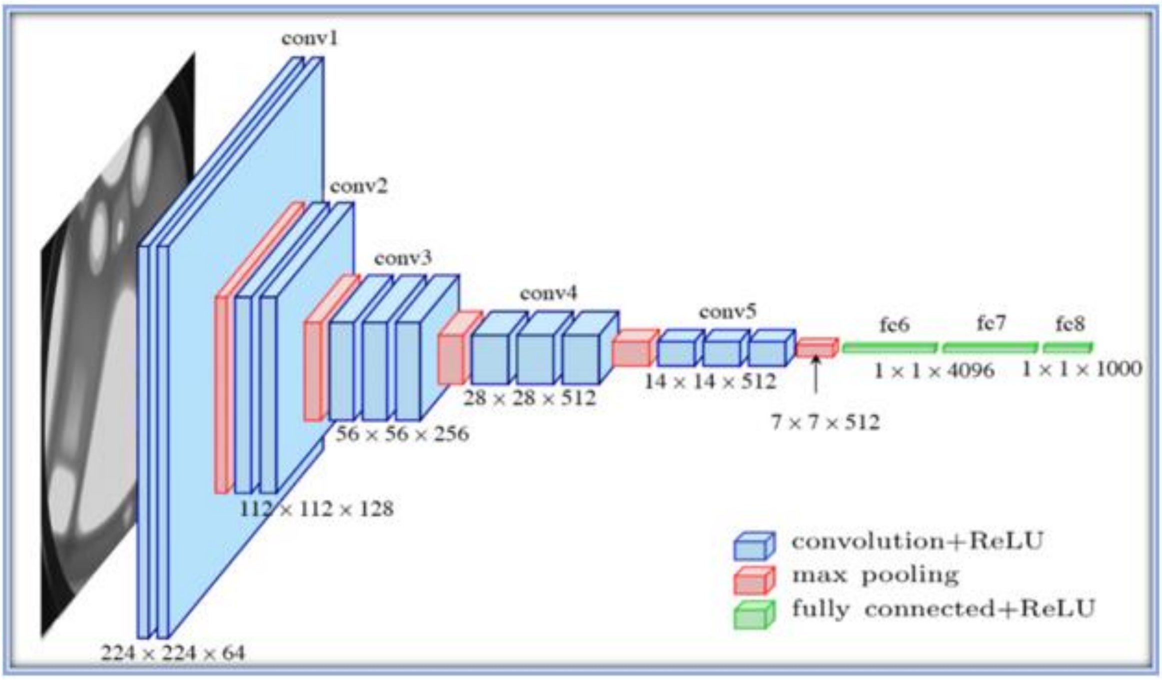

Figure 4. VGG19

The main characteristics of the VGG-19 architecture include:

- **Convolutional Layers:** VGG-19 begins with a series of convolutional layers, each of which has a fixed stride of 1 and a modest 3x3 filter size. The network can efficiently learn local patterns thanks to the tiny filter size.
- **Max-Pooling Layers:** VGG-19 includes max-pooling layers with a 2x2 filter size and a stride of 2 after each pair of convolutional layers. The feature maps' spatial dimensions are decreased through max-pooling, which also contributes to some degree of translation invariance and a reduction in computing cost.
- **Fully Connected Layers:** There are three fully connected layers in the network's final section. The final completely connected layer acts as the output layer for classification and has as many neurons as classes in the classification job, with the first two fully connected layers each having 4096 neurons.

ResNet50

The second model that we used in our proposed method is ResNet50 that contains combination of different layers (Pooling layers, Convolutional Layers, Residual Blocks and Fully connected Layers) ResNet-50 is a specific variant of the ResNet architecture and the "50" in its name indicates the number of layers in the network. It consists of 50 layers, including convolutional layers, pooling layers, and residual blocks. ResNet-50 has a total of 49 convolutional layers and one fully connected layer for classification. The following are the major elements of the ResNet architecture:

- **Convolutional Layers:** ResNet-50 starts with a single convolutional layer followed by four stages of convolutional blocks. Each block contains multiple convolutional layers with batch normalization and ReLU activation functions.
- **Residual Blocks:** The key building blocks of ResNet are the residual blocks, which contain one or more convolutional layers with skip connections. Each residual block has a shortcut connection that allows the output of a previous layer to bypass the subsequent layers and be added directly to the output of the block. This way, the network can learn residual mappings, which are easier to optimize than directly learning the underlying mappings.
- **Pooling Layers:** Max-pooling layers are used to reduce the spatial dimensions of the feature maps, which helps in managing computational complexity.

