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A Novel Periodontal Disease Grade Classification Methodology using Convolutional Neural Network

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Abstract: With the advancement of artificial intelligence, the demand of automated assistance in the domain of medical imaging has become important to reduce time and inaccuracy in physical examination. Modern lifestyle choices are resulting in a variety of dental diseases which led tomultiple researches challenges which are carried out for pre-emptive detection in order to dealwith these diseases within time. Periodontal diseases (PD) is a type of dental disorder which israpidly increasing and being the major cause of early teeth loss. The machine learning based convolutional neural network (CNN) model is carried out in detecting grade wise classification of the periodontal disease. A dataset containing 350 dental images in Radio Visio Graphy (RVG) format belonging to an age group of 18-75 years is used for both training as well as testing. This method has successfully detected mild periodontitis, moderate periodontitis and severe periodontitis by achieving a satisfactory accuracy of as high as 94% with minimum loss, precision value, recall and F1score of 0.41, 0.93-0.95 and 0.91-0.94 respectively for all the three classes of Periodontitis.

Keywords: Artificial Intelligence, Convolutional neural network, Dental diseases, Performance parameters, Periodontal Diseases, RVG Images.

1. INTRODUCTION

Periodontal disease, also known as periodontitis which is a severe gum infection and its one among the six prevalent kinds of inflammation disease [1,2]. It mainly starts with untreated gingivitis (a type of gum disease) when left untreated for a long duration resulting periodontitis which need intense dental care for teeth recovery and sometimes need extraction and teeth implants which comes with a high cost [3-6]. Early detection of this type of disease can help the patient to retain their natural tooth till old ages. Periodontal disease can be considered as one of the biggest threats in dental health this is found in different class of population divided in age and their existing lifestyle. The severity of the periodontal disease will become worst with the increase in age [7,8]. According to various studies cited in literature, people from both developing and underdeveloped countries suffer from this disease and is affecting almost 30-50% of the global population. According to data from the Centers for Disease Control and Prevention (CDC), almost 50% of the people of American above the age of 30 have been diagnosed with grade III or severe periodontitis. [9-11].

Periodontal disease is characterized by analysing the condition of tooth mobility, connective tissue attachment (CAL), probing pocket depth (PPD), and moreover, the bleeding on probing (BoP) [2]. For diagnosing as well as detection of periodontal disease various conventional methods are used where the teeth and gums of the patient are studied and examined for pocket depth of the gum and the CAL [12.13]. Mainly, the grades of Periodontal disease are divided in three classes: Grade I or Mild periodontitis, Grade II or Moderate Periodontitis and Grade III or Severe Periodontitis [14,15].

In dentistry, machine learning is progressively blowing its head within the sector of radiology with a stronger focus on electronic Intraoral periapical radiographs (IOPAs) / RVGs diagnostic images, three Dimensional (3D), as well as cone beam computerized tomography (CT scan). Machine learning helps in much data collected and quick calculation to build system which help in diagnostic and therapeutic plans. These devices also have a mildly higher advantage over human beings, as they are able to work tirelessly for hours. While intellect and mind need a break before competing duties are performed [16,17].

In Periodontal disease detection, a CNN can be trained X-Ray dataset or CT scan dataset images of the teeth and gums, and then used to automatically identify signs of periodontal disease such as inflammation, bleeding, and bone loss in new images. This work concentrates in developing a CNN model for classification of grades of periodontal disease [18].

Over the last decades, artificial intelligence (AI) has opened the doors to various imaging processing related domains. More precisely, CNN is one of the core model in AI and deep learning (DL) which proves to be a powerful tool in solving problems of segmentation, recognition, detection and classification of

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images by giving a higher value of accuracy. It is difficult to ignore the present blow around of artificial intelligence which combines with virtual assistants such as Siri, Google Assistant and Alexa, making its way into our everyday life [19-21]. In current years, the evolvement of AI in healthcare is seen to be growing significantly in the detecting and diagnosing of disease from X-rays, CT and MRI which in the past decade primarily depends on the physician's support. The virtual aids that are built based on AI assist dentists to predict correct diagnosing without lacking any unidentified information [22,23].

