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Deep Learning-Based Classification of Dental Disease Using X-Rays

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Abstract: Dental radiography is crucial for diagnosis, treatment, and quality assessment in dentistry. To enhance clinical quality, digitalized dental X-ray image analysis systems have been developed. In this study, we preprocess a dataset of dental X-ray images and evaluate treatment quality using these images. Our aim is to propose an automated clinical quality evaluation tool to aid dentists in making decisions. We employ deep learning, a form of artificial intelligence, to detect diseases in X-ray images. The dataset consists of 126 images, labeled as Normal or Affected by dental experts. Data augmentation is applied to increase the dataset size for effective training of deep learning models. A Convolutional Neural Network (CNN) architecture is constructed, comprising convolutional, max-pooling, flatten, dense, and output layers, to classify the images as Normal or Affected. The CNN model is trained on the augmented dataset to automate clinical quality evaluation. The model's performance is evaluated based on metrics such as accuracy, loss, precision, recall, and F1-score. Our method achieves an accuracy of 97.87% and an F1-score of 60%, demonstrating comparable performance to expert dentists and radiologists.

Keywords: Convolutional Neural Network, Panoramic Radiography, Dental Disease, X-Ray, DeepLearning.

1. Introduction

In routine clinical practice, the examination of dental radiographs is a crucial step in the diagnosing process. The reason for this is that throughout the diagnosis procedure, the dentist must analyze a variety of dental issues, including tooth counts and associated disorders. Since the dental image dataset is fairly small, data collection is the main challenge for working on a medical image. Getting most researchers to focus on definitive tasks, such as filtering, segmentation, and feature selection, is significantly more challenging. In this, we will develop a classification model that classifies X-ray pictures into two classes. This classification will be done by using a convolutional neural network (CNN) that can perform multiple tasks of classification. The convolutional neural networks used in this study are represented by a model with varying numbers of activation functions, dropout layers, and max-pooling layers. An improved and preprocessed version of the data will be used before a multioutput model is constructed. Finally, the model will be assembled and trained; loss and accuracy curves are utilized as evaluation criteria for the model analysis. Prior knowledge of several jobs is required for the segmentation and identification of dental caries to be done more easily. Understanding the different parts of the tooth and the precise location of the lesion on the tooth is important. Understanding the several dental image types that will be used, such as panoramic or bitewing radiographs, is also necessary. To select the best approach for segmenting and detecting caries, it is also necessary to clearly define the exact sections or areas of interest that must be considered.

To achieve high-performance segmentation and identification of dental caries, all of this information is necessary.

"Cavities (tooth decay), gum disease (periodontitis), and oral cancer are some of the most prevalent illnesses that affect our oral health. In the past year, more than 40% of individuals reported experiencing oral pain, and by the age of 34, more than 80% of people would have experienced at least one cavity. Your general health and well-being depend heavily on your dental and oral health. Poor oral hygiene has been related to heart disease, cancer, and diabetes as well as tooth cavities and gum disease." To keep your teeth and gums healthy, it takes a lifetime. It will be easier for you to avoid costly dental procedures and long-term health issues if you start practicing healthy oral hygiene habits early on, such as brushing, flossing, and consuming less sweets.

