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Application of deep learning neural network to create a multi-class identifier to detect and categorize periodontal diseases

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Abstract

Periodontal diseases is the major cause of bad breath and loss of tooth in adults worldwide. The comprehensive intention of the present study is to detect and categorize the type of periodontal diseases. In order to achieve the objective a Convolution Neural Network (CNN) model is proposed in the study. The proposed CNN model is built using the Tensorflow framework which is coded in python 3.8. The proposed model is trained using 3241 images of periodontal and non-periodontal diseases. The CNN model is tested using 90 images. The training and testing accuracy of the CNN model is 97.82% and 73.61% respectively whereas the loss computed by Mean Squre Error (MSE) for training and testing is 0.07 and 0.006 respectively.

Keyword: Convolution Neural Network (CNN), Multi-class classification, Periodontal diseases, Early diagnosis

1. Introduction

In this present knowledge-based world, researchers are developing better, robust and highly sophisticated technology to be applied for early detection of cancer, periodontal diseases, brain tumors, blood vessel diseases and heart disease etc. In this direction, deep learning has established itself as one of the most reliable tool in application to such type of complex problems. Deep learning algorithms' uniqueness lies in its ability to predict and classify different labelled and unlabeled data which makes it the most preferred tool for early diagnosis.

Convolution Neural Network (CNN), is an unsupervised deep-learning tool which is mostly applied to analyze visual imagery [1]. CNN mimics the biological process of connectivity organization of the animal visual cortex [2]. Due to this, CNN is applied to diagnose different diseases such as periodontal diseases also called gingival diseases in the early stage. It is characterized in the early stage with red, swollen and bleeding gums. Gingival diseases mostly affects the tissues surrounding the teeth and is the root cause for bad breath and loss of tooth in adults worldwide [3]. Early diagnosis of gingival diseases is necessary for controlling the prevalence of periodontal disease. The periodontal diseases is classified into eight categories which are listed below in the table 1.

Table 1: Classification of periodontal diseases

Sl. No.	Type of gingival diseases	Examples	Picture
1	Genetic/development disorder	Hereditary gingival fibromatosis	
2	Specific infection	Necrotizing periodontal diseases	
3	Inflammatory and immune condition	Orofacial granulomatosis	
4	Reactive process	Epulides	

5	Neoplasm	Squamous cell carcinoma	
6	Endocrine, nutritional and metabolic diseases	Parathyroid disorder and diabetes mellitus	
7	Traumatic lesion	Injury	
8	Gingival pigmentation	Smoker's melanosis	

1.1. Motivation and Novelties

With the development made in the field of deep learning and its application in medical image analysis, it is applied in early diagnosis of periodontal diseases [5]. There exist numerous literatures that applies CNN for detecting periodontal diseases. However in this study tries to extend the existing literature by developing a multi-class classifier to identify the different categories of periodontal diseases.

In the present study, the visual representation of the healthy gum and different categories of periodontal diseases is taken as input to build the particular multi-class classifier. For the execution of the present study, a total of 3241 images which are resized to $200 * 200$ pixels using OpenCV are taken as input. Out of which 572 images are that of healthy teeth, 431, 367, 385 377, 159, 303, 346 and 301 images of first, second, third, fourth, fifth, sixth, seventh and eighth category respectively. These images are used to train the CNN classifier built using Tensorflow library. Another 90 images of $200 * 200$ pixels is used to validate and test the accuracy of the classifier.

The remaining of the paper is drafted into five sections. The first section is the introduction that highlights the importance of the study. The second section reviews the contemporary researches followed by secton three that discuss about the methodology adopted to build the classifier. Section four summarizes the results and briefly discuss about the findings in the study. Finally, section five concludes the paper.

2. Review of the contemporary researches

A recent literature that involved the application of AlexNet architecture which is a modified CNN model to detect teeth from the dental panoramic X-ray images [6]. In the study, the images were taken from three different X-ray machines. By estimating the gap of the mouth for determining the possible placement of the teeth. The entire oral region is divided into four quarter and the teeth position is determined using AlexNet model. Another research of the time involves application of CNN to diagnose a small labelled dental dataset [7]. Two CNN classification model is develop to classify the Dental Caries, Periapical Infection, or Periodontitis. In the paper, the activation was performed using VGC16 model. In the next research that applied CNN technique to dental dataset involved the developing of a noninvasive procedure of detecting periodontitis. The developed classification model was trained based on the symptoms and risk factors of the different periodontal diseases [8]. In the next literature, the picture of the teeth with dental plaque is taken as input to develop a CNN classifier with AlexNet architecture using Tensorflow to identify periodontitis [5]. CNN is also applied to classify the intensity of the periodontal diseases [10]. The dataset used for the study comprises of images of healthy and periodontal diseases. The paper classified the intensity of periodontal diseases as healthy, mild, severe and not periodontal image. In [11] the Mask R-CNN technique is used for automatic tooth detection and segmentation. Some other literatures were reviewed but restricting the papers only to the most recent and significant articles.