The three different categories of periodontal disease have been successfully classified using a CNN-based machine learning algorithm in this work, which focuses on the detecting and classifying of oral illness using RVG X-ray images. This work is based on the classification and detection of dental disease using RVG X-ray images using CNN based ML algorithm which have successfully classifythe three different grades of periodontal disease.

2. MATERIAL AND METHODS

A CNN model is developed to classify the different grades of periodontal disease. A generalized method used in this work is shown in Figure 1. It basically consists of data collection which in this case is the dental RVG images, preprocessing of these images alongwith data augmentation. 20% of the images in the dataset are used for testing the model and same has been trained using 80% of the images. The accurateness of the proposed model is assessed using various performance metrics.

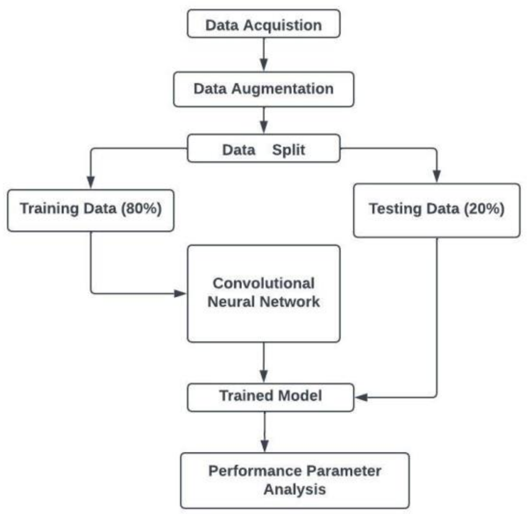

Figure 1. Generalized approach for classification

2.1 Data Collection/ Acquisition

Dental RVG (RadioVisioGraphy) periapical X-ray images are collected from School of Dental Sciences, Sharda University, India with ages ranging from 18-70 years as online labelled dataset for medical images are not available due to privacy issues and government policies. The process of labelling the classes of dataset is performed manuallywith the help of dentist and radiologist. A total of 350 RVG periapical X-ray images are collected and analyzed.

2.2 Data Preprocessing

Image processing starts with the suppression of unwanted distortions and enhancement ofthe image to extract relevant features. The format of the input RVG images used are in Joint Photographic Experts Group) JPG/JPEG however, other formant can also be considered. Scaling of images is performed and are resized to 255*255*3 in order to fit theclassification model. Keras image data generator (library) provides a host of various imageaugmentation techniques like shifting, brightness range and rescale etc. At each epoch, new variations of images are received by the model and image augmentation is performed on the dataset to come up with new transformed images of the original dataset.

2.3 Classification

In the classification step, a random division is done into two subsets training class and testing class. The training segment of the data is used for training the model to predict the desired outcome. The test class data is used to test the trained model to measure the performance and efficiency of the model. The dataset is split into 70% training and 30% testing. The labelled images were fed into the classification model.

2.4 Network Architecture

CNN is a kind of deep learning(DL) algorithm that is precisely well-suited to image as well as video processing tasks. CNNs are modeled after theway the human visual system processes information, and they are able to learn and recognize patterns and features in the images. In a CNN, the image is passed through multiple layers of filters, each of which is designed to detect a specific feature or pattern in the image. These filters are convolved with the image, which means that they are multiplied element-wise with small regions of the image, known as the receptive field. Asthe image is passed through the layers, the filters become increasingly complex, and are able to detect more abstract and higher-level features. CNNs are commonly used in imageclassification tasks, where the goal is to assign an image to one of several predefined categories. They are also used in object detection tasks, where the goal is to locate and identify objects within an image.