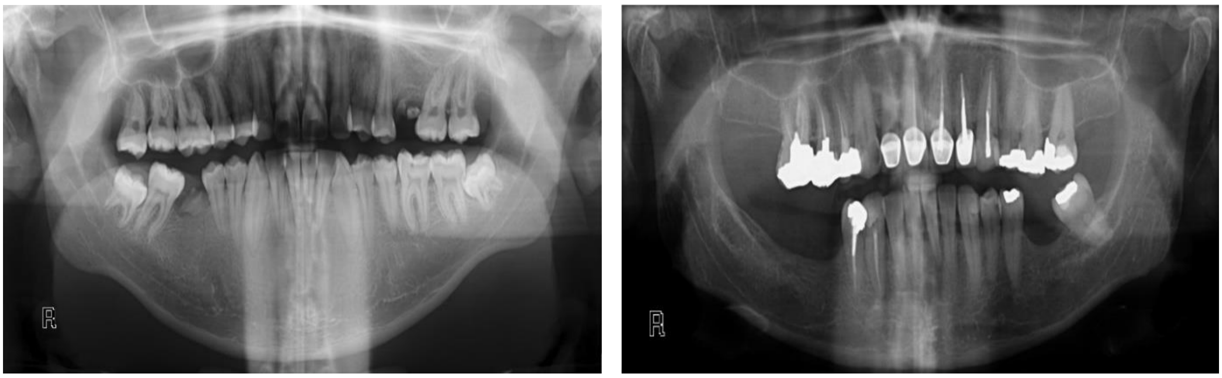

Figure 1. X-Ray image sample

The objectives of the study are to propose a DL model to detect dental disease efficiently and accurately, to construct a DL model that identifies dental disease from dental x-ray images, To Construct a custom CNN using different layers to detect the disease and to evaluate the performance of proposed CNN model performance with Accuracy and Loss, Precision, Recall, and F-1 score. The rest of the document is as follows, in second Section we will discuss some related research in dental disease detection, many methods used to identify dental illness from x-ray pictures, and the history of this disease. Third section of the paper outlines our recommended strategy for identifying dental disease using convolutional neural networks and standard machine learning classifiers, as well as for classifying the disease using basic image processing techniques. Result section presents the performance measurements, our proposed approach for performance evaluation, and a discussion of the experimental results. Finally, we will wrap up our investigation. In this section, we discuss the limitations of our research and recommended directions for further work.

2. Literature work

The following section provides a thorough assessment of the literature on current methods for creating Deep learning frameworks for the identification of many dental illnesses. The previous section evaluation criteria are provided simply as general guidelines. We discuss current classification techniques for dental disease diagnosis. Three general categories can be used to classify these techniques: 1) Semi-automatic procedures the framework of the categorization scheme, along with statistical classifiers based on machine learning (ML) and the classification models based on deep learning (DL).

In [1] a new framework for the detection of dental disease from an image dataset is proposed in which a CNN is constructed. A NASNet model representing the convolutional neural networks utilized in this study has various amounts of layers with max pooling, activation functions and dropout layers. An enhanced and preprocessed version of the data will be used before a multioutput model is constructed. An then the model will be assembled and trained; loss and accuracy curves are utilized as evaluation criteria for the model analysis. The model beat other existing algorithms by achieving an accuracy of more than 96 percent. A total of 116 patients' anonymous, deidentified panoramic dental X-ray scans made up the dental image dataset, which was obtained from the Noor Medical Imaging Center in Qom, Iran.

In [17] construct a study to distinguish different caries degrees from panoramic radiographs, they suggest a unique deep-learning architecture dubbed CariesNet. A high-quality dataset of panoramic radiographs with 3127 clearly defined caries lesions, including shallow, intermediate, and deep caries, is what we first gather. Then, using a second full-scale axial attention module, we construct CariesNet using a U-shape network to segregate these three caries types from the oral panoramic images. We also compare CariesNet's segmentation performance to those of other industry standards. Studies reveal that our approach can segment teeth with three different stages of caries with an average 93.64 percent Dice coefficient and 93.61 percent accuracy.

A new technique for the detection of dental disease is proposed by [26]. In this proposed work order to determine the amount of periodontal alveolar bone loss as well as the precise location and shape of the alveolar bone loss, three skilled periodontists highlighted important locations on a total of 640 panoramic photographs. A two-phase deep learning architecture made up of UNet and YOLO-v4 was created in order to accurately calculate the percentage of periodontal bone loss in alveolars and stage periodontitis. The model's ability to recognise these characteristics was evaluated and compared to dentists in general. With an overall classification accuracy of 0.77, the model performed differently for various tooth placements and categories; in general, the model's categorization was more accurate than that of general practitioners. Conclusions: Radiographic periodontal alveolar staging and assessment can be done using a deep learning model.

In [16] explains that the most common chronic ailment worldwide is dental caries. The necessity for invasive treatments can be decreased and treatment outcomes can be considerably improved with early identification. Recently, it has been demonstrated that early-stage lesions can be found using near-infrared trans illumination (TI) imaging. In this study, we present a DL model for the automated identification of dental lesions in TI images. CNNs trained on semantic segmentation tasks are the foundation of our approach. We employ a number of techniques to reduce problems caused by a lack of training data, an unbalanced class," and over fitting Our model successfully completed a 5-class segmentation assignment with only 185 training samples, achieving a mean intersection-over-union (IOU) score of 72.7 percent overall and 49.5% and 49.0 percent, respectively, for proximal and occlusal carious lesions. Furthermore, we developed a condensed job where regions of interest were evaluated for the existence or disappearance of serious lesions on a binary basis. For this task, the occlusal and proximal lesions of our model had areas over the receiver operating characteristic curve of 83.6 percent and 85.6 percent, respectively.

