Grenze International Journal of Engineering and Technology, Jan Issue

Enhancing Oral Health Assessment through Convolutional Neural Networks based Detection

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***Abstract*— Oral diseases are highly prevalent globally. Oral health also affects the general health of people. Therefore, the prevention and early treatment of oral diseases is important and beneficial. Diagnosis of oral health and diseases is conventionally done by clinical examination and, at times, by various investigations. Clinical examination is subjective and, hence, susceptible to error. One of the emerging trends of late is the use of machine learning and deep learning in healthcare. The current available systems tend to focus on a single image type and also consider fewer diseases at a time. To overcome these shortcomings, we developed a system, which is presented in this paper titled "Enhancing Oral Health Assessment through Convolutional Neural Networks Based Detection." By using various machine learning and deep learning algorithms, training multiple models, and integrating them, our proposed system can overcome these limitations. With the input given to the system in the form of an image, it would be able to detect any disease present, classify it, and give it as an output to the dentist. This paper explores the system's background, the work done on various systems developed so far, the proposed system, and the techniques involved in making it. The expected results, the methods to verify the accuracy of the output, and the future scope are also discussed. The proposed system would be a significant contribution to the field of oral healthcare as it can assist dentists in diagnosing diseases and treating patients swiftly and efficiently.**

***Index Terms*— Oral Health, Machine Learning, Deep Learning.**

I. Introduction

Oral diseases currently have a high prevalence globally. Early and correct detection of these diseases is vital to prevent the conditions and for early intervention to prevent complications. While conventional methods of examination and diagnosis by visiting a dentist cannot be replaced, the process could be made considerably easier and more accurate by tapping into advanced technology. The progress made in the fields of machine learning and deep learning has paved the way for a lot of assistance for treatment in oral healthcare. This paper presents the work titled "Enhancing Oral Health Assessment through Convolutional Neural Networks Based Detection," which integrates machine learning to help dentists. The main goal of this paper is to go beyond using a single type of image, like the currently existing systems, and use both radiographs and color images of the mouth to detect any disease that might exist. This way, it would be significantly more convenient for the dentist to diagnose a disease. This system also has the advantage that it can detect more diseases than would have been possible with the previous

Grenze ID: 01.GIJET.10.1.94

systems. Examining patients and diagnosing diseases takes up a considerable amount of time, and the diagnosis could be subjective and affected by human error. Also, systems that can scan images and detect diseases increase productivity and accuracy. In this paper, we explore the background of oral diseases, review the existing literature, and examine the progress and achievements of the current systems. We also discuss the proposed system, its architecture, and all the technologies involved in it. Further, we talk about the future scope of the work and conclude by emphasizing the potential, impact, and benefits of the proposed work in the field of oral healthcare.

II. LITERATURE SURVEY

L. Liu et al. [1] highlighted the prevalence of dental issues in China and the lack of in-home dental healthcare research. Their paper discussed the potential of the Internet of Things (IoT), deep learning, and mobile technology in revolutionising dental care. It presented the development of a smart dental health IoT system for in-home dental care. It enabled seamless interaction between dentists and home-based patients. It also described the intelligent dental health IoT platform's layers, including the front-end, cloud-end APIs, server service, and database. Along with that, the paper explained the process of image capture, AI analysis, appointment scheduling, and offline medical procedures through mobile terminals. The creation of a training sample set for dental images was also discussed. Images were labelled and enhanced using the Retinex algorithm to highlight dental disease features. The paper also explained the methods for coarse localization and classification of dental diseases using histogram matching and Tamura texture feature algorithms. Manual confirmation by dental experts and mask dataset generation were discussed. The paper discussed the use of the MASK R-CNN method for accurate detection and segmentation of dental targets, addressing the limitations of RoI pooling. It employed the ResNet-50-C4 backbone for feature extraction.