• **Fully Connected Layer:** At the end of the network, there is a global average pooling layer followed by a fully connected layer for classification.

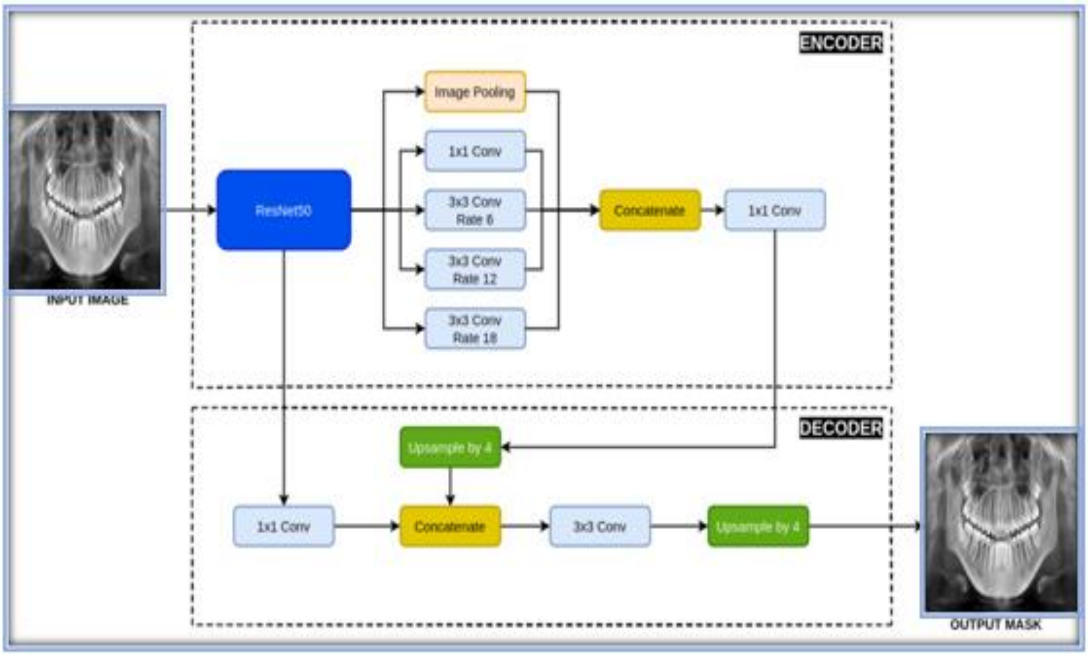

Figure 5. ResNet50

Figure 5 shows the architecture of ResNet50 that divided into two parts one is for encoder and second is for decoder. Encoder contain input layer and 4 convolutional layers with different parameters (1*1 Conv, 3*3 Conv, 3*3 Conv and 3*3 Conv).

EXPERIMENTS AND RESULTS

The evaluation of results and evaluation of our proposed models are based on training accuracy, testing accuracy, training loss, testing loss, presicion, recall, f1score, specificity and sensitivity.

Accuracy: In deep learning and machine learning, accuracy is a popular evaluation parameter used to assess the effectiveness of a classification model. It displays the percentage of the dataset's total number of instances (samples or data points) that were successfully categorised. In other words, accuracy represents the frequency with which the model predicts correctly. Accuracy can be calculated as follows:

$$\text{Accuracy} = (\text{Number of Correct Predictions}) / (\text{Total Number of Predictions}) \quad (2)$$

Loss: Binary-Entropy Loss, also known as Binary Log Loss, is used for binary classification tasks, where the model predicts the probability of a sample belonging to one of two classes. Equation:

Binary Cross-Entropy Loss = - (y_true * log(y_pred) + (1 - y_true) * log (1 - y_pred)) (3)

Here, y_true is the true binary label (0 or 1), and y_pred is the predicted probability that the sample belongs to class 1.

Precision: A performance indicator known as precision is frequently utilized in classification tasks, particularly when working with unbalanced datasets. It calculates the percentage of all positive predictions made by the model that were real positive predictions (i.e., properly predicted positive instances).