In Sultan Imangaliyev et al., [6] proposed a new DL model for the classification of dental disease (DD) by constructing CNN model and used Quantitative Light-induced Fluorescence (QLF) image data. The proposed CNN model beats other cutting-edge classification methods, achieving an F1-score of 75 percent and 5 percent on the test dataset. When all three color channels were employed, the model performed better because the images were represented in several channels. The used dataset was collected as part of a clinical intervention study at the Academic Centre for Dentistry in Amsterdam's Department of Preventive Dentistry, which examined the changes occur in red plaque illumination during an experiment gingivitis procedure. During this intervention, 427 QLF photos were gathered, and we converted them into a dataset of 216324 raw intensity values in three Red-Green-Blue (RGB) multichannel images with a lower resolution. A new technique for the detection of dental disease is proposed by Linhong Jiang et al., [26]. In this proposed work order to determine the amount of periodontal alveolar bone loss as well as the precise location and shape of the alveolar bone loss, three skilled periodontitis highlighted important locations on a total of 640 panoramic photographs. For the purpose of precisely calculating the proportion of periodontal alveolar bone loss and staging periodontitis, a two-stage deep learning architecture based on UNet and YOLO-v4 was developed. The model's capacity to identify these traits was assessed and contrasted to that of general dentists. The model performed differently for different tooth placements and categories, with an overall classification accuracy of 0.77; in general, the model's classification was more precise than that of general practitioners. Conclusions: It is possible to create a deep-learning model for radiographic periodontal alveolar assessment and staging.

In F. Casalegno al., [16] explains that the most common chronic ailment worldwide is dental caries. The necessity for invasive treatments can be decreased and treatment outcomes can be considerably improved with early identification. Recently, it has been demonstrated that early stage lesions can be found using near-infrared Transillumination (TI) imaging. In this study, we present a model using DL for the automated identification of dental lesions in TI images. CNNs trained on semantic segmentation tasks are the foundation of our approach. We employ a number of techniques to reduce problems caused by a lack of training data, an unbalanced class," and over fitting. Our model successfully completed a 5-class segmentation assignment with only 185 training samples, achieving approximate intersection-over-union (IOU) evaluations of 72.7 percent throughout and 49.0% and 49.5 percent, respectively, for the proximal and occlusal lesions that are carious. Furthermore, we developed a condensed job where regions of interest were evaluated for the existence or nonexistence of carious lesions on an absolute basis. For this task, our model's occlusal and proximal lesions had areas around the receiver operating parameter curve of 83.6 percent and 85.6 percent, respectively. Our research shows that using deep learning to analyze dental photos has the potential to boost caries detection's speed and precision, support dentists' diagnoses, and enhance patient outcomes.

Table 1. A recent Literature of Dental Diseases diagnose based on deep Learning

Ref	Year of publication	Data set type	Size of data set	Methods	Proposed Algorithm	Classes	Evaluation Metrics	Accuracy
AbdullahS.AL-Malaise AL-Ghamdi et al.	2022	Image data set	371	Deep learning (DL)	NASNet	3	Accuracy & Loss	96 %
Haihua Zhu et al.	2021	panoramic radiographs	3127	DL	CariesNet	4	Accuracy	93.64 %
Linhong Jiang et al.	2022	panoramic photographs	640	DL and IP	UNet and YOLO-v4	2	Loss and Accuracy	77 %
F. Casalegno al.	2019	transillumination imaging (TI)	185	DL	CNNs	Binary	Accuracy, loss and Presicion	85 %
Sultan Imangaliyev et al.	2022	QLF-images	427	DL	Custom CNN	Multi class	Accuracy, loss	75 %
Toshihito Takahashi et al.	2021	oral photographic pictures	1904	Ensemble DL model	CNN model	2	Accuracy	93 %
Mircea Paul Muresan et al.	2020	X-Ray images	1000 images	DL and IP techniques	Optimized CNN	5	Accuracy, loss and F-1 Score,	89%
Amir Hossein Abdi et al.	2015	X-Ray images	95	DL	Segmentation	Binary	Coefficient	94%
Vanessa De Araujo Faria et al.	2021	PyRadiomics	105 images	DL	ANN	Binary	Accuracy and Loss	98%
Reyes LT et al.	2022	Dental images	Different datasets	ML and DL	N/A	Binary and Multi class	Accuracy, Presicion and Recall	74% to 98%
Jie Yang et al.	2018	X-Ray	196	DL	CNN	Binary	F1-Score	75%
Prerna Singh and Priti Sehgal	2020	panoramic image	400	DL and IP	Deep CNN	Binary	Accuracy	95%

3. Methodology

Our suggested methodology contains 7 phases that depicted in the Figure 2 (X-Ray Images, Filtering of images, Data Splitting, CNN Model Construction and Training, Feature Extraction, Classification and Performance Evaluation). In first phase, the input X-Ray images are collected then in second phase the filtering process is applied on the images to remove the noisy and unclear images. Third phase split the X-Ray images into Training and Testing Dataset, in fourth phase a Deep Learning model (CNN Model) is contrast and trained on the dataset.