3. Methodology

CNN showed ground breaking results over the past decade in a variety of fields related to pattern recognition; from image processing to voice recognition. The steps carried out for identifying and classifying the periodontal diseases by CNN is shown as a flow diagram in figure 1.

3.1. Datasets

The dataset gathered for the study are pictures of the eight categories of periodontal diseases and healthy gum. A total of 3331 images are used for the developing the CNN model. Out of the 3331 pictures, 3241 pictures are used for training and remaining 90 images are used for testing and validating the CNN model.

3.2. Pre-processing the dataset

All the pictures have different aspect ratio, size, shape and format. In this step, the images were resized to $200 * 200$ pixels and changed the format to Joint Photographic Experts Group (jpeg) format using OpenCV. All the images were sheared, zoomed and added 10% Gaussian noises to prevent model over-fitting and enhance learning capability [9].

3.3. Feeding the dataset

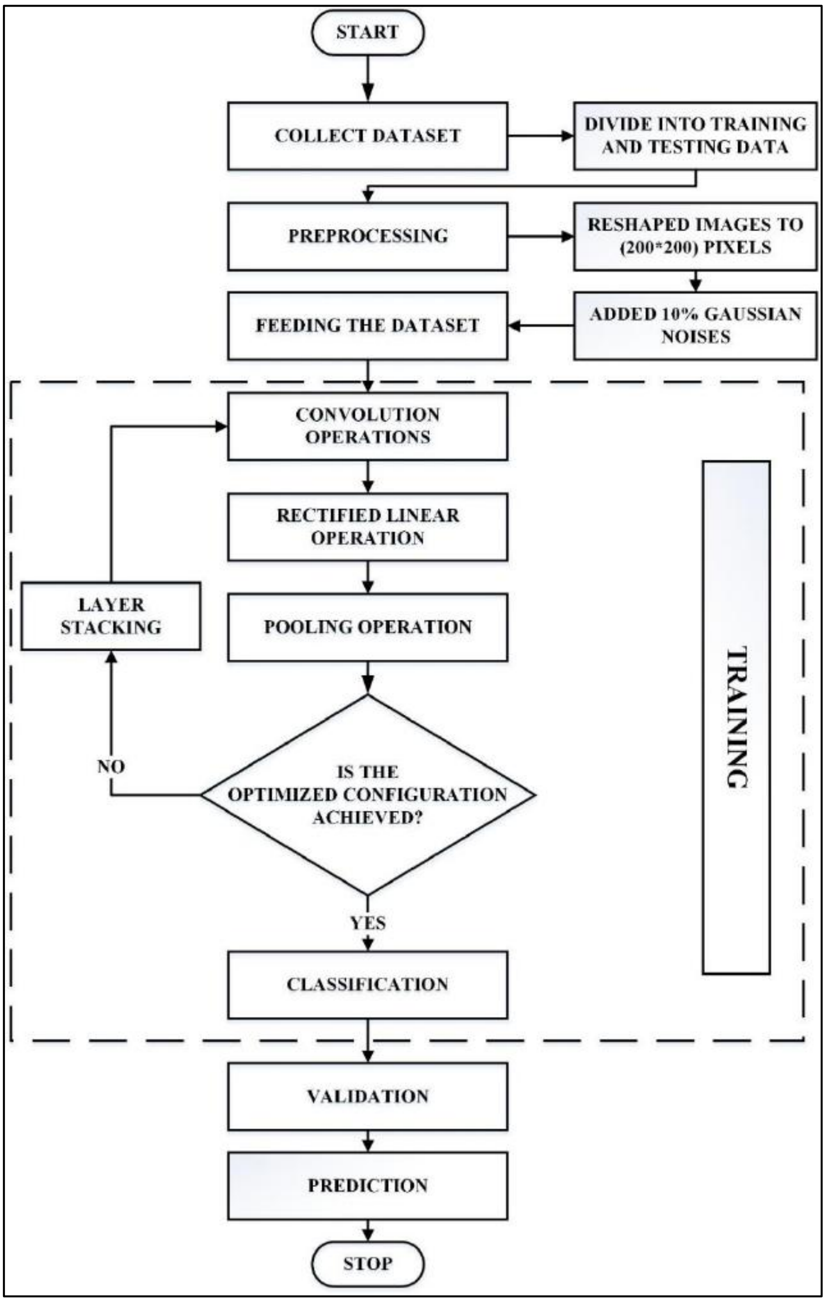

Figure 1: Flowchart for the proposed CNN model

The images of the periodontal diseases were divided according to the batch to which it belonged i.e. training and testing images. Within each folder images were categorized if it is healthy or unhealthy and if unhealthy then the category of the periodontal diseases.