The equation for precision can be expressed as:

$$\text{Precision} = \text{True Positives} / (\text{True Positives} + \text{False Positives}) \quad (4)$$

Recall: Recall, sometimes referred to as sensitivity or the true positive rate (TPR), is a performance indicator used in classification tasks to calculate the percentage of true positive predictions (i.e., occurrences of positive data that were correctly predicted) among all instances of positive data in the dataset.
The equation for recall can be expressed as:

$$\text{Recall} = \text{True Positives} / (\text{True Positives} + \text{False Negatives}) \quad (5)$$

F1-Score: The F1 score is calculated using the following equation and represents the harmonic mean of precision and recall:

$$\text{F1 Score} = 2 * (\text{Precision} * \text{Recall}) / (\text{Precision} + \text{Recall}) \quad (6)$$

Specificity: True negative rate (TNR), another name for specificity, is a performance statistic used in binary classification problems. When compared to all of the actual negative cases in the dataset, it calculates the percentage of true negative predictions (negative instances that were accurately predicted).
The equation for specificity can be expressed as:

$$\text{Specificity} = \text{True Negatives}/(\text{True Negatives} + \text{False Positives}) \quad (7)$$

Sensitivity: In binary classification problems, sensitivity—also referred to as recall or true positive rate (TPR)—is a performance indicator. It calculates the percentage of genuine positive predictions (positive cases that were predicted correctly) among all of the dataset's actual positive instances.
The equation for sensitivity can be expressed as:

$$\text{Sensitivity} = \text{True Positives} / (\text{True Positives} + \text{False Negatives}) \quad (8)$$

Results of Dense169

We used Google Colab GPU for running our models and run DenseNet169 with 50 epochs on the processed dataset. Adam optimizer is used with learning rate of 0.0001 and our dataset is binary classified so we use binary class mode and binary_crossentropy loss function
.

Table 3. Architecture of Dense169

Parameters	**Description**
No of epochs	50
Optimizer	Adam
Learning Rate	0.001
Loss	binary_crossentropy
Batch size	32
Class mode	Binary

All of the DenseNet169 parameters are given in the table 3. Figure 6 shows the training and testing accuracy of the DenseNEt169 with each epoch. Blue line in the graph is used for the training accuracy and orange line is used for the testing accuracy. Y-Axis shows the percentage values of the accuracy from 0 to 100 and the X-Axis shows the number of epochs for the models that start from 0 and ends at 50.

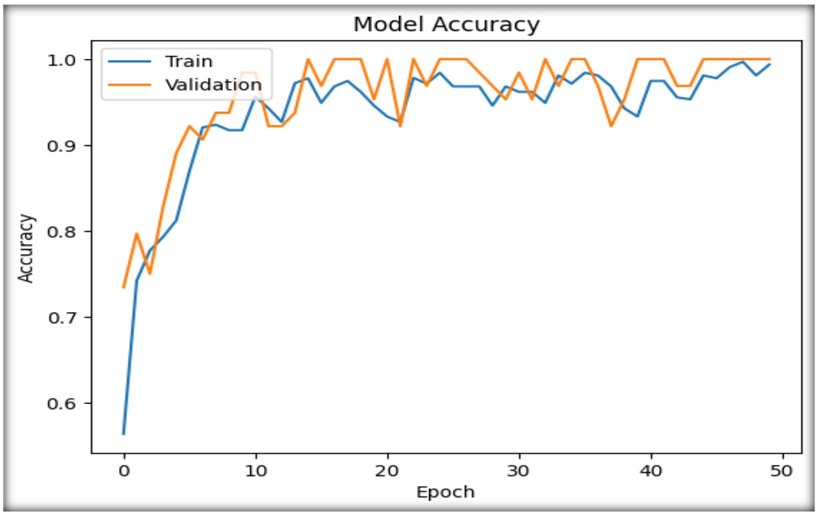

Figure 6. Accuracy of Sense169

Figure 7 shows the training and testing loss of the DenseNEt169 with each epoch. Blue line in the graph is used for the training loss and orange line is used for the testing loss. Y-Axis shows the percentage values of the loss from 0 to 0.3 and the X-Axis shows the number of epochs for the models that start from 0 and ends at 50.