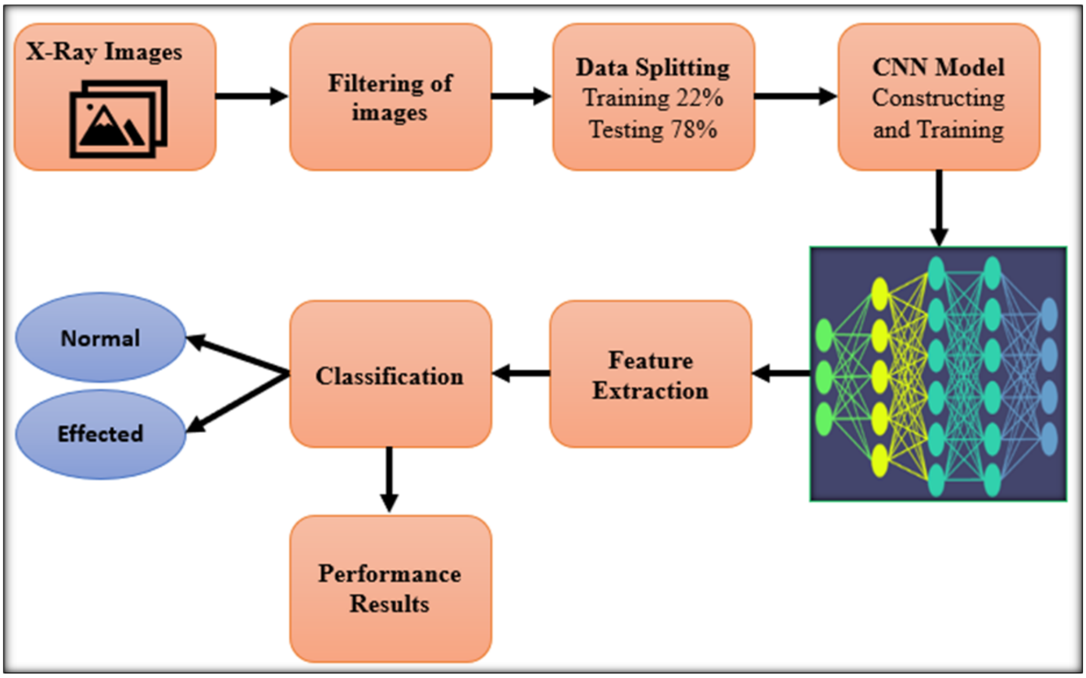

Figure 2. Proposed Methodology

Next a feature extraction process is start to extract important features from the dataset. Finally, the model classifies the X-Ray images into Normal and Effected and evaluate the trained model on the testing dataset.

3.1. X-Ray Images

In this step Dental X-Ray images of more than one hundred patients are collected from the Kaggle dataset repository ("https://www.kaggle.com/datasets/shanecandoit/dental-xrays"). The images dataset is annotated in two classes (Normal and Effected). The class Normal contains the Dental X-Ray images of the healthy teeth patients and the Class Effected contains images of disease teeth patients (Fully and Partially effected are mixed in the same class Effected). The annotation of dataset is done by expert dentist. Figure 3 represent the X-Ray images of Normal Cases and shows the X-Ray images of Effected Cases.

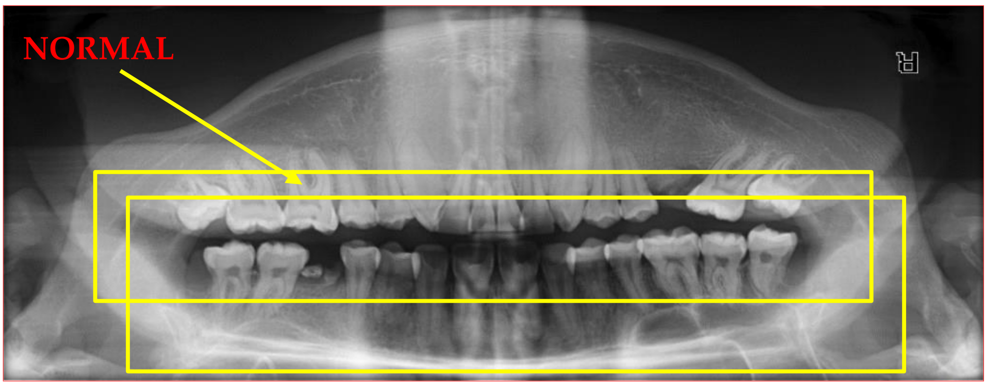

Figure 3a. Samples of Normal and Effected Cases

Figure 1b. Samples of Normal and Effected Cases

3.2. Filtering of Images

The Filtering of X-Ray images is done manually to remove the Noisy and unclear images [17-22]. The X-Ray images of less than 20-year age patients are remove from the images collection. The total number images we collect are 126 X-ray images. After apply the filtration the remaining images are 112. We use these images and expand the images by zoom in and zoom out. After expanding the dataset our total number of collected images are extend to 440. The Table 3.3 contains the three formats of the same image with Zoom, Normal and Zoom in. the expanding of dataset is necessary to train the DL models.

