Migration Letters

Volume: 20, No: S13(2023), pp. 341-347

ISSN: 1741-8984 (Print) ISSN: 1741-8992 (Online)
www.migrationletters.com

An Intelligent System for Dental Disease Detection Using Smart R-CNN Technique

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Abstract

Artificial intelligence (AI) in the medical system has more with the development of research in the field of deep learning, demand has increased. However, only a few Deep Learning models can deliver solutions in real-time applications. In these type of real time medical systems, the primary concern is data availability and the same occurred for dental dataset. In this paper the most optimized and accurate method is discussed. Dataset is classified and labeled into 5 different datasets. We propose a faster neural network with a Densenet model in this research. Densenet is a useful tool in deep learning for overcoming obstacles such as picture segmentation, accurate categorization of images with high levels of recognition, and powerful optimization algorithms that speed up convergence speeds. lowers the local computation on each subsequent outer iteration. We discovered from the current system that when there is a large dataset, the Densenet model exhibits good classification in original picture classification issues. We have identified three different diseases associated with various types of cavities, such as frontal teeth cavities, inner cavity teeth, and oral cancer, which will determine the difference between diseased and healthy teeth in teeth disease detection using this network construction framework on real clinical data at various levels. In order to incorporate the built ML model into the webapp, it is being stored and translated into JSON file format. An interface for diagnosing dental problems will be provided by the web application.

Index Terms: *Densenet, Quicker R_CNN, Deep Learning, Image Classification, and Dental Diagnosis*

Introduction

Food is broken down by teeth and makes digestion simpler. Primary diseases that affect the teeth can stifle this process and are difficult to detect by the patient. This problem can be solved using a Deep learning application-based recognition method. With the rapid growth of deep learning, there has been a strong demand for CNN applications in health-related applications. However, there are very few machine learning (ML) programmes that work well and are compatible with user apps

An automated diagnosis model was trained and constructed for identifying various cavities and oral disorders using Quicker R-CNN and Densenet architecture using data from dental

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clinical photos collected from various private dental clinics. and classification of three related dental disorders, such as frontal cavity, inner cavity, oral cancer disease, and others, with higher diagnosis accuracy, sensitivity, and specificity. Finally, the developed machine learning model is combined with a real-time interface Webapp to provide dental diagnosis via mobile phone [1]. It would save the patient's life without the need to see a dentist.

Quicker R-CNN Method

Algorithm

Input data: Dental clinical data

Output data: Dental issue prediction using trained clinical photographs

1. Begin
2. Clinical information is gathered, and it is divided into five different labels.
3. Densenet121 is used to create resizing and feature extraction.
4. The top layer of an image is used to extract features to create a regional proposal network.
5. The proposals gathered are utilized to create a detecting network.
6. Apply the data to train the built-in network.
7. The test data, which is an input, is used to obtain predictions.
8. Compare trained and tested data to determine accuracy.
9. Close.

   The dataset was collected from several dental clinics in the city of Chennai. The data is in the form of images. From this dataset, we extracted the Different features which are used to train the model. Using this trained set of data, Diagnosing and predicting the user Dental disease. According to the prediction, patient can decide to take treatement. Model Architecture is shown in fig-4

Implementation

Dataset Access and Pre-Processing

Dataset was obtained from 3private clinics of Vijayawada. Dataset contains 1409 clinical dental images. The data is classified into 5 categories depicted in list -2

1. Front teeth with no abnormalities
2. Inside teeth with no abnormalities
3. Anterior cavities
4. Inner cavities
5. Oral cancer

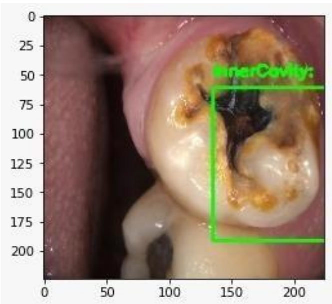


Figure 1: Cavity

Data dimensionality reduction is component preprocessing of dataset. According to the various studies ,serious redundancies among the various dimensions is not only a only problem in a data network[2].The studies have shown that there also exists high correlation between the data of particular dimension. Learning efficiency in the training and reaction time for data reduction of detection system is done by the redundancy and the correlation. Hence reduction of dimensions for data is done here.

