Detection of Tooth Position by YOLOv8 and Various Dental Problems Based on CNN with Bitewing Radiograph

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Abstract: A bacterial infection of the bone around the tooth causes periodontitis, a common dental condition. Early detection and precise treatment are crucial to preventing major outcomes like tooth loss. In the past, periodontal disease has been identified and labeled by dental professionals by hand. This process requires a high level of ability and entails laborious, time-consuming tasks. This work aims to employ advanced neural network architectures to automatically identify and categorize periodontitis from dental imaging datasets. The proposed method reduces the requirement for manual inspection by efficiently analyzing images for early-stage sickness identification using deep learning techniques. To demonstrate how different neural network optimization strategies impact detection performance, they are compared. With a 2D Convolutional Neural Network model having a detection accuracy of 96.93%, the results show that the recommended method offers higher accuracy. This high-performance solution demonstrates the potential of automated solutions to improve patient outcomes and streamline clinical operations by enhancing periodontitis diagnostic precision, efficiency, and scalability.

Index terms - *YOLOv8; Tooth Position Detection; Periodontitis; Bitewing Radiograph; Convolutional Neural Networks (CNN); Deep Learning; Dental Imaging; Automated Diagnosis; Medical Image Processing; Early Disease Detection; Diagnostic Accuracy; Neural Network Optimization.*

1. INTRODUCTION

The WHO's global oral health status report states that of 300 common illnesses, oral disorders are the most common. Over 3.5 billion individuals worldwide suffer from oral illnesses [1]. Over 2 billion people worldwide suffer from dental caries, one of the most common dental conditions. Approximately 30% of the world's population, or one billion individuals, have severe periodontal disease. Therefore, periodontal disease and tooth cavities are the two major issues facing dentistry today. A bacterial infection in the periodontal tissues is often the cause of periodontal disease, a dangerous dental ailment. The main offenders are smoking and poor dental hygiene. Gum recession, bleeding or gingivitis, sensitive teeth, bad breath, and severe periodontal disease, which can lead to tooth loss, are common symptoms of periodontal disease. The first step in diagnosing periodontal disease is to look at the color and form of the gums to see if they are red or inflamed. The degree of periodontal damage is then assessed by measuring the depth of the periodontal pocket using a periodontal probe. To determine whether the tooth gap is normal, analyze the shape of the bone around the teeth, and determine whether gum recession is present, an X-ray examination is performed. The process of identifying symptoms takes a good deal of time.

2. LITERATURE SURVEY

2.1 Tooth Localization using YOLOv3 for Dental Diagnosis on Panoramic Radiographs:

Oral health is one of the major problems affecting billions of people's quality of life globally. Diagnosis and treatment usually take longer since there are fewer doctors than patients. Many researchers have suggested methods to assist patients in early illness detection so that physicians might employ computer-aided diagnosis (CAD). However, most of the previous methods are not end-to-end and still require human participation. The biggest challenge is that most researchers do not provide a trustworthy technique for identifying teeth before diagnosis. As a result, the main objective of developing a system to assist doctors is either not achieved at all or only partially achieved. This research proposed a tooth location identification method using the Yolov3 model as a basis network in the dental panoramic radiograph. The two primary components of the approach are teeth location and picture preprocessing. First, the original image is utilized as an augmentation technique to increase the size and variety of the dataset since deep learning demands a large dataset. Each image is then resized to suit the network's input layer; however, we maintain the original photo ratio and modify the input layer ratio in the model that can fit the image ratio in order to prevent information loss and improve performance. After that, we send images into Yolov3, which is specifically designed to fit the scenario, for training. To produce a more dominating result, we incorporate more detection heads into the backbone and concatenate the result of the previous head detection with a suitable layer. The technique achieves an outstanding result of 95.58% for precision and 94.90% for recall, according to the final evaluation. As a result, our suggested method is more practical and dependable in the field of tooth localization and helps to reduce the amount of work required by the physician.