3.3. Data Splitting

The total number of X-Ray images used by this study are 440. About 78% portion (346 images) of total images are used for training of the models and 22% images (94) are used for the evaluation of trained models.

Table 2. Splitting of Data into Training and Testing

Distribution Dataset into Training and Testing	
Training	346
Testing	94
Total Images	440

Training dataset contains total of 346 images in which 158 images are from Normal Class and 188 images are from Effected Class.

Table 3. Distribution of Training dataset into classes

Distribution of Training Dataset	
Normal Cases	158
Effected Cases	188
Total	346

Testing dataset contains total of 94 images in which 40 images are from Normal Class and 94 images are from Effected Class.

Table 4. Distribution of Testing dataset into classes

Distribution of Testing Dataset	
Normal Cases	40
Effected Cases	54
Total	94

Most of the literature work researcher use 75% dataset for training and 25% for testing and some researcher use 70% and 30% respectively. Cross Validation Techniques is also used for the evaluation of most of the models. In this study we use 78% and 28% for Training and Testing.

3.4. CNN Model Construction and Training

In this Phase we construct CNN model using different layers. Our proposed CNN is CDDCNN (Classification of Dental Disease using Convolutional Neural Network) [23-26]. The name of our proposed model is based on the name of this thesis. Our Proposed Model contains seven layers (Convolutional Layer/Input Layer, 2-Dimensional Convolutional layer, Max Pooling2d Layer, 2nd Dimensional Convolutional layer with on dimensional, Max Pooling 2D, Flatten Layer, Dense Layer 1 and Dense Layer 2) and each layer having different working from one another. The first layer of our proposed model is Conv2d_Input that display the shape of input images feature as 32, 32 and 2. This layer take input (32, 32 and 2) and give output same as input. The output the first layer is stored in the feature and mapping to the next layer as an input feature [27-32]. The second layer of our proposed model is two-dimensional convolutional Layer that takes input vector (32, 32, 2) from the previous layer and store output to the new Conv2D for mapping on the next layer (32, 32, 16). Max-Pooling Layer in our proposed model is to reduce the feature of the previous layer and map the output to the next layer. Max-Pooling layer received the vector with parameters (32, 32, 16) and map the output with minimize features (16, 16, 16). Max-Pooling [33-35] Layer is used again for the reduction of feature to mapping to the next layer. This Max-Pooling layer take (16, 16, 32).