Tanriver G. et al. [2] stated the applications of deep learning to detect oral cancer with the help of photographic images. The goal was to detect and classify oral lesions in real-time and show how feasible it is. A two-stage model was suggested to identify the detected region with a second-stage classifier network and detect the lesions using a detector network. Each lesion was classified as 'benign', 'OPMD', or 'carcinoma' based on the disease and the chances of it changing into oral cancer. Around the lesion areas, bounding polygons were drawn, and the corresponding class values were added as a region attribute. Since some images contained several lesions, close-up lesion areas were classified separately for the classification task rather than being given an entire image general class. Various Convolutional Neural Network (CNN) architectures were evaluated for the lesion classification task, such as ResNet-152, DenseNet161, Inception v4, and EfficientNetb4. Along with that, an ensemble model of DenseNet161 and ResNet-152 was built. To condense model predictions, the confusion matrices on the test set were calculated. For pixel-wise semantic segmentation, U-Net models performed well on the segmentation task. The EfficientNet-b7 model achieved a dice score of 0.926 without TTA and 0.929 with TTA. As a single-stage object detector, the performance of the YOLOv5 model performed the best, with an AP of 0.644 and an AP50 of 0.951 on the test set, among all versions. With TTA applied, YOLOv5l achieved 0.953 on AP50. EfficientNet-b4 achieved the highest F1-score of 0.855 on the test set among all the models. In their pipeline, the lesion regions were identified from the entire image using YOLOv5l, and they were then categorised into groups using EfficientNet-b4. The chosen networks demonstrated good overall performance in terms of accuracy and inference time.

Chen H. et al. [3] stated that deep convolutional neural networks (CNNs) were used in their study to construct an auxiliary diagnosis tool for dental periapical radiographs. The study's goal was to train CNNs to identify lesions on radiographs of the mouth while comparing their performance across disease groups, seriousness levels, and training techniques. Deep CNNs were built using region proposal techniques for disease diagnoses such as decay, periapical periodontitis, and periodontitis at mild, moderate, and severe levels. They tried four distinct training procedures and assessed measures such as intersection over union, precision, recall, and average precision across diseases, severity levels, and training strategies. Deep convolutional neural networks were found to be successful at detecting lesions on dental periapical radiographs, according to the study's findings. The precision and recall values for lesion detection ranged from 0.5 to 0.6, showing adequate accuracy in detecting disease presence. An analysis of variance (ANOVA) demonstrated that numerous parameters influenced the performance of the CNNs. The network's performance was significantly influenced by the training method, disease type, and severity level. According to the study, deep 3 CNNs can detect diseases on dental radiographs. The CNNs perform better in recognising lesions with high severity levels, and it was advised that the CNNs should be trained with tailored methodologies for each disease. Overall, this study shed light on the application of deep CNNs for tooth radiographic interpretation, emphasising the significance of disease groups, intensity levels, and training procedures in increasing CNN's effectiveness.

Almalki et al. [4] described the main fields of dentistry and mentioned the paper's primary contribution as reaching an excellent accuracy rate in dental disease recognition. The importance of image annotation for deep learning was discussed in their paper. The YOLOv3 model and its format requirements for annotation files were also explained. The paper highlighted the evaluation of the YOLOv3 model's performance using metrics like the F1-Score. The model achieved a high accuracy of 99.3 percent when tested on images. The focus was on object detection and localization. The paper discussed testing precision values, summarised results for various testing parameters, and showcased output images obtained using the best weight.

Imak et al. [5] focused on research on dental caries, a common dental disease, and its consequences if left untreated. The use of intraoral periapical radiography for diagnosis was highlighted, and it was suggested that image processing and machine learning approaches should be used to enhance caries detection. The study introduced a brand-new deep convolutional neural network ensemble model that could identify dental cavities with a stunning 99.13 percent accuracy. The study of the literature provided an overview of numerous studies on the detection of dental disease, including deep learning models, conventional methods, and image processing procedures. It discussed the range of approaches employed as well as the success rates for caries diagnosis in earlier research. The research emphasised how deep learning and image processing can boost precision and effectiveness. The paper also described the MIDCNNE-recommended methodology for identifying dental caries. Pre-processing, deep convolutional neural networks (CNN), and final analysis were its three phases. Fusion was based on scores. The research highlighted the value of the MIDCNNE model in spotting dental caries.