A convolutional neural network (CNN) typically consists of several layers, each of whichperforms a specific function in the processing of the image. These layers can be broadly classified as summarized below:

2.4.1 Convolutional layers

A set of filters are put to the image for extraction of the unique

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features and patterns, which in short is known as convolution operation. The extracted features are fed to the network to learn them during the training phase. The output of these layers is called feature maps.

In the first layer an input image with dimensions N x N is fed to a set of convolutional filters (kernels) with dimensions K x K where each set of filter produces a single output feature map. sliding each filter across the input feature map, multiplying the filter weights by the corresponding input values element-by-element, and adding up the results are the steps involved in the convolution operation. This process is repeated for each position of the filter across the input feature map which further generating the output feature map. And mathematically it can be commuted in equation 1.

$$Y_{i,j}(k) = f(\sum K_{m=1,n=1} \quad X_{i+m-1,j+n-1} \quad \times W_{m,n}(k) + b(k)) \qquad (1)$$

Where, $Y_{i,j}^{(k)}$ represents the value of the k-th output feature map at position (i, j),

$X_{i+m-1,j+n-1}$ represents the value of the input feature map at position $i + m - 1$ and $j +$

$n - 1$, $W_{m,n}^{(k)}$represents the weight of the kth filter at position (m, n), $b^{(k)}$ represents the bias term associated with the kth filter and f(×) denotes activation function.element-wise to the summed value.

2.4.2 Pooling layers

These layers are used for reduction of the spatial resolution of the feature maps, which helps to decrease the computational cost of the network and make it more robust to reduce reduce the translations and distortions in the image.

$$Y_{i,j}^{(k)} = max\left(X_{i.P+m-1,j.P+n-1}\right) \qquad (2)$$

In this layer a pooling window of size $P \times P$ is process for sing position i,j. And the mathematical model is commuted in equation 2.

Where, $X_{i.P+m-1,j.P+n-1}$ represents the value of the input feature map at position $i.P +$

$m - 1$ and $j.P + n - 1$,

2.4.3 Fully connected layers

With addition of a set of weights to the feature maps and calculating a score for each class, these layers are used to determine the ultimate finalization for the input image. The highest-scoring classis then chosen as the final prediction of the network.

An output feature vector Y with size M is obtained by assuming an input vector X of dimension D. Every neuron in this layer is coupled to every other neuron in the layer before it. And the mathematical model is commuted in equation 3.

$$Y^{(k)} = f(\sum^{D}{}_{d=1} X^{(d)} \,.\, W^{(k)} + b^{(k)}) \qquad (3)$$

Where, $Y^{(k)}$ represents the kth element of the output feature vector, Y and $X^{(d)}$ represents thedth element of the input feature vector, X, $W^{(k)}$ represents the weight connecting the dth input neuron to the kth output neuron.

2.5 Brief working of the model

The above three layers are executed with a model consisting of 17 layers out of which 1layer is an input layer, 9 layers are trainable layers and 7 layers are non- trainable layers.

Further, these 9 trainable layers consist of 6 Convolutional 2-D layers and 3 Fully connected layers. And the 7 non-trainable layers consists of 3 Dropout layers, 3 Max Pool2D layers with pool size 2*2 and valid padding and 1 Flatten Layer. In first block the convolutional layers are having 32 filters of 2 kernel size. The activation is 'ReLu' is used in this classification model. There is dropout of 20% neurons. After this there is a Flatten layer to change the dimension of data into linear form. The final layer is having SoftMax activation. The learning rate is a hyperparameter in a convolutional neural network (CNN) that controls the step size at which the algorithm updates the weights of the network during training. The learning rate determines how quickly or slowly the network adapts to the training data. Learning rate used in this model is 0.0005. Stochastic Gradient Descent (SGD) is used that is the most basic optimizer and it moves in the opposite way to update the network's weights by evaluating the gradient of the loss function in regard to the weights.