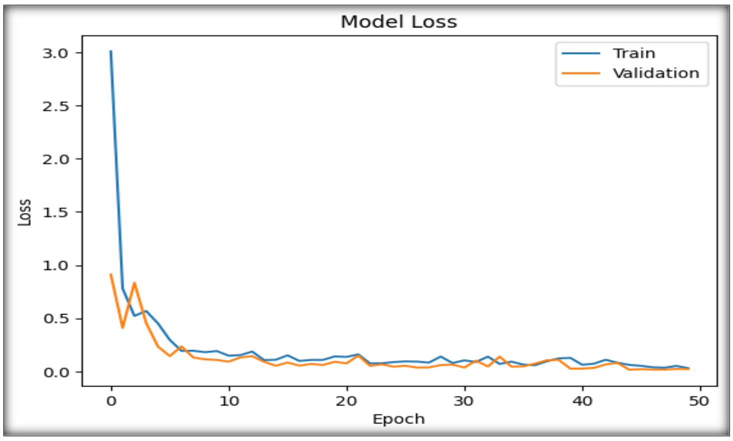

Figure 7. Loss of Dense169

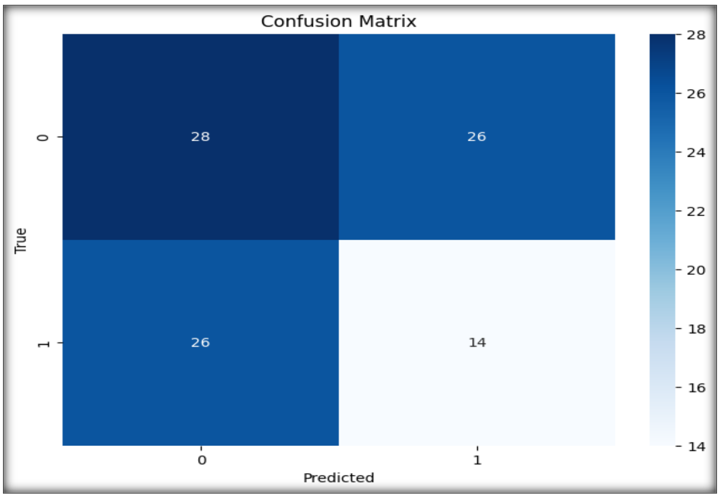

Figure 8. Confusion Matrix Graph of Dense169

Confusion matrix graph of DenseNet169 is shown in the figure 8. In right side of the Y-axis number images are shown that belongs to each class and left side of the Y-axis true classes are shown that is true according to the dataset. X-axis show the number classes that is predicted true by the model. the graph shows that 28 images form class 0 is predicted as true and 14 images from class 1 are predicted as true all the other images are predicted wrong.

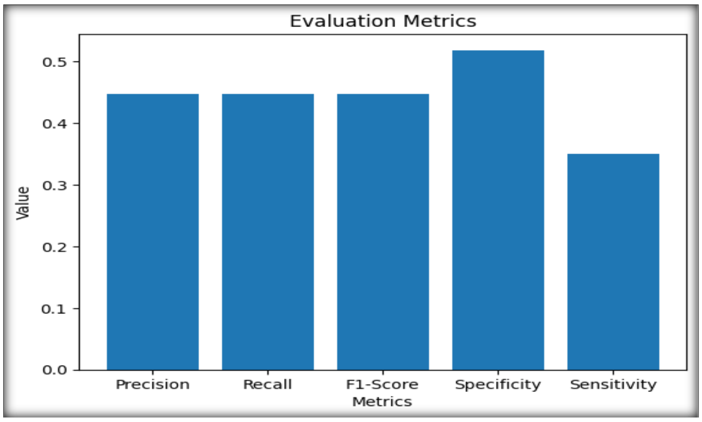

Figure 9. Dense169 Evaluation Metrics

VGG19

We run VGG19 on the processed dataset with 50 epochs and an 8-batch batch size using Google Colab GPU. Our dataset is binary categorized, so we utilize binary class mode and binary_crossentropy loss function with the Adam optimizer at a learning rate of 0.0001.

Table 4. VGG19 Architecture

Parameters	**Description**
No of epochs	50
Optimizer	Adam
Learning Rate	0.002
Loss	binary_crossentropy
Batch size	8
Class mode	Binary

In table 4, all of the VGG19 parameters are listed. Figure 11 displays the VGG19's training and testing accuracy for each epoch. The graph's blue line represents training accuracy, while the orange line represents testing accuracy. The X-Axis displays the number of epochs for the models that start at 0 and conclude at 50, while the Y-Axis displays the percentage values of correctness from 0 to 100.