3.4. Training of the dataset

For training the network, the labeled images were be fed to the model. After which the images were divided into batch of 64. The model was trained for 100 epochs which is run for 50 cycles per epoch. The steps followed for training the CNN model includes:

a. Convolution layer

The convolutional layer in CNN model extracts features from the image and discards the noises. Convolution operation is a mathematical process of two functions typically represented by $(f \; and \; g)$ to produce a third function (φ) that expresses how the shape of one is modified by the other. In the proposed CNN model the expression for computing the value of φ is the dot product of $f \; and \; g$ which is given in Eq. (1).

$$\varphi = f.g \tag{1}$$

b. Activation function

In neural network models, activation function transfers the input to the node to the output of the node. The activation function used in the CNN model is called rectified linear unit (ReLU). The ReLU is mathematically expressed as:

$$y = \varphi(x) = \begin{cases} 0, & if \; x \leq 0 \\ x, & if \; x > 0 \end{cases} \tag{2}$$

Graphical representation of ReLU is shown in figure 2.

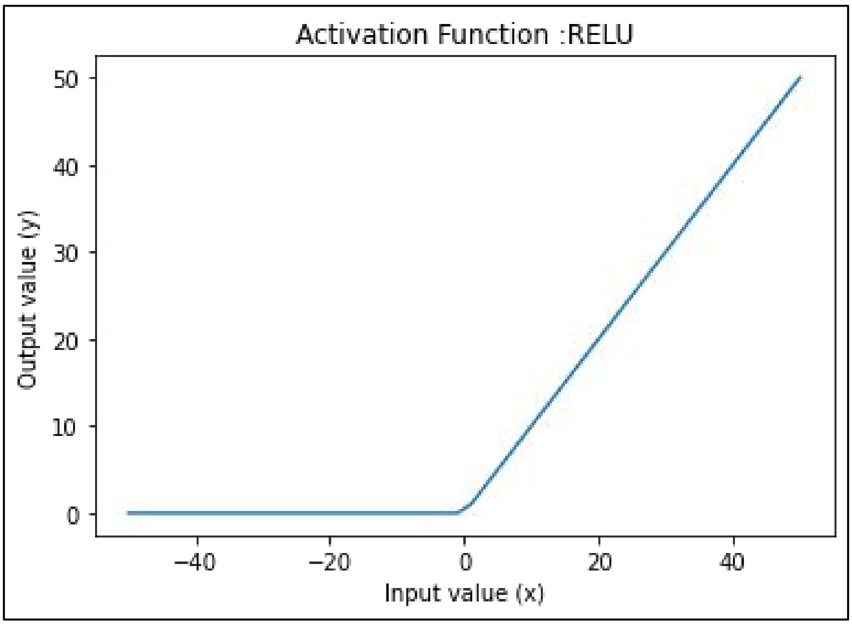

Figure 2: Graphical representation of ReLU

c. Pooling operations

The pooling operation reduces the dimension of the feature maps which in turn reduces the number of parameters to learn and the amount of computation performed in the network. The importance of pooling layer is to summarize the feature present in a region of the feature map generated by the convolution layer. So, further operations are performed on summarized features instead of precisely positioned features generated by the convolution layer. This makes the model more robust to variations in the position of the features in the input image.

d. Layer stacking operations

In layer stacking operation, the convolution operation, activation and pooling operation is repeated until the output obtained is a minimized matrix of the input image.

e. Fully connected layer

The Fully Connected (FC) Layer consists of neurons that are fully connected with the neurons from the previous layers. The FC layer predicts the output or the label of the input class. In case of multi-class problems, different activation functions used classify the label of the inputs. In this study, SOFTMAX activation function is used to classify the label. Hence, it has an output dimension of $[1 \times 1 \times M]$ where M is the number of classes or labels used for classification

f. Classification

Classification is a process related to categorization. In the study, the CNN model classify the healthy and unhealthy gums. If the gum is classified as unhealthy then the proposed CNN model identify the periodontal diseases of the patient. The list of classification of the periodontal diseases is tabulated in table 2.