The study done by Abdullah S. et al. [6] discussed the difficulties in identifying dental caries and the possible applications of deep learning and convolutional neural networks (CNNs) in dental informatics. It underlined the need for early caries identification and proposed that by analysing high-resolution medical pictures and biosensor data, deep learning might improve diagnosis and treatment planning. The paper described the dataset as consisting of 116 panoramic dental X-ray images, manually segmented into three categories: cavity, filling, and implant. Data augmentation techniques were applied, and preprocessing involved scaling and resizing. The dataset was split into training and validation sets. The CNN architecture, including max-pooling and dropout layers, was used for classification, along with a mention of NASNet. The paper presented the results of the implemented models, showcasing accuracy and loss metrics. The proposed model achieved an accuracy of 96.51 percent with data augmentation.

Shih-Lun Chen et. al. [7] suggested implementing deep learning towards the enhancement of dental lesions diagnoses and classification efficacy by utilising dental panoramic X-ray images. This approach used artificial intelligence and image processing technology to overcome the shortcomings of manual diagnosis by dentists. It involved the application of image cropping by using histogram equalisation and flat field correction and improved bone structure details with respect to noise resolution. That was followed by the application of a polynomial function for tooth separation purposes. The upper and lower jaws are then separated by using discontinuous horizontal lines. This developed approach linked interstitial strands together and resulted in a smoother curve that offered improved assessment of tooth segments. It implemented image pre-processing and covering techniques to improve reliability. The research incorporated transfer learning with CNN models. The performance of the three CNN architectures was evaluated in order to obtain the maximum accuracy for lesion diagnosis. AlexNet and SqueezeNet both had recall values of 92.9%, and GoogleNet had a recall value of 98.1%.

Senbao Hou et al. [8] emphasised the crucial role of dental images in diagnosing and treating dental diseases, given the rising incidence of oral health issues due to poor dietary habits and insufficient dental hygiene. Computer intelligence was proposed as a solution to reduce the high cost and time associated with dental professional training. The paper specifically concentrated on the application of panoramic dental X-ray images and tooth segmentation technology to analyse dental health and aid in preoperative diagnosis and surgical planning. The paper highlighted different deep learning-based tooth segmentation techniques that have been developed for computer-aided diagnosis. Among them were the Mask R-CNN, U-Net, and a network called Efficient Encoder-Decoder (EEDNet), which has demonstrated competence in dividing and counting teeth in dental field images. Using residual units, attentional mechanisms, and dense connections leads to better image analysis and exact segmentation, according to the paper. To deal with the issue of accuracy, the paper introduced the Teeth U-Net for tooth segmentation. The model made use of a thick connection mechanism, blocks of multiscale aggregated attention, and hybrid dilation. The paper concluded that the Teeth UNet model is an effective tool for precise dental imaging.

Muhammad Adnan Hasnain et al. [9] set out to design a system to assist dentists in inpatient treatment. They utilized a dataset of dental X-ray images, which underwent pre-processing, and the quality of the treatment was subsequently assessed. The dataset was classified into two categories: one having healthy images and the other having affected images. A Convolutional Neural Network (CNN) model was constructed and trained on the dataset. The convolutional neural networks used in this study were represented by a model with varying numbers of activation functions, dropout layers, and max-pooling layers. Data augmentation was also applied. Their suggested methodology contained seven phases, which were: X-ray image collection, filtering of the images, data splitting, CNN model construction and training, feature extraction, classification, and performance evaluation. Their proposed model consisted of seven layers, which were: convolutional layer/input layer, 2-dimensional convolutional layer, max pooling 2D layer, 2nd dimensional convolutional layer with one dimension, max pooling 2D, flatten layer, dense layer 1 and dense layer 2, and each layer had a unique working. The paper concluded that an accuracy of 97.87 percent and an F1-score of 60 percent were achieved by them.

Anum Fatima et. al. [10] proposed a new model for finding dental diseases using radiographs. Here, a particular procedure was developed by employing an effective mask-RCNN model with a mobile backbone architecture integrated together with a customized region proposal network, which was used for localization, classification, and identification of dental periapical lesions. To improve the accuracy of the model, the images were processed using Contrast Limited Adaptive Histogram Equalization (CLAHE). The areas in which lesions were present were pointed out by using bounding polygons with the help of a VGG Image Annotator (VIA) tool, and the annotations were saved in a JSON file. Features were extracted using lightweight M-RCNN and MobileNetv2, which were then passed to the backbone network (pointwise convolution with ReLu6 and depth wise convolution layer) to reduce the number of parameters. Feature maps were passed to the region proposal network to identify regions of interest. Mean average precision was one of the performance metrics used to assess the model, and it was 85%.