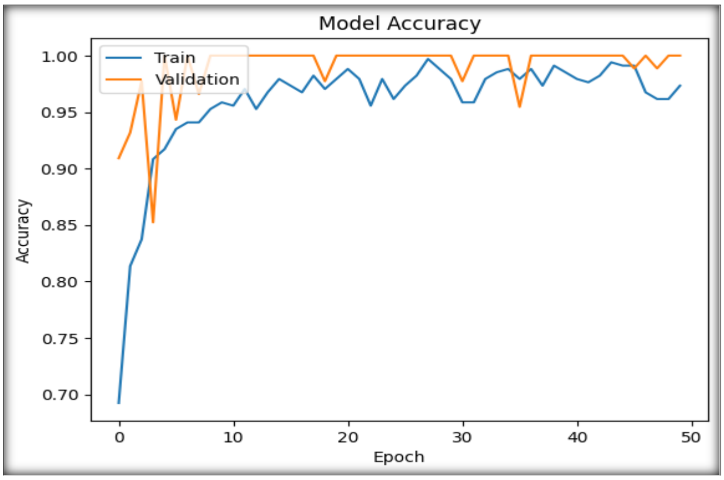

Figure 10. VGG19 Accuracy

Figure 12 shows the training and testing loss of the VGG19 with each epoch. Blue line in the graph is used for the training loss and orange line is used for the testing loss. Y-Axis shows the percentage values of the loss from 0 to 12 percent and the X-Axis shows the number of epochs for the models that start from 0 and ends at 50.

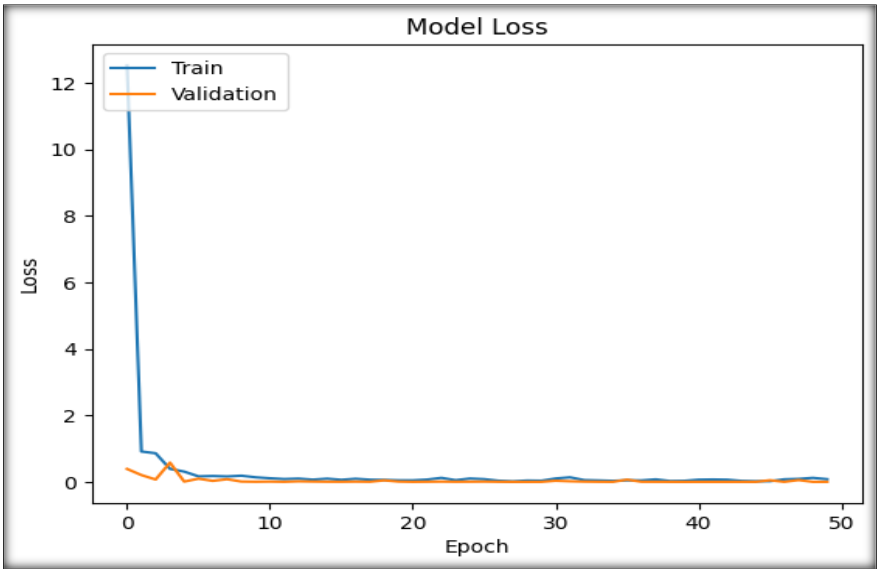

Figure 11. VGG19 Loss

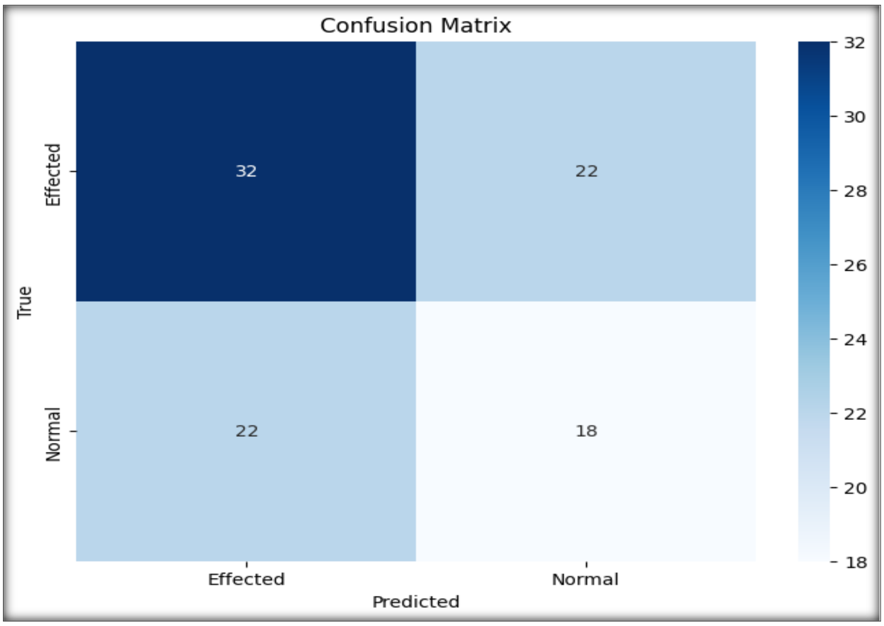

Figure 12. VGG19 Confusion Matrix

Figure 13 displays the VGG19 confusion matrix graph. Number photos belonging to each class are displayed on the Y-axis's right side, while the dataset's true classes are displayed on the axis's left. The number classes that the model predicts to be true are displayed on the X-axis. The graph demonstrates that just 32 photographs from class 0 and 18 images from class 1 are correctly predicted; all other images are incorrectly forecasted.