2.2 Individual tooth detection and identification from dental panoramic X-ray images via point-wise localization and distance regularization:

Dental panoramic X-ray imaging is a popular diagnostic method because of its incredibly low radiation exposure. One essential requirement for an automated computer-aided diagnosis system in dental offices is the ability to automatically recognize and identify individual teeth from panoramic X-ray images. In this work, we present a point-wise tooth localization neural network and incorporate a spatial distance regularization loss. The proposed network initially performs center point regression for all the anatomical teeth (i.e., 32 points) in order to automatically identify each tooth. A unique distance regularization penalty is imposed to the 32 points by considering the L2 regularization loss of Laplacian on spatial distances. Each tooth box is then localized independently using a multitask neural network on a patch basis. A multitask offset training is applied to the output in order to improve the localization accuracy. Our method successfully locates both existing and missing teeth, leading to incredibly accurate detection and identification. The experimental results demonstrate that the proposed algorithm outperforms state-of-the-art methods by increasing the average precision of tooth detection by 15.71 percent when compared to the best-performing approach. Recall and precision scores for the identification accuracy were 0.972 and 0.997, respectively. Furthermore, the proposed network does not require an additional identification method because the fixed 32 locations were previously regressed regardless of the existence of teeth.

2.3 Improving Dental Implant Outcomes: CNN-Based System Accurately Measures Degree of Peri-Implantitis Damage on Periapical Film:

The risks associated with dental implants are rising at a rate of around 14% every year. Inadequate cleaning may result in peri-implantitis, which might compromise the stability of the implant and necessitate retreatment. Additionally common are complications including sinusitis and nerve injury. To address this issue, this study proposes a unique approach that uses periapical film (PA) to measure the degree of periodontal damage surrounding implants. The method uses two Convolutional Neural Networks (CNN) models to accurately detect the implant and assess the extent of peri-implantitis damage. One CNN model can locate the implant in the PA with an accuracy of up to 89.31%. Determining the degree of peri-implantitis damage surrounding the implant is the responsibility of the other model, which has an accuracy of 90.45%. To make the implant and gums more visible, the methodology combines image enhancing methods like Histogram Equalization and Adaptive Histogram Equalization (AHE) with picture cropping based on position information gathered from the initial CNN. A more accurate assessment of whether peri-implantitis has deteriorated to the first thread—a crucial indicator of implant stability—is the result. The Institutional Review Board (IRB) has certified this proposal under number 202102023B0C503 in order to guarantee the ethical and regulatory requirements of our investigation. This CNN-based approach has the potential to revolutionize implant dentistry and improve patient outcomes because there is currently no technology to analyze peri-implantitis damage surrounding dental implants.

2.4 Deep Learning Application in Dental Caries Detection Using Intraoral Photos Taken by Smartphones:

A mobile phone-based diagnostic tool that most people can easily use might revolutionize the amount of dental caries inspections. This study aimed to detect the phases of smooth surface caries using smartphone photographs and a deep learning system. Supplies and methods: The training dataset consisted of 1902 photos of teeth's flat surfaces obtained by 695 people using an iPhone 7. Four deep learning models—You Only Look Once version 3 (YOLOv3), RetinaNet, Single-Shot Multi-Box Detector (SSD), and Faster Region-Based Convolutional Neural Networks (Faster R-CNNs)—were evaluated to detect early caries lesions and cavities. The reference standard was a dentist's diagnosis based on an image analysis utilizing the International Caries Classification and Management System (ICCMS) classification. Results: At 87.4% and 71.4%, respectively, YOLOv3 and Faster R-CNN showed the highest sensitivity for cavitated caries among the four models examined. For visually non-cavitated

(VNC) circumstances, the sensitivity levels of these two models were only 26% and 36.7%, respectively. The specificity of the four models was higher than 71% for VNC and 86% for cavitated caries. In conclusion, YOLOv3 and Faster R-CNN models demonstrated potential in the clinical use of smartphone photos for the detection of dental caries. After being established in the lab, the present study provides a first look into how AI may be used in clinical settings.