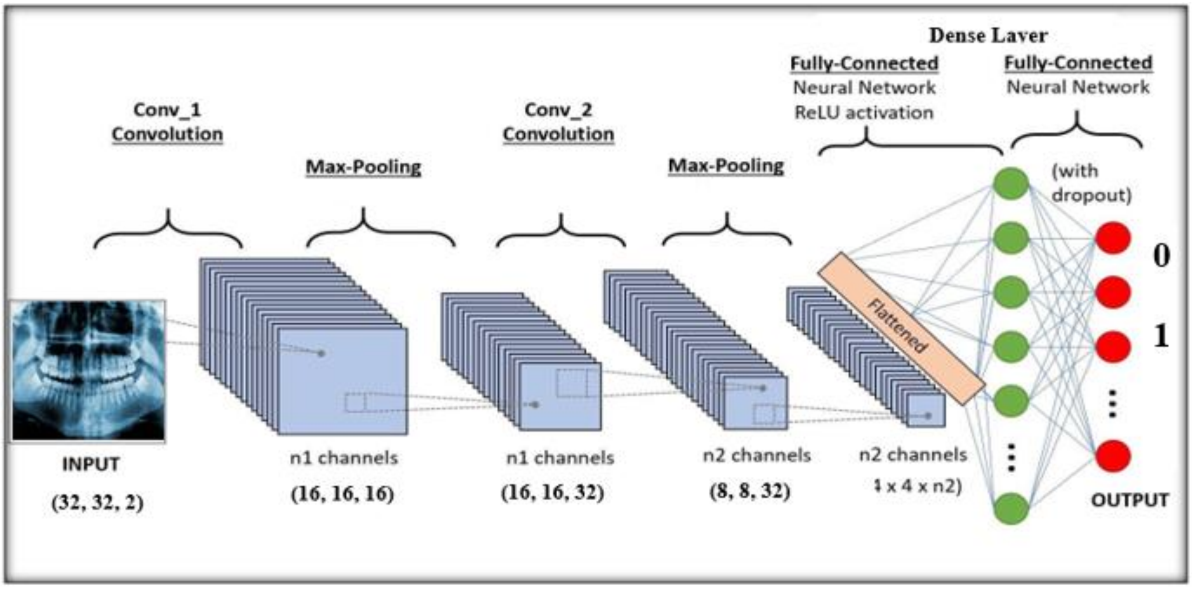

Figure 4. Proposed CNN model

Parameter from the previous layer map a vector of reduced features with (8,8,16). The next layer to Max-Pooling is Flatten Layer. We used a Flatten layer in our model before the features mapping to the dense layer. The Flatten layer get input feature vector from the Max-Pooling layer and flat the feature matrix into vertical array to mapping on the dense layer for classification of image. The second last layer of our proposed model is fully connected dense layer to map the output of the flatten layer and minimize the features to send the output to the last layer [36-42]. This layer contains 64 units and Relu activation function for performance. The last layer of our proposed model is fully connected dense layer to map the output of the flatten layer and minimize the features to send the output to the last layer [43-46]. This layer contains only 2 units because our dataset contains 2 classes (Normal and Effected) and a Relu [47-51] activation function for performance.

Table 5. Summary of Proposed CDDCNN Model

Layer	Output Shape	Params

Conv2D	(None,32,32,16)	304
Maxpooling2D	(None,16,16,16)	0
Conv2D	(None,16,16,32)	4640
Maxpooling2D	(None,8,8,32)	0
Flatten	(None,2048)	0
Dense	(None,64)	131136
Dense	(None,2)	130

3.5. Feature Extraction

Feature extraction is a process that converts raw data into manageable numerical features while preserving the original data set's information. It yields superior results when compared to utilizing ML on the raw data directly [50-52].

3.6. Classification

Classification is a supervised ML method that involves asking the model to determine the proper label for certain input data. The model is fully trained using training data, evaluated using test data, and then utilized for making predictions using brand-new, unused data while doing classification [53-56]. The Dental X-Ray pictures are classified into Normal and Affected during the classification step.

4. Result and Experiments

In this Section we evaluate the proposed model in terms of accuracy, Loss, Precision, Recall and F1-Score. We use two other models (VGG-16 and ResNet) for comparing results of our proposed model. VGG-16 and ResNet evaluated on the same data on which our proposed CNN model is evaluated but give poor results.

The experiment is conducted on the given below system.

Table 6. Used System

Parameters	Specification
Processor	CORE i5 4th generation
Model	Dell Latitude E6440
RAM	8 GB
HDD	320 GB
SSD	256 GB
OS	Windows-10-Pro
Tool	GPU and Google Colab
Language	Python3

We used 20 epochs in our model to improve the accuracy. Table 6 shows the average testing and training accuracy of the proposed CNN model.

Table 7. Accuracy

Model	Training Accuray	Testing Accuracy
Proposed CNN	0.9480	0.9887

VGG-16	1.00	1.00
Resnet	1.00	0.4255

The above table shows that the training accuracy of our proposed model is 0.9480 and the testing accuracy is 0.9787. we compare our propsed model with two other deep learning models (VGG-16 and ResNet). The result of both comparable models is less than the proposed model.

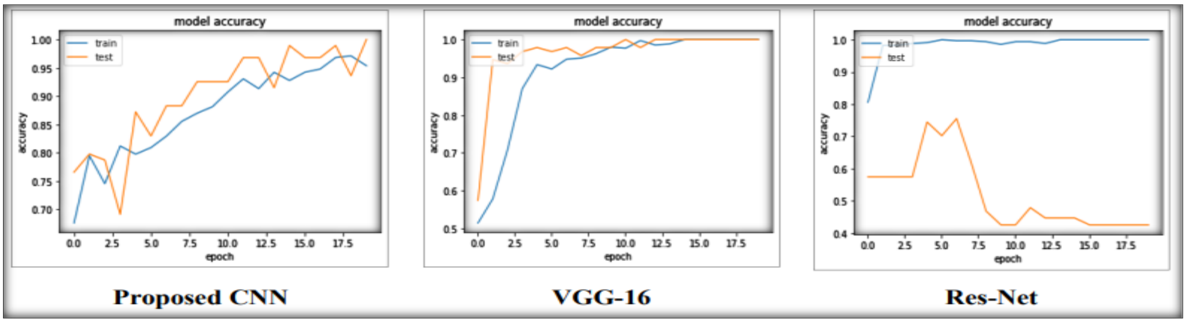

Figure 5. Models Accuracy

Figure 5 shows the Training and Testing accuracy of all three models. The accuracy of Propsed model is low at the epoch 1 and it gradually increases as the epoch is increases it means that our model is trained well and perform better on the testing dataset. The result of VGG-16 and ResNet is lower than our proposed model. We used 20 epochs in our model to improve the accuracy. Table 8 shows the average testing and training accuracy of the proposed CNN model as well as other models. The training accuracy of all three models is lower than the testing accuracy.