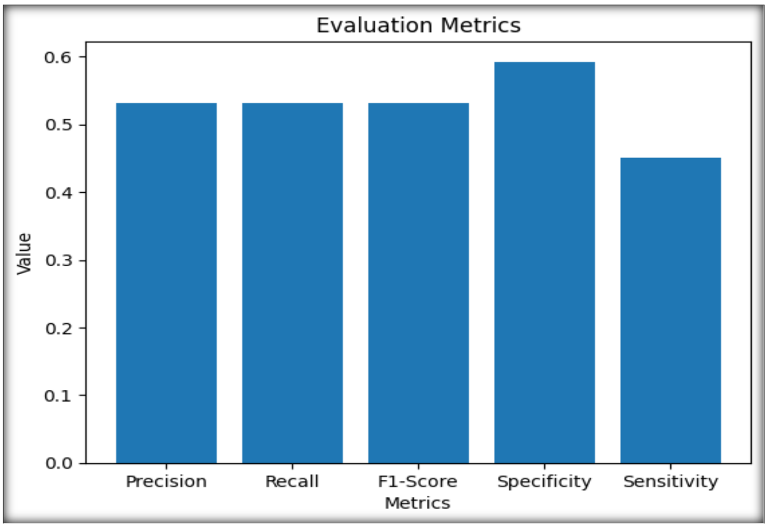

Figure 13. VGG19 Evaluation Matrices

ResNet50

Using the Google Colab GPU, we run VGG19 on the preprocessed dataset with 50 epochs and a batch size of 16. We use binary class mode and binary_crossentropy loss function with the Adam optimizer and a learning rate of 0.0001 because our dataset is binary categorized.

Table 5. ResNet50 Architecture

Parameters	**Description**
No of epochs	50
Optimizer	Adam
Learning Rate	0.001
Loss	binary_crossentropy
Batch size	16
Class mode	Binary

All of the ResNet50 parameters are provided in table 5. The ResNet50's training and testing accuracy is shown in Figure 15 for each epoch. The orange line on the graph reflects testing accuracy, and the blue line on the graph represents training accuracy. The Y-Axis shows the percentage values of correctness from 0 to 100, while the X-Axis shows the number of epochs for the models with starting values of 0 and 50.

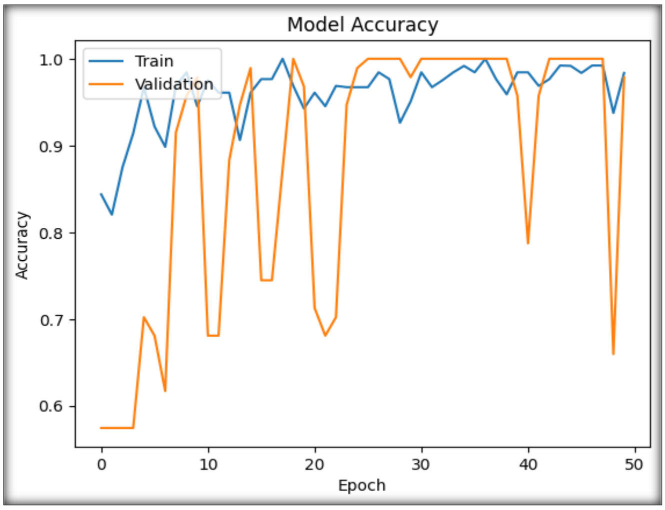

Figure 14. Resnet50 Accuracy

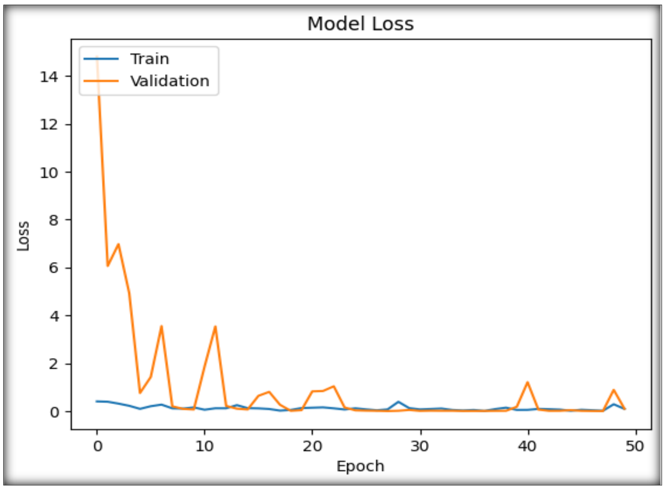

Figure 15. Resnet50 Loss

The ResNet50 confusion matrix graph is shown in Figure 17. The Y-axis's right side shows the number of images in each class, and the left side shows the dataset's actual classes. The X-axis shows the number classes that the model assumes to be accurate. The graph shows that only 16 photographs from class 1 and 32 photographs from class 0 have accurate predictions, whereas all other images have inaccurate predictions.