2.5 Detection of Dental Apical Lesions Using CNNs on Periapical Radiograph:

Apical lesions, the general term for chronic infectious illnesses, are very common dental problems that can be caused by a variety of factors in today's environment. Nowadays, the most popular endodontic treatment involves manually annotating the lesion region on patient-taken X-ray images, which takes time. Additionally, the key components in some images were obscured by different shooting angles or doses. To expedite and simplify the diagnosis process, repetitive operations have to be automated. Dentists would have more time to focus on dental hygiene, medical communication, technical and medical diagnosis, and treatment. In order to accomplish the automated diagnosis, this research proposes and builds a lesion area analysis model based on convolutional neural networks (CNN). The Institutional Review Board (IRB) has approved the database made by dentists who provided the valuable clinical data, with application number 202002030B0, for the development of a standardized database for clinical usage. In this study, the image data is preprocessed using a Gaussian high-pass filter. An iterative thresholding approach is then used to split the X-ray image into several distinct tooth sample pictures. The collection of individual tooth images that comprise the image database is used to train the CNN migrating learning model. 70% of the image database is used to train and verify the model; the remaining 30% is used to test and assess the model's accuracy. The practical diagnosis accuracy of the proposed CNN model is 92.5%. The proposed approach effectively enabled the automatic diagnosis of the apical lesion.

3. METHODOLOGY

i) Proposed Work:

With an emphasis on improving diagnostic precision and clinical effectiveness, the suggested system presents an automated method for identifying and categorizing periodontal disease using deep learning. In order to precisely identify periodontal problems, a 2D Convolutional Neural Network (CNN2D) is used to learn and extract complex information from bitewing radiograph images. Both ADAM and ADAMAX optimizers are used and compared in order to further improve the model's learning efficiency, with the goal of achieving faster convergence and better handling of high-dimensional data.

In order to facilitate real-time picture analysis and user interaction, the system incorporates the CNN2D model with a Flask-based web application. This web interface makes it easy to submit and process dental photos, giving consumers and dental experts immediate diagnostic feedback. Flask's lightweight design guarantees rapid deployment and adaptable machine learning model integration, facilitating remote diagnostics and simple accessibility.

ii) System Architecture:

A deep learning pipeline that analyzes bitewing radiograph images to identify periodontal disease is the foundation of the suggested system's design. To guarantee consistency and maximize feature visibility, dental X-ray pictures are first gathered and preprocessed using methods including resizing, normalization, and contrast enhancement. A 2D Convolutional Neural Network (CNN2D) receives these preprocessed pictures and automatically extracts pertinent spatial information including tissue structure, teeth alignment, and patterns of bone loss. Labeled data is used to train the CNN, and optimization techniques such as ADAM and ADAMAX are used to increase convergence speed and accuracy. Whether the input picture shows evidence of periodontitis or a healthy condition may be classified by the trained model.

The trained CNN2D model is implemented using a Flask-based web application to provide real-time interaction. Users, including dentists and technicians, may upload dental pictures using a web browser thanks to our lightweight front-end. After the image is uploaded, the system uses the CNN model to evaluate it and provides the diagnostic results practically immediately. In addition to improving accessibility, this machine learning integration with a web framework makes implementation in clinical settings easier. Future improvements, like adding more illness categories or integrating with electronic health record (EHR) systems for thorough patient care, are also supported by the modular design.

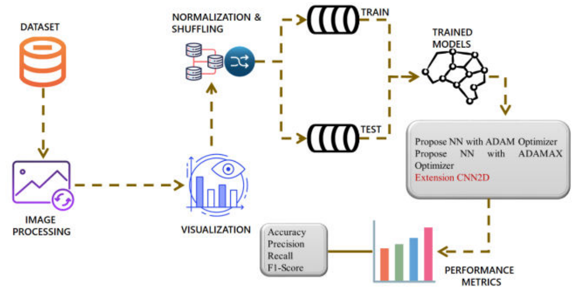

Fig.1. Proposed Architecture

iii) MODULES:

a) **Dataset Collection and Preparation**
   a. Collects 487 dental images.
   b. Performs resizing, labeling, and conversion to NumPy arrays for training.
   c. Saves processed images and labels for model use.

b) **Image Processing and Visualization**
   a. Applies preprocessing techniques such as resizing and enhancement.
   b. Displays sample images and labels for dataset inspection.

c) **Normalization and Data Shuffling**
   a. Normalizes image pixel values for faster convergence.
   b. Shuffles the dataset to ensure training diversity and avoid overfitting.