Table 2: Classification of periodontal diseases

Sl. No.	**Classification**	
	Healthy/Unhealthy gum	**Periodontal diseases**
1	Healthy	---
2	Unhealthy	Genetic/development disorder
3	Unhealthy	Specific infection
4	Unhealthy	Inflammatory and immune condition
5	Unhealthy	Reactive process
6	Unhealthy	Neoplasm
7	Unhealthy	Endocrine, nutritional and metabolic diseases
8	Unhealthy	Traumatic lesion
9	Unhealthy	Gingival pigmentation

3.5. Testing of the CNN model

For testing the performance of the CNN model, the 90 images that were that were segregated from the training images were feed into the model. The output label of the test images obtained from the CNN model is compared with the actual label of the images.

3.6. Prediction

Prediction of CNN model is its ability to detect and classify the different periodontal diseases as mentioned in table 2. Figure 3 shows the diagrammatical representation of the proposed CNN model.

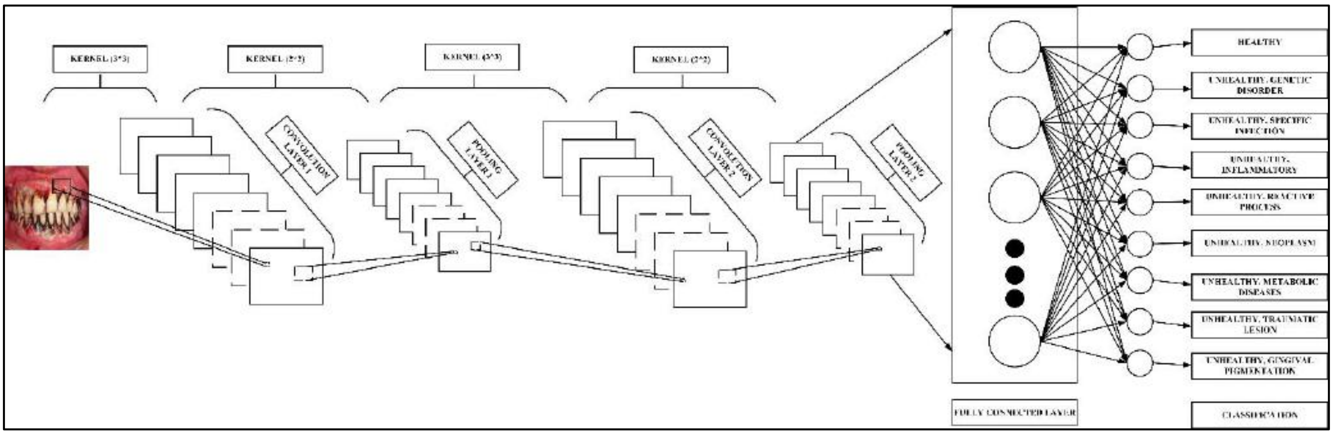

Figure 3: Diagrammatical representation of the proposed CNN model.

4. Application to gingival diseases

The proposed CNN model is built using the Tensorflow framework which is coded in python 3.8 and ran on a 64-bit windows 10 system with 8GB RAM and i5, 1.6GHz processor. The proposed model is trained with the help of 3241 images. The main objective of the proposed model is identify and categorize the different periodontal diseases.

4.1. Results

Adam optimizer is used to get the optimized CNN model configuration. The performance of the CNN is measured by computing the loss as computed by Mean Square Error (MSE). The proposed CNN model is executed for 100 epochs. The training accuracy of the proposed CNN model is increased from 43.84% in the first epoch to 97.82% in the 100th epoch. On the other hand the value of the training loss decreased from 1.54 to 0.07.

4.2. Validation

For validating the CNN model, the 90 test images are fed into the model and the value of accuracy and loss is computed. The validation accuracy of the proposed CNN model increased from 57.24% to 73.61% whereas the value of the validation loss decreased from 0.036 to 0.006. The graphs for training and testing accuracy and the training and validation loss is shown in figure 4 and 5 respectively.