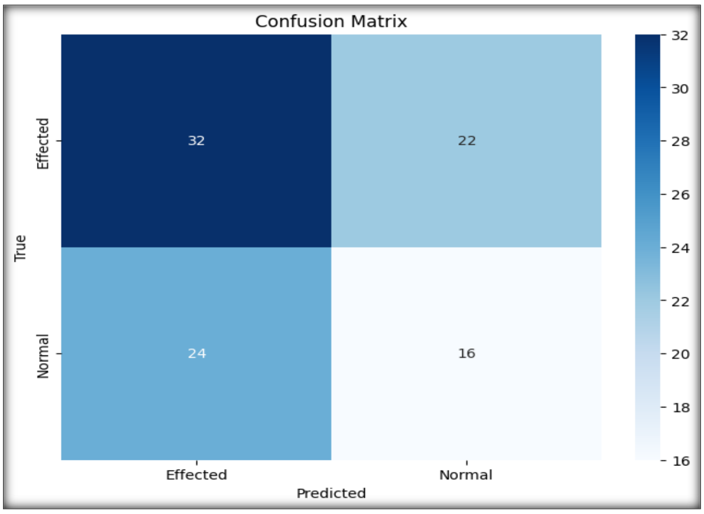

Figure 16. Confusion Matrix of Resnet50

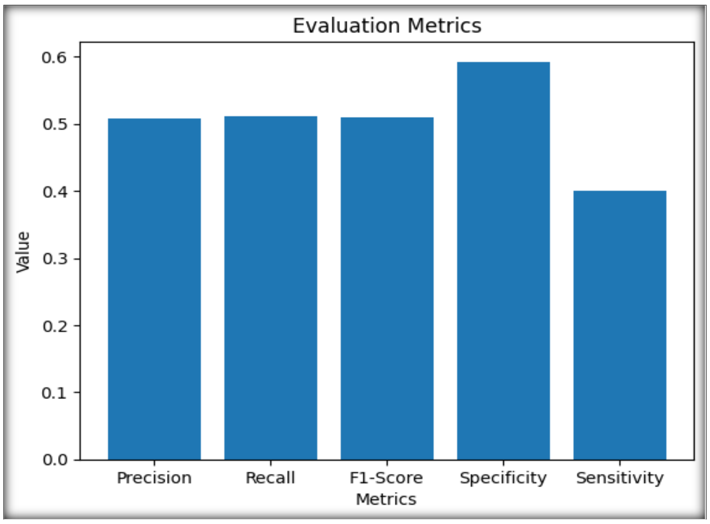

Figure 17. Resnet50 Evaluation Metrices

Comparative Analysis

Table 6 shows the comparison of models with training and testing accuracy. DensNet169 perform well as compared to other models with training accuracy of 97 percent and testing accuracy of 99.90 percent. VGG19 perform average with training accuracy of 95 percent and testing accuracy of 99 percent.

Table 6. Comparison of Accuracy

Model	Training Accuracy	Testing Accuracy
DesNet169	97	99.90
ResNet50	96	95
VGG19	95	99

Model ResNet50 perform poor with training accuracy of 96 percent and testing accuracy of 95 percent.

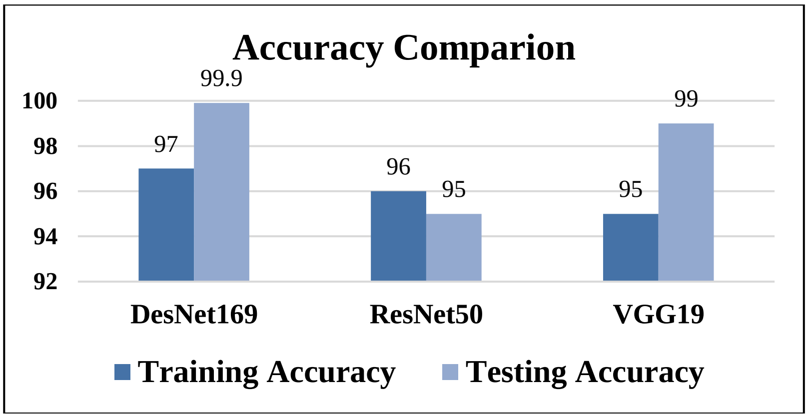

Figure 18. Accuracy Comparison of Models

Table 7. Comparison of Loss

Model	Training Loss	Testing Loss
DesNet169	0.03	0.02
ResNet50	0.09	0.09
VGG19	0.08	0.001