III. Techniques Used Previously For Detecting Oral Diseases

Dentists utilize two types of radiographic pictures to diagnose diseases such as tooth caries. The first is a radiographic image that includes the surrounding teeth and the root of the teeth; the second is a radiographic image that displays information about the internal structure of the teeth and the bone around the teeth. Dentists can identify caries using these images, however, due to labour load or mistakes, diagnosis is not always done correctly. Deep convolution neural networks are very useful while working with object detection, and classification of images into particular classes. DCNN mainly consists of a convolution layer, activation function, pooling layer, and fully connected layer. Convolutional layers are the essential components of a DCNN. These layers are constructed from up of several filters that are learnable or kernels, which are basic 2D grids. To discover local patterns and features, each filter is passed over an input frame. They can distinguish boundaries, appearances, and more complicated structures. DCNNs are particularly effective because numerous filters in every convolutional layer collect distinct features at the same time. Non-linearity is brought into the network through activation functions (for example, ReLU- Rectified Linear Unit), helping the activation function to record difficult arrangements. The ReLU exchanges negative values with zero while leaving values that are positive untouched. Pooling layers are frequently put forward after convolutional layers. Pooling decreases the spatial dimensions of feature maps while preserving important information. Pooling strategies that are frequently utilized include max-pooling and average-pooling. A fully connected layer takes the input from all the previous layers and combines it to give the final output.

DCNN model is commonly used in dental disease detection and it includes:

- *AlexNet*: It is the revolutionary DCNN architecture used in dental disease detection systems. Deep layers of AlexNet are very useful for extracting minute features from dental radiographic images.
- *VGGNet*: It is used quite often to detect dental diseases because of its simplicity and effectiveness. Its numerous configurations like VGG16, and VGG19 offers different functionality like depth and number of features.
- *ResNet*: Residual connections of their Resnet allow it to overcome the problem of vanishing gradient which allows it to develop deep networks.
- *RCNN*: R-CNN models are a type of object identification architecture that detects regions that are important inside an image, making them especially suitable for situations in which certain regions contain important data

A. Segmentation and Classifications

In the field of dental disease identification, the use of segmentation and classification methods are frequently utilized to accurately determine and classify dental diseases within images.

1) Techniques for Segmentation: In dental images, methods of segmentation are utilized to identify areas of relevance. These methods allow for the separation of dental features and irregularities from the surrounding environment. Semantic segmentation is a popular segmentation technique that separates every pixel in an image into certain groups, allowing separate areas to be labeled. This approach is useful for detecting various dental components within a picture. Instance segmentation is used for more specific activities, such as highlighting the exact form and position of dental issues. Mask R-CNN, a Faster R-CNN modification, integrates object identification and segmentation to provide exact masks for dental abnormalities.

2) Techniques for Classification: Upon the segmentation of areas of interest, methods of classification are used to separate these regions according to the kind of dental problem they represent. Depending on the intent, classification in dental disease detection might be binary or multiclass. Images are classified into two categories: having a dental disease or being healthy in binary classification. This method is beneficial for determining the existence or missing of specific conditions like lesions. Whenever there are numerous types of dental problems, at that time, multiclass classification is used. Every category correlates to a distinct condition or aberration, enabling images to be classified as caries, periodontal disease, or malocclusion. Deep learning models, especially convolutional neural network models (CNNs), are frequently used in dental image detection applications.

IV. PROPOSED SYSTEM

The main aim of this work is to create a system that aids dentists in detecting and classifying diseases. Unlike existing systems that only consider a few diseases at a time, and focus on only one type of dataset, our proposed system would use both radiographs (or X-rays) and colour images of mouths to detect and identify any existing diseases. This way, a dentist would only need one system to get the final result, instead of having to use multiple systems. We plan to train multiple models separately on different datasets, and depending on the image given as input, the targeted model would work and detect the disease. The system would take an image of the patient's mouth submitted by the dentist as input, and detect whether the patient has any dental disease using CNN in case one is present. The result of the system would then be presented to the dentist for assistance with the diagnosis of the patient.