Reconstruction error concept is useful for evaluating the effect of reduction in dimensionality. Errors discovered from the provided input data are referred to as reconstruction errors

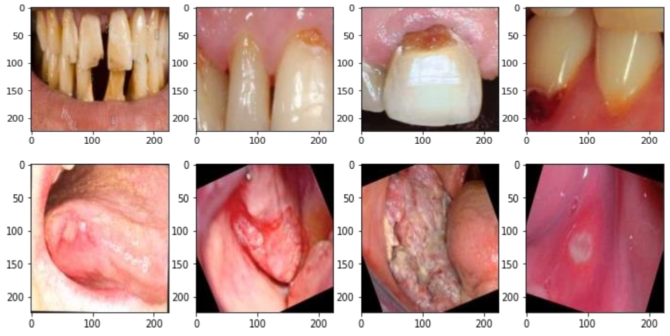


Figure 2: Resized image of Inner Normal teeth and oral cancer

Background & Noise Removal

Separating the background and background plays an important role in many computers viewing programs, including action recognition, motion capture, telephone communication and surveillance tracking [3]. Pre-image processing is a key function of moving object discovery. Minor changes in the pixel lead to false detection. Noise can be added for a variety of reasons. Due to noise the pixel values can be changed. So processing the image first is very important [4]. The effect of the sounds on the signal and image signal display is complex.

Object Detection Network

Faster R-CNN Architecture is shown in fig-4. It has three levels: Dental feature extraction, Disease place search and find disease .The input data was given to CNN Densenet121 for the extraction features from the clinical image dataset[5].Then the RPN(Regional Proposed network is used for bounding boxes. Bounding boxes will provide Disease regions and disease predictions.

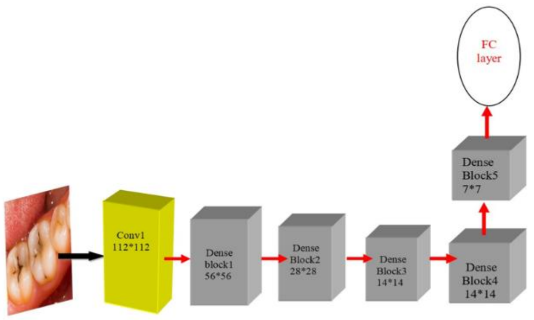


Figure 3: Densenet architecture

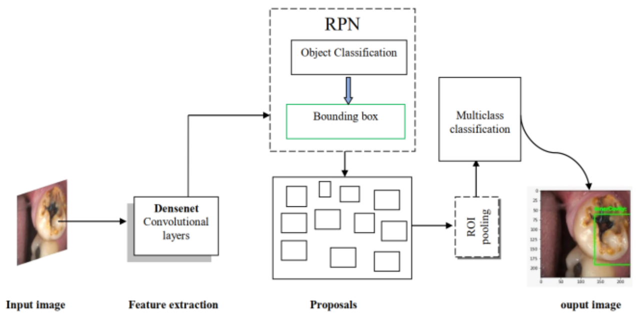


Figure 4: Faster R-CNN architecture

Prediction

The proposed Architecture has 121 hidden layers. convolutional layers and a pooling layer are included in implied layer mapping of sample data to the high dimensions by convolutional layers [6]. Reduction of computation and improvement of detection efficiency is done by pooling layer. Then the RPN classification takes place. In RPN (regional proposal network) objection classification takes place and generates the regional proposals, using these multiple classification takes place in image detecting the regions [5].

Inference

The overall dataset is depicted in table-2. The accuracy or recognition rate with densenet model is 96%.on testing, which is depicted in Table-1.The architecture to prepare the model is depicted with the figure-4 .Figure-5 is shows the recognition rate of cavity diseases[7]. The graph also depicts that we can achieve Decent result by Faster R-CNN even in difficult situations, such as the presence of saliva, gap between teeth, and in other bad conditions. The overall prediction rate of algorithm is 96%. It is analyzed that if there is a blur image then image cannot be detected. The Dental image should have alteast medium level of pixels.