Table 8. Loss

Model	Training Loss	Testing Loss
Proposed CNN	0.1301	0.0568
VGG-16	0.0243	0.0186
ResNet	6.6096	12.5052

The above table shows that the training loss of our proposed model is 0.1301 and the testing Loss is 0.0568. The results shoes that our model is well trained on the dataset and performed well on the testing dataset. The training loss of VGG-16 is 0.0243 and testing loss is 0.0186 but it performs poor as compared to the proposed model. The training loss of ResNet is 6.6096and testing loss is 12.5052 but it performs poor as compared to the proposed model.

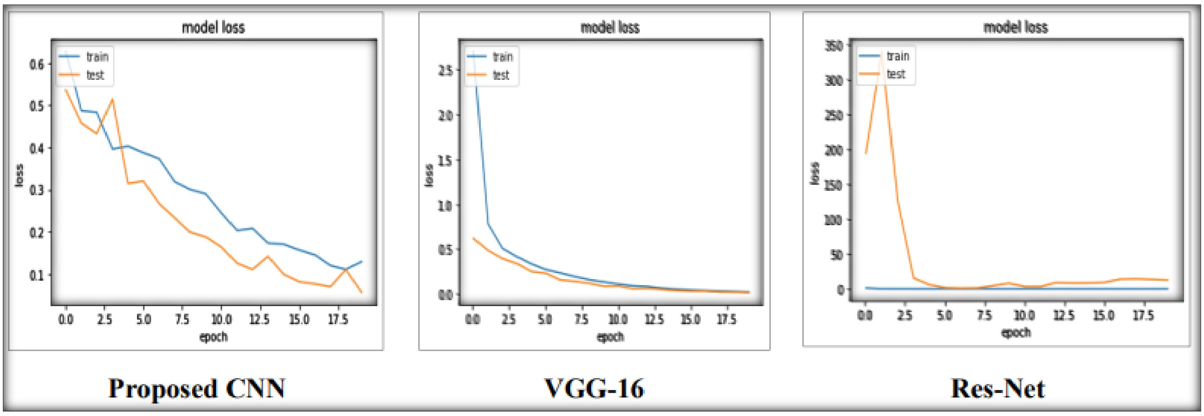

Figure 6. Models Loss

Figure 6 shows the Training and Testing Loss of model. The Loss of models is high at the epoch 1 and it gradually decrease as the epoch is increases it means that our model is trained well and perform better on the testing dataset. Figure 7 shows the confusion matrix graph of proposed CNN model. In this graph 94 images are classified into TP, FP, TN, and FP prediction.

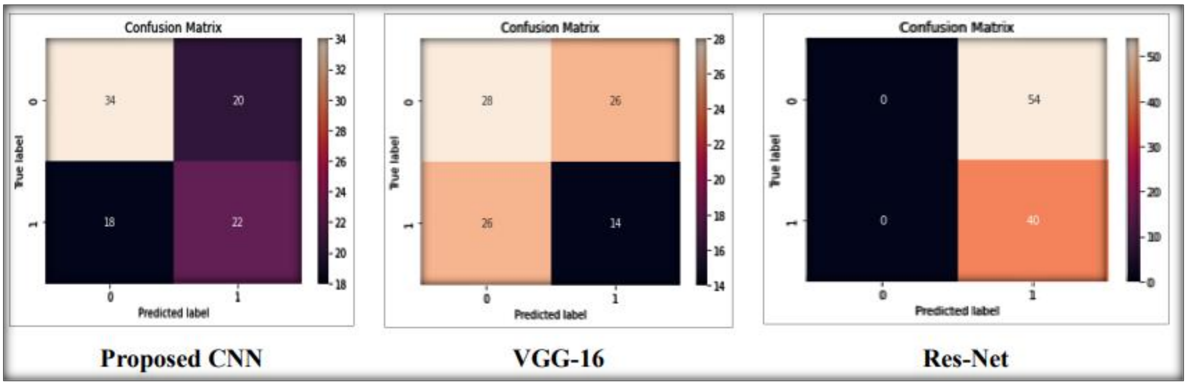

Figure 7. Confusion Matrix graph of Models

In first row of the confusion matrix 34 images are true predicted in class Normal (0) and 20 images are predicted as False Negative. In the second row of the matrix 18 images are predicted as True and 22 images are predicted as Negative.

True positives (TP) are predictions that turn out to be correct.

False positives (FP): Positive predictions that turn out to be negative.

True negatives (TN): Predicted negatives that turn out to be negative.

False negatives (FN) are predicted negatives that turn out to be positive.