Below enumerated is the summary of the model of the proposed work in Table 1.

Table 1 Model Summery of proposed classification model

Layer (type)	**Output Shape**	**Parameters**
conv2d (Conv2D)	(None, 255, 255, 32)	416
conv2d_1 (Conv2D)	(None, 254, 254, 32)	4128
dropout (Dropout)	(None, 254, 254, 32)	0
max_pooling2d (MaxPooling2D)	(None, 127, 127, 32)	0
conv2d_2 (Conv2D)	(None, 126, 126, 64)	8256
conv2d_3 (Conv2D)	(None, 125, 125, 64)	16448
dropout_1 (Dropout)	(None, 125, 125, 64)	0
max_pooling2d_1(MaxPooling2D)	(None, 62, 62, 64)	0
conv2d_4 (Conv2D)	(None, 61, 61, 256)	65792
conv2d_5 (Conv2D)	(None, 60, 60, 256)	262400
dropout_2 (Dropout)	(None, 60, 60, 256)	0
max_pooling2d_2(MaxPooling2D)	(None, 30, 30, 256)	0
flatten (Flatten)	(None, 230400	0
dense (Dense)	(None,100)	23040100

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dense_1 (Dense)	(None, 50)	5050
dense_2 (Dense)	(None, 3)	153

Total parameters: 23,402,743

Trainable parameters: 23,402,743

Non-trainable params: 0

2.5. Validation and Performance Analysis

The model is validated using 1397 test images which was classified into three grades of periodontal disease. The accurateness of the suggested model is predicted by evaluating performance indicators such as precision value , recall value , and F1-score value.

RESULTS AND DISCUSSION

The proposed classification model is trained on 3265 augmented images and validated on 1397 images. For classification purpose, CNN is employed with the model's learning rate is 0.0005 and its dropout value is 0.2. This model gives a multiclassification output of the grades of periodontal diseases. For each class of periodontal disease, the different performance metrics are calculated. Figure 2 depicts the confusion matrix of the 1397 test images used in validation of the model. Table 2 depicts the performance indicator metrics of the classification model on the three classes of periodontal disease.

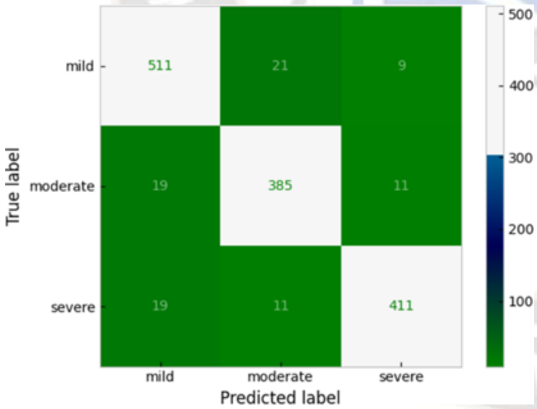

Figure 2 Confusion Matrix for validation Dataset

Table 2 Performance Indicators

Classes	Precision	Recall	F1-score
Mild	0.93	0.94	0.94
Moderate	0.92	0.93	0.93
Severe	0.95	0.93	0.94

From the above Table 2, another comparative analysis can be drawn which compares the score of different classes of periodontal diseases based on their precision value, F1-Score and recall value. The below mentioned figure 3(a), 3(b) and 3(c) shows the comparison.