The comparison of models with training and testing loss results is shown in Table 7. With training loss of 0.03 percent and testing loss of 0.02 percent, DensNet169 provides the least loss when compared to other models. With training losses of 0.08 percent and testing losses of 0.001 percent, VGG19 performs averagely. Model ResNet50 performs poorly, with training and testing losses both equal to 0.09 percent.

Table 8. Comparison of Evaluation Matrices

Model	DesNet169	ResNet50	VGG19
Precision	45	50	53
Recall	45	51	53
F1-Score	45	50	53
Specificity	52	59	59
Sensitivity	35	40	45

Table 8 Shows the evaluation matrices of all three used models. DensNet169 gives Precision, Recall, F1-Score, Specificity, and Sensitivity of 45 percent, 45 percent, 45 percent, 52 percent and 35 percent respectively. ResNet50 gives Precision, Recall, F1-Score, Specificity, and Sensitivity of

50 percent, 51 percent, 50 percent, 59 percent and 40 percent respectively. VGG19 gives Precision, Recall, F1-Score, Specificity, and Sensitivity of 53 percent, 53 percent, 53 percent, 59 percent and 45 percent respectively.

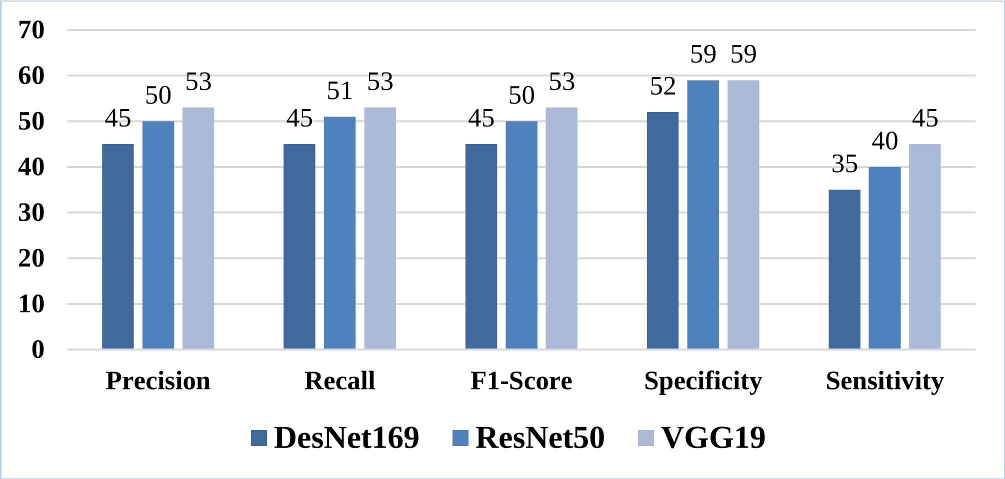

Figure 19. Comparative Analysis

Conclusion

Dental problems had affected a sizable section of the population and were a common global health problem. It was essential to get an early and precise diagnosis of dental disorders to treat them effectively and avoid subsequent consequences. Deep learning algorithms had recently demonstrated astounding effectiveness in a variety of medical imaging applications. Through the use of dental radiographs, the study had investigated the potential of deep learning for the classification of dental illnesses. A dataset with a variety of dental radiographs was gathered, including both healthy teeth and those with affected dental conditions. Dental radiographs were utilized as a source to extract distinguishing features using convolutional neural networks (CNNs). Different CNN architectures, such as VGGNet19, ResNet50, and DenseNet169, were used to assess how well they performed in classifying dental diseases. The outcomes had shown that deep learning models were effective at classifying dental diseases. The top-performing model had outperformed conventional machine learning methods and achieved a classification accuracy of over 99.90%. The models had been effective at distinguishing between various dental disorders, such as healthy and affected teeth. They had also demonstrated good specificity, sensitivity, recall, precision, and F1 score, as well as training and testing accuracy, highlighting their potential as trustworthy diagnostic tools.

DATA AVAILABILITY

The corresponding author can provide the data used in this paper upon request.

CONFLICTS OF INTEREST

The authors declare that there are no conflicts of interest.

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