Table 9. Confusion Matrix of proposed Model

Class	Presicion	Recall	F1-Score
Normal (0)	0.65	0.63	0.64
Effected (1)	0.52	0.55	0.54
Average	0.59	0.59	0.60

Table 10. Confusion Matrix of VGG-16 Model

Class	Presicion	Recall	F1-Score
Normal (0)	0.52	0.52	0.52
Effected (1)	0.35	0.35	0.35
Average	0.43	0.43	0.43

Table 11. Confusion Matrix of ResNet Model

Class	Presicion	Recall	F1-Score
Normal (0)	0	0	0
Effected (1)	0.43	1.0	0.60
Average	0.21	0.50	0.30

Table 09 shows the Presicion Recall and F1- Score of the model. The presicion of Class Normal is achieved 65 percent and Class Effected give 52 percent presicion. Recall is 63 percent is achieved by class Normal and 55 percent recall is calculated by the class effected. F1-Score of 64 percent is achieved by the class Normal and 40 percent by the Class Effected.

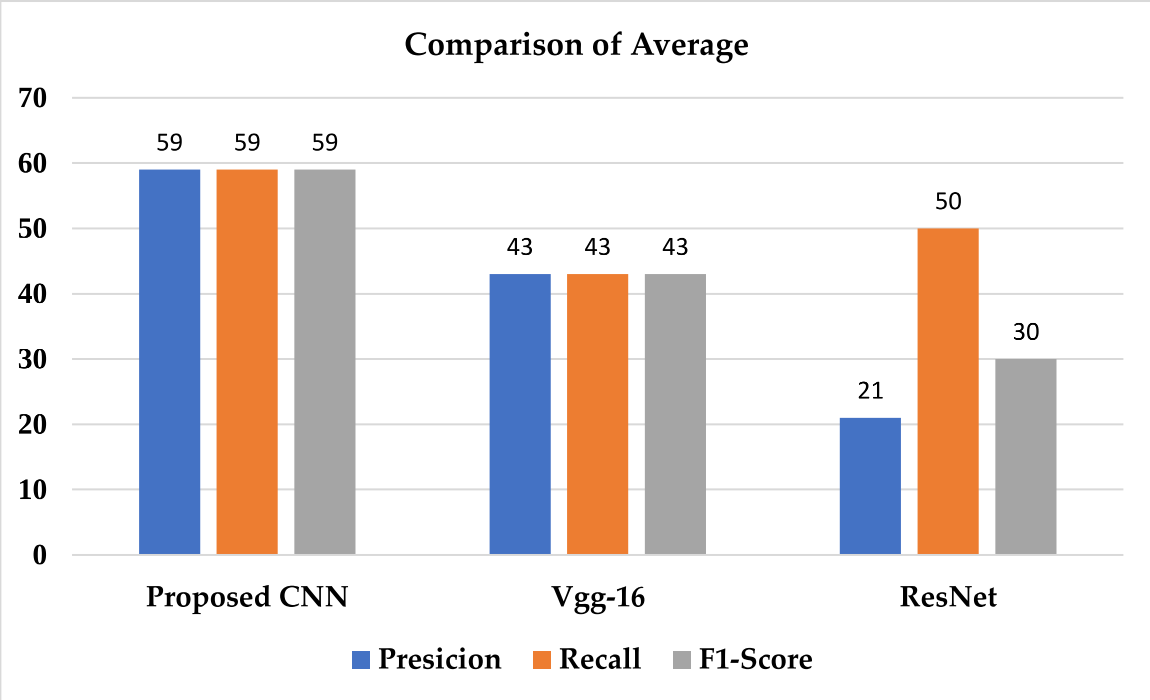

Figure 8. Proposed Model Results

5. Conclusion

Dental radiography can help with medical assessment, treatment, and quality control. To improve clinical quality, much effort was put into developing digitalized dental X-ray image analysis tool. We present the dataset preprocessing, procedures, and results of a dental treatment quality evaluation using periapical dental X-ray images taken before and after the operations. To assist dentists in making clinical decisions, we proposed a tool pipeline for automated clinical quality evaluation. AI (Machine Learning and Deep Learning) is a well-known automated technology. We used the Deep Learning method to identify the disease from X-Ray illustrations. The used dataset was downloaded from the Kaggle website which contains 126 dental X-Ray images. Designated dental experts label X-Ray images as Normal or Affected. Firstly, we take the images and used data augmentation to increase the size of the dataset because Deep Learning models required more data for training. Secondly, we build a Convolutional Neural Network (CNN) with many layers (Convolutional Layer, Max-Pooling Layer, Flatten Layer, Dense Layer, and Output Layer) and classified the images into Normal and Affected classes. On the augmented dataset, we trained the CNN model and evaluate clinical quality. Accuracy, Loss, Precision, Recall, and F1-Score are calculated to evaluate the model. Our method has achieved an accuracy of 97.87 percent and an F1 score of 60 percent, which is comparable to that of expert dentists and radiologists.

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