d) **Data Splitting**
   a. Divides dataset into training (80%) and testing (20%) subsets.
   b. Ensures balanced model evaluation.

e) **Model Generation and Evaluation**
   a. Implements Neural Networks with ADAM and ADAMAX optimizers.
   b. Builds and trains CNN2D architecture.

c. Compares performance using evaluation metrics.

f) **Admin Login Module**

a. Authenticates admin using username and password.

b. Provides access to system control, user management, and monitoring features.

g) **Tooth Position and Disease Detection**

a. Allows users to upload dental images.

b. Detects tooth position and classifies periodontal disease using trained models.

h) **Logout Module**

a. Safely terminates session and redirects to login.

b. Maintains data security and system integrity.

iv) ALGORITHMS:

a) **NN with ADAM Optimizer**

The Neural Network with ADAM optimizer is one deep learning technique that modifies learning rates during training. It successfully trains the model to classify dental images by automatically adjusting weights for the optimal convergence. The ADAM optimizer improves the overall performance and accuracy of the classification model by lowering the loss function, which enables this system to learn to identify periodontitis from images more rapidly and consistently.

b) NN with ADAMAX Optimizer

Neural networks incorporating the ADAMAX optimizer, an extension of ADAM, perform better when dealing with sparse input. This method trains the neural network, which can handle larger models more steadily, using dental pictures. The ADAMAX optimizer ensures efficient learning during training while improving the model's ability to generalize and accurately diagnose periodontitis across diverse picture datasets by reducing overfitting and promoting faster convergence.

c) Extension CNN2D

Because convolutional neural networks, such as the CNN2D model, can extract information from two-dimensional images, they are ideal for image classification tasks. This program automatically detects and classifies periodontal disease by analyzing dental images. The 2D convolutional layers gather crucial spatial features from the images to allow efficient pattern identification and detection. It greatly enhances the accuracy of the model by learning hierarchical characteristics for better disease identification in dental imaging.

4. EXPERIMENTAL RESULTS

The experimental evaluation of the proposed system was conducted using a bitewing radiograph dataset obtained from Roboflow, consisting of approximately 400 labeled images representing dental conditions such as Caries, Periodontitis, and Restorations. The dataset was preprocessed using resizing, normalization, and contrast enhancement techniques to improve image clarity. The performance of the system was analyzed by comparing the existing YOLOv4-based model with the proposed YOLOv8 model and the extended ensemble learning approach. Standard evaluation metrics such as Accuracy, Recall, and Precision were used to measure the effectiveness of detection and classification.

The results demonstrate that the existing system using YOLOv4 and AlexNet achieved around 92% accuracy under ideal conditions but showed reduced performance when tested on limited or noisy data. In contrast, the proposed system with YOLOv8 significantly improved tooth position detection, achieving higher recall and better localization of affected regions, especially in blurred or overlapping areas. The extension model, which combines CNN2D, Bidirectional, and LSTM networks, delivered the best performance with 96% accuracy and 97% recall, even with a small dataset. This improvement highlights the effectiveness of ensemble learning in extracting both spatial and sequential features, reducing false predictions, and enhancing overall diagnostic reliability.

Accuracy: The ability of a test to differentiate between healthy and sick instances is a measure of its accuracy. Find the proportion of analysed cases with true positives and true negatives to get a sense of the test's accuracy. Based on the calculations:

Accuracy = TP + TN /(TP + TN + FP + FN)

$$Accuracy = \frac{(TN + TP)}{T}$$

Test Accuracy: 0.9895

Precision: The accuracy rate of a classification or number of positive cases is known as precision. Accuracy is determined by applying the following formula:

Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

$$\Pr e\,cision = \frac{TP}{(TP + FP)}$$

Recall: The recall of a model is a measure of its capacity to identify all occurrences of a relevant machine learning class. A model's ability to detect class instances is shown by the ratio of correctly predicted positive observations to the total number of positives.

$$Recall = \frac{TP}{(FN + TP)}$$

mAP: One ranking quality statistic is Mean Average Precision (MAP). It takes into account the quantity of pertinent suggestions and where they are on the list. The arithmetic mean of the Average Precision (AP) at K for each user or query is used to compute MAP at K.