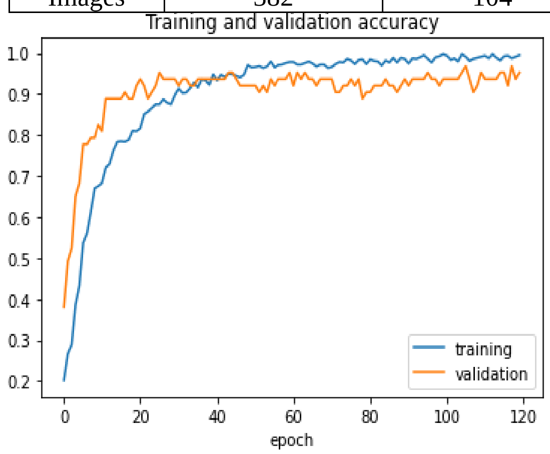
a) If TF < TF ⟶ **an excessive fit**. Images are taken with higher noise when a model is overfit. With test case photographs, outcomes won't be more accurate if an excessive fitting occurs.
b) If VF < TF ⟶ **Under fitting.** It will arise when the model cannot capture the pattern of the data, Under fitting spoils the accuracy of the Ml model
c) If VF ~TF ⟶ **Perfect fit.** Where there is less of a gap between TF and VF, this fits the best. As a result, accuracy rate is higher when compared to (a) & (b). Our model is flawless and has increased accuracy while reducing data loss.
d) ***Note***: TF = training failure, VF = validation failure

Table 1: Accuracy and loss

Total Period: 120	Accuracy	loss
Exercise	98%	0.27
Authentication	95%	1.7
Examination	97%	1.4

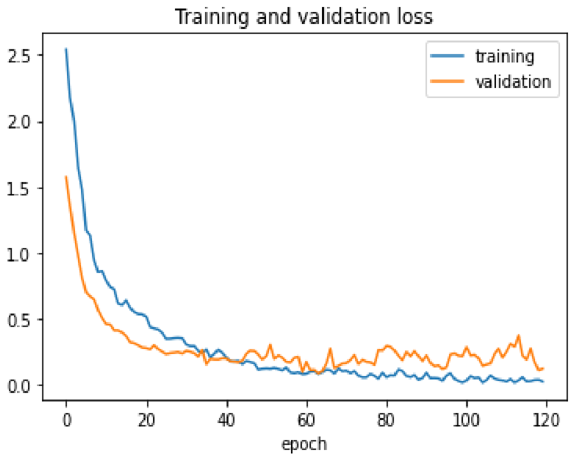
Table 2: Dataset containing labels and the number of pictures

DATASET	Front teeth with no abnormalities	Inside teeth with no abnormalities	Anterior cavities	Inner cavities	Oral cancer	Total
Images	382	104	267	336	320	1409



Y-axis = accuracy X-axis = Epoch

Figure 5: Training and validation accuracy



Y-axis = loss   X-axis = Epoch

Figure 6: Training and validation loss

Evaluation

Evaluation of the result can be done by precision and recall values. By using precision and recall values the weighted averages are calculation the below table depicts the values of precision and recall [8].

1. Precision is the ratio between True positive value and overall positive (true positive +false positive). The overall precision is 0.95 i.e 95%
2. Recall means wrongly predicted images. Recall avg is 96.5%.
3. The weighted average of recall and accuracy is the F1-score. It displays the accurate balance.
4. Maintenance: It is the number of images used in evaluation 240 images are used [19]. These number of images were classified into 5 categories. Front normal have support of 65 images, inner normal have 18, front cavity has 45 support value, inner cavity has 57 and oral cancer have 55 supports

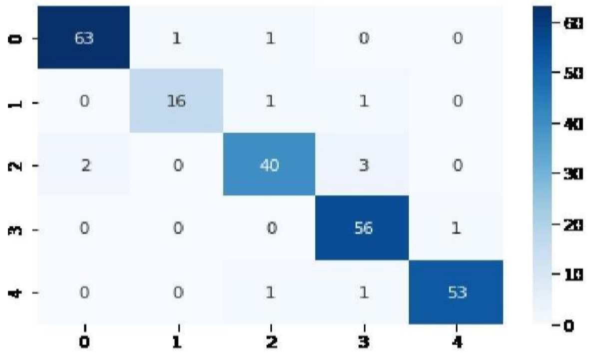
$$Precision = \frac{TP}{TP + FP}$$

Table 3: Metrics

	PRECISION(P)	***RECALL(R)***	***F1_SCORE***	***SUPPORT***
Front Normal	**0.97**	**0.97**	**0.97**	**65**
Inner Normal	**0.94**	**0.89**	**0.91**	**18**
Front Cavity	**0.93**	**0.89**	**0.91**	**45**
Inner Cavity	**0.92**	**0.98**	**0.95**	**57**
Oral Cancer	**0.98**	**0.96**	**0.97**	**55**
Exactness	**0.96**	**0.98**	**0.95**	**257**
Instruction Accuracy	**0.97**	**0.95**	**0.96**	**257**
Weighted mean	**0.96**	**0.96**	**0.96**	**257**