A. Methodology

- *Data Collection*: The first step would be to collect data for training and testing our model. We plan to use radiographic dental X-ray and visual camera image datasets, some of which are publicly available and some collected from clinics. After the collection of images, data augmentation techniques will be applied to increase the size of the datasets.
- *Data Pre-processing*: The next step would be to pre-process the data to ensure that it is usable and of good quality. Data cleaning, handling missing data, normalization of images, resizing of images into the same format, and reducing noise from the images would be done. Apart from this, image annotation and labelling would also be done.
- *Image Enhancement*: The first step would be sharpening edges to easily identify the region of the tooth and cavity present between the upper and lower jaws. This will be beneficial for the tooth segmentation step. Edge sharpening would be done by adding the first laplacian pyramid. To create a laplacian pyramid, the first step would be gaussian pyramid creation. The laplacian pyramid is then created by subtracting each level of the gaussian pyramid from its expanded version. This enhanced image will be reconstructed by adding levels of laplacian pyramid. At last, the brightness and contrast of the image are adjusted using auto-contrast by adjusting its hyperparameters to reduce the information loss due to brightness or low exposure to the light.
- *Tooth Segmentation*: Each tooth will be identified independently using greedy algorithms. This will be utilised to detect the teeth with diseases. To segment the tooth based on pixel strength and fluctuation, a perpendicular line will be plotted on the image after a curve across the middle of the tooth is drawn.
- *Image Annotations*: The next step would be creating a bounding box for the region where disease is present for each image. The exact region of interest will be identified with the precession. This will be helpful for the model to learn the patterns present in that region.
- *Feature Engineering*: This step would involve extracting only the relevant features from the datasets and getting rid of the rest. This would help to save resources later on and help in model training.

- *Model Training*: This is the most important step in which the deep learning models will be trained on the datasets to detect dental diseases. YOLO-v8 and RCNN would be used for training two separate models. The YOLO-v8 model would be used on radiographs whereas the RCNN model would be used on colour images of the mouth.
- *Training the YOLOv8 Model*: YOLO is an object-detected model that detects the area of the tooth where disease is present along with the bounding box. A bounding box with an appropriate shape and size will be generated based on different images given at the time of the training. It would be beneficial for detecting diseases based on radiographic images. YOLO v8 consists of two main parts: the backbone and the head. The backbone consists of a modified CSPDarknet53 architecture, which consists of 53 convolutional layers along with cross-stage partial connections. The head part consists of multiple convolution layers, followed by a flattening layer to detect bounding boxes.
- *Training the RCNN Model*: To detect the diseases present in the visual camera images, the RCNN model is helpful. The RCNN model detects diseases based on visual camera images. RCNN consists of region proposal, CNN feature extraction, region classifiers, and bounding box regression. Region proposal is the first step; it uses selective search to identify the regions based on low-level image features. The next step would be CNN feature extraction, with a region proposal given to the pre-trained model like AlexNet or VGG to generate a feature vector for each proposal. These features are classified into classes using classification algorithms. At the last bounding box, regression is performed to define the bounding box more accurately.
- *Testing of the Model*: For the proposed system to be put to use in the actual world, it must work properly. To demonstrate that the model is dependable and functional, its accuracy must be assessed. The accuracy of the model would be checked based on evaluation metrics like accuracy, precision, recall, F1 score, and AUC ROC curves. Testing would ensure that the model works as it is supposed to. Any minor bugs would also be removed in this step.
- *Interface Designing of the System*: This step would involve developing a web interface for the dentist to use every time he wishes to use the application. This would make it easier for him to interact with and use the system. The interface would have provisions for entering the type of image being uploaded and for uploading the image as well. There would also be a section for displaying the diagnosis to the doctor.
- *Testing of the Entire System*: To make sure that the system takes in all the types of inputs, gives correct results, and that the interface works properly too, various test scenarios and test cases would be made and performed.
- *Deployment:* After ensuring that the system works as intended, the application will be deployed on a cloud platform so that it can be accessed by dentists from anywhere at any time.