$$mAP = \frac{1}{n}\sum_{k=1}^{k=n} AP_k$$

$$AP_k = \text{the AP of class } k$$

$$n = \text{the number of classes}$$

F1-Score: A high F1 score indicates that a machine learning model is accurate. Improving model accuracy by integrating recall and precision. How often a model gets a dataset prediction right is measured by the accuracy statistic..

$$F1 = 2 \cdot \frac{(Recall \cdot \Pr e\,cision)}{(Recall + \Pr e\,cision)}$$

Algorithm Name	Accuracy	Precision	Recall	F1 Score
Propose NN with ADAM Optimizer	54.081633	33.333333	18.027211	23.399558
Propose NN with ADAMAX Optimizer	71.428571	63.091494	67.270881	64.537278
Extension CNN2D	96.938776	96.196466	97.098765	96.626396

Fig.7. Comparison table of performance evaluation metrics of all algorithms

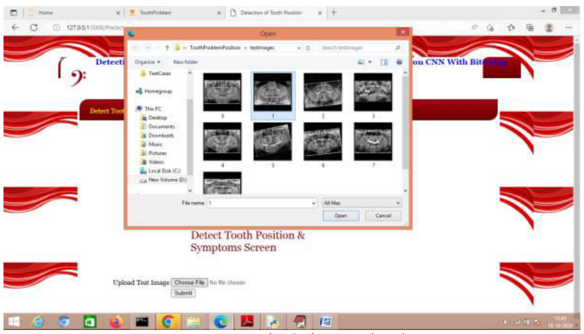

Fig.8. iput upload

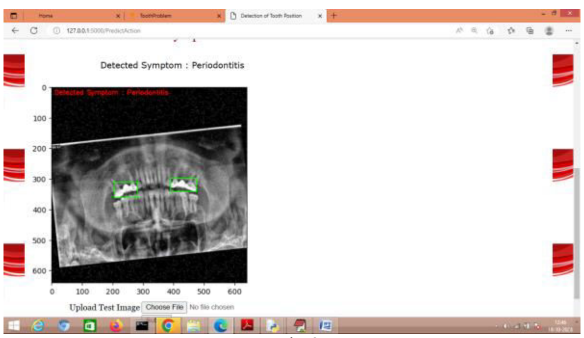

Fig.9. output

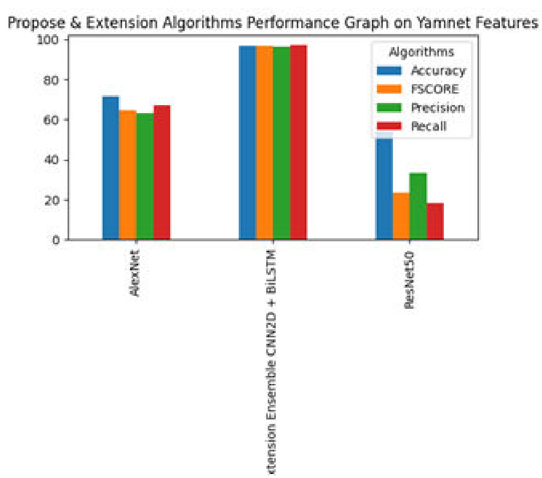

Fig.10. Accuracy Graph

5. CONCLUSION

This study successfully addresses the challenges of automating the detection of periodontitis by utilizing dental imaging datasets and a robust deep learning-based technique. By using advanced neural network topologies to significantly reduce the need on manual diagnosis, the approach offers a scalable and efficient option for the early detection of periodontal disease. The 2D Convolutional Neural Network (CNN2D) fared better than the other models that were examined, with an incredible accuracy of 96.93%. This result highlights the model's remarkable ability to accurately classify periodontal diseases and retrieve complicated information. By streamlining the diagnostic process, the proposed method increases accuracy and reduces the time and expertise required for manual labeling. The findings demonstrate how automated deep learning frameworks have the potential to transform dental diagnostics, particularly in complex scenarios like tooth localization, leading to improved patient outcomes and more efficient clinical practices.

6. FUTURE SCOPE