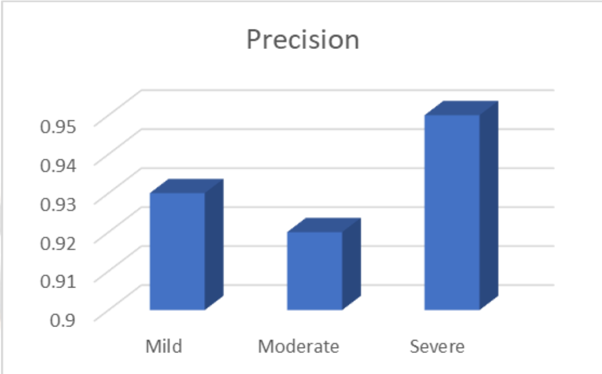

Figure 3(a) Precision value of grades of periodontal disease

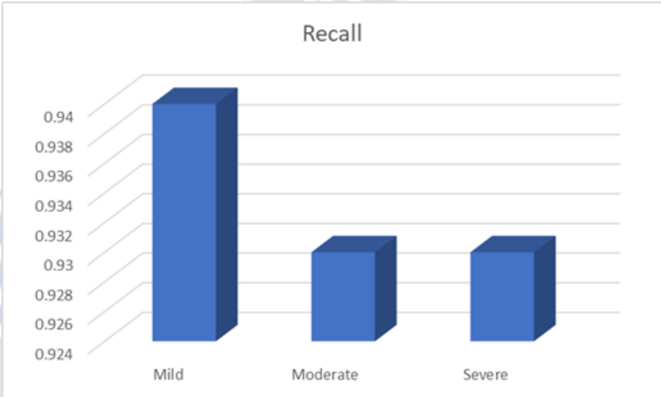

Figure 3(b) Recall value of grades of periodontal disease

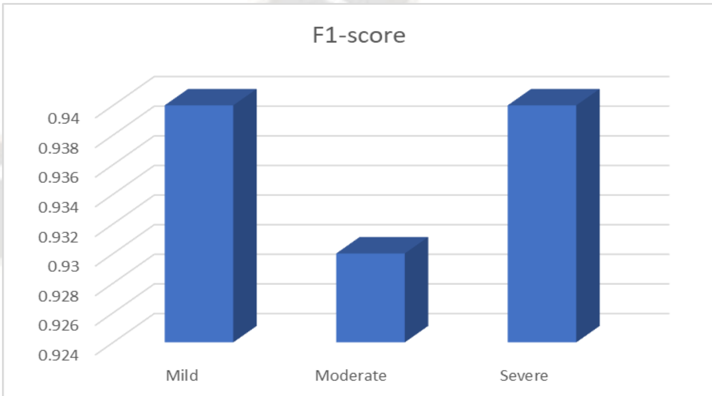

Figure 3(c) F1-score value of grades of periodontal disease

Figure 4 (a) shows attained accuracy of 94% of the model and (b) shows with minimumloss on the validation set.

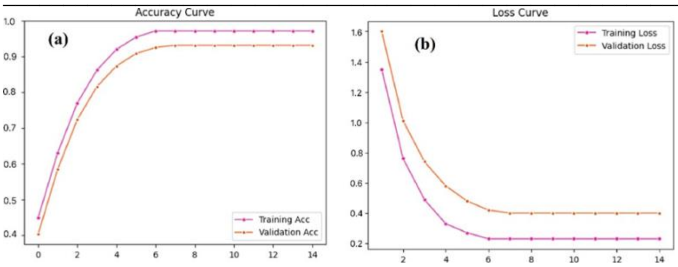

Figure 4 (a)Training accuracy VS Validation accuracy, (b) Training loss VSValidation loss

3. CONCLUSION

Accurate detection and early diagnosis of periodontal disease are vital factors for implementation of prevention and treatment of the patients suffering from this disease. This work tries its best to classify three grades of periodontal disease by proposed methodology that enhances the existing accuracy. Based on the statistical analysis of the proposed model, the accuracy, precision, recall and F1- score are obtained which have successfully classify the images most of the times correctly. The current study succeeded to obtain a satisfactory accuracy 94% using a small dataset of around 350 images. The data augmentation played a vital role by overcoming the scarcity of the training images by minimizing overfitting issues and also improving the overall model's accuracy. Resultsproves CNN to be more efficient and effective in dental disease detection.

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