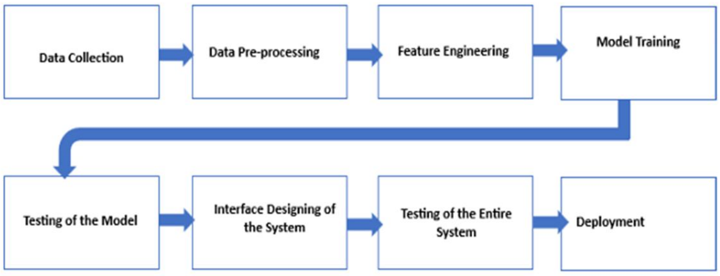

Figure 1. Block Diagram of Oral Disease Detection System

V. Result And Performance Measures

It is imperative for the proposed system to be effective so that it can be used in the real world. The accuracy of the system needs to be determined to show that it is dependable and usable. This section discusses the final output and results, as well as the metrics used to measure the performance and accuracy of the system.

A. Final Output

The name of the detected and identified disease is given as the output to the dentist using the application. With the help of this, the dentist can quickly come up with a good treatment plan for the patient. Not only does this save time, but it also increases overall productivity and reduces the margin of human error. The entire process becomes more efficient this way. By implementing machine learning and deep learning algorithms, a precise and understandable diagnosis is given.

B. Accuracy and Performance Measurement

Measuring the accuracy and performance is important to understand how reliable the system is and whether it is ready to be used. This can be done using various metrics and techniques: Accuracy- The accuracy shows the percentage of diseases that were correctly recognized. Precision- The precision shows the capacity of the system to make precise positive predictions. It gives the percentage of real positives out of all the positive predictions. Recall- The recall, or sensitivity, shows how well the system can find all the instances of the disease. It gives the percentage of true positives among all the actual cases. F1 Score- The F1 score combines recall and precision to show the system's ability to correctly identify the diseases.

C. Receiver Operating Characteristic (ROC) Analysis

The trade-off between the true positive rate and the false positive rate is assessed using ROC analysis. It shows the system's performance by determining how well it can differentiate between images with and without any diseases.

D. Confusion Matrix

The confusion matrix shows the true positives, true negatives, false positives, and false negatives. This makes it very useful in understanding and evaluating the system's accuracy and performance.

VI. FUTURE SCOPE

Our work exhibits a lot of potential in the field of dental healthcare. Potential areas for future development include the following:

- *Accessibility to Common People and Patients*: One of the most intriguing future directions for the "Oral Disease Detection System" is to develop a user-friendly interface that enables regular individuals and patients to operate the system on their own. People would be able to evaluate their oral health from the comfort of their own homes, thanks to this innovative approach. This could help in early detection of the diseases and ease the whole process of the patient getting diagnosed.
- *Real-Time Image Analysis:* The system could be further developed to perform real-time image analysis to improve accessibility and usability. Users might use the system to take advantage of the capabilities of their smartphones' cameras rather than having to upload photographs taken using high-definition cameras. Patients may take real-time pictures of their dental issues, and the system would immediately identify the disease.
- *Development of Mobile Applications*: The creation of user-friendly mobile applications for the Android and iOS platforms is a logical step towards opening up the "Oral Disease Detection System" to a larger audience. Users of these programs might enjoy a simple experience that allows them to take pictures, get quick diagnoses, and access informational materials on oral health. The application could also be used to preserve the patient's medical history and data.

VII. CONCLUSION

Oral health plays an important role in every individual's life. While machine learning and deep learning have been applied to develop systems to help diagnose diseases, they have their shortcomings. Our proposed system has the capacity to make it considerably easier for dentists to diagnose diseases with minimal effort while overcoming the existing limitations. By using both radiographs and colour images of the mouth, the system can quickly detect diseases and assist dentists in their treatment of patients, making the process efficient. The system presented in this paper is thus very valuable and has the potential to have a significant and lasting impact in the field of oral healthcare.

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