Confusion Matrix

240 test images are depicted in confusion matrix on x-axis it shows the wrongly predicted images on the y axis the actual image class is shown, by this matrix we can find the wrongly predicted dental images. if x=y, subsequently, the forecast was accurate. The appropriately predicted pictures with support size are shown in Figure 7's shaded region (x=y). Therefore, the x, y values (0,0), (1,1), (2,2), (3,3), (4,4) shows correctly predicted images with number of images. Confusion matrix is used for evaluating the quality and efficiency of the output. If the diagonal values are higher, then we can say the prediction is efficient



y-axis = actual X-axis = predicted

Figure 7: confusion matrix

Table 4: labels for dataset

Total Test images	**240**
Correct prediction	**228**
Wrong prediction	**12**

Table 5: labels for dataset

DATASET	**Front teeth with no abnormalities**	**Inside teeth with no abnormalities**	**Anterior cavities**	**Inner cavities**	**Oral cancer**
Label	0	1	2	3	4

Integration of machine learning model with web application

Convert the above constructed ML model into JSON file format using the TensorFlow for integration into a web application, the model's python code is transformed to a JSON file format. The entire design is prepared by using Nodejs modules. In nodejs TensorFlow libraries are installed for attaining ML. The converted model. JSON file is saved and loaded into web app files [10]. Thus, the model is integration other dental problems like Dental plaque, Artho treatments, Perio dental

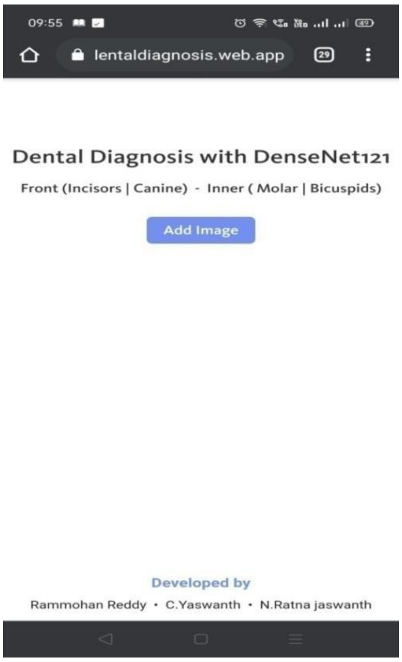


Figure 8: Web app Interface

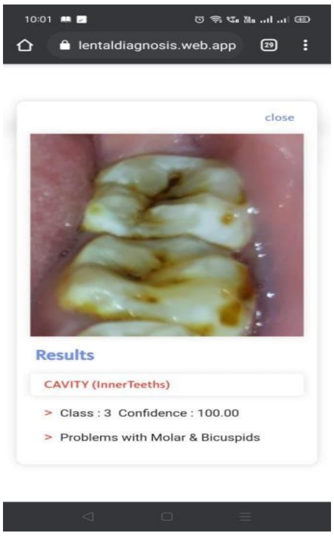


Figure 9: post diagnosis result

Conclusion

This paper proposed an intelligent AI method to dental diagnosis. The webapp which is integrated with the ML saves the patient time by detecting problem of the teeth without consulting the dentist, with fewer data losses, the AI algorithm attained an accuracy rate of more than 95%. The webapp will detect 3 dental diseases, which are front cavity, inner cavity and oral cancer with high reliability in practical application. In future the project can extended to treatments, Conservative, Pedo, Oro maxilla fascial Oncology etc. and providing appointment platform between dental clinics and the patients. Patient diagnosis data in this Webapp is taken for futher predictions with their acceptance. By this we can enhance the efficiency of the predictions. We can understand the data patterns from user data. Location based services will be added by using different map based algorithms to make patient to find the nearby Dental clinical resources easily.

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