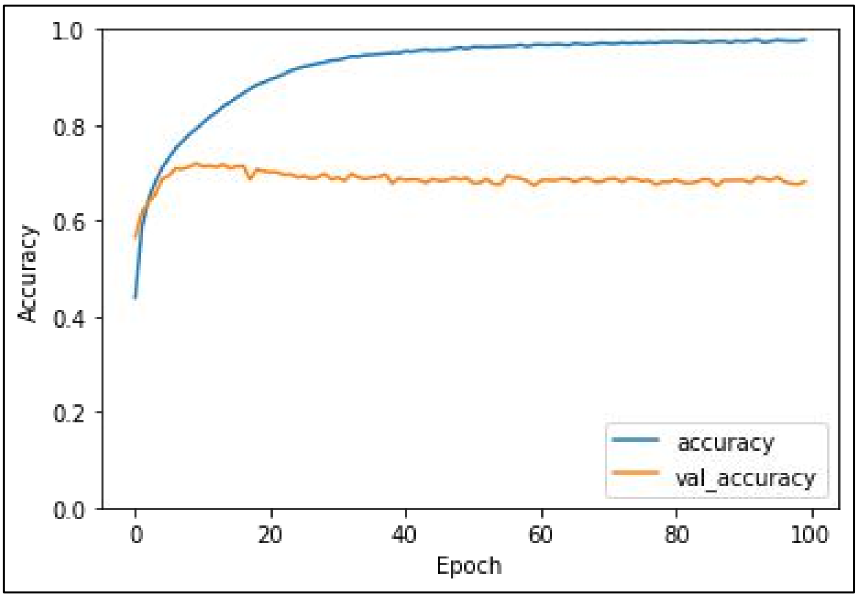

Figure 4: Training and testing accuracy graph

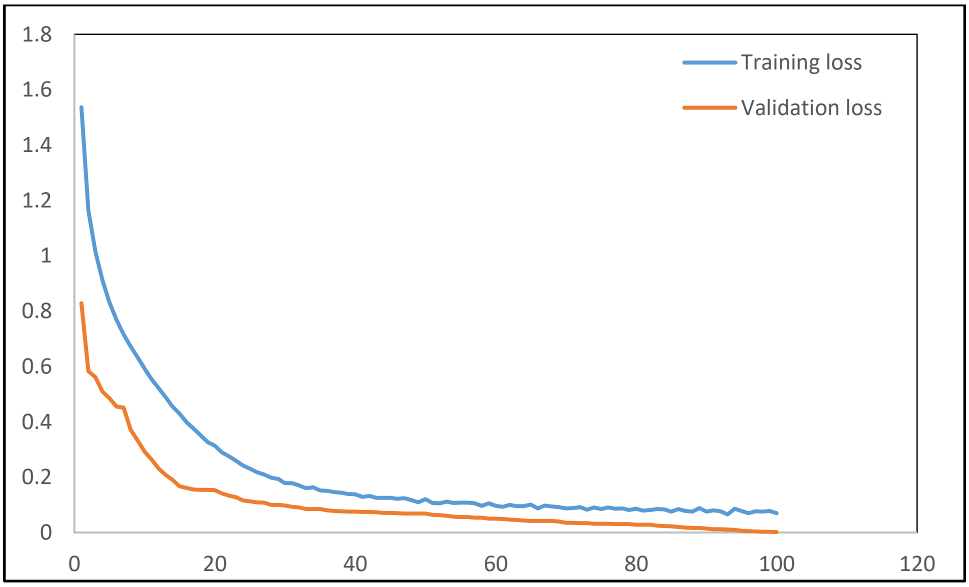

Figure 5: Training and testing loss graph

5. Conclusions

The comprehensive intention of the present study is to detect and classify the category of the periodontal diseases. There exist a lot of researches that involve detection of periodontal diseases. There are a few literatures that involves the application of deep learning technique such as CNN in detecting periodontal diseases. However, there are very few literature that involves the application of CNN in detecting and categorizing the type of periodontal diseases. In this paper, to achieve this objective, a CNN model is proposed. The proposed CNN model is built using the Tensorflow framework which is coded in python 3.8. The dataset comprises of 3331 images of both healthy and gum effected by different categories of periodontal diseases. Out of the 3331 images 3241 images are used to train the CNN network whereas the 90 images are used for testing the model. The computed value of the training and testing accuracy of the CNN model 97.82% and 73.61% respectively. On the other hand the training and testing loss value computed for the CNN model is 0.07 and 0.006 respectively. From the overall discussions, it could be expected that this paper is able to lay the foundation for developing an ideal classification technique that is capable of not only detecting the periodontal diseases but also able to classify the type of periodontal diseases. Also, it can be concluded that the model proposed in the paper can be applied for detecting and identifying the category of the periodontal diseases.

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Conflict of interest

The authors would like declare that there is no conflict of interest. The authors would also like to declare that to the best of their knowledge for carrying out the project no fund is received from any government or private institute.

Ethical standard

The authors would like to declare that all the ethical standards are practiced during data-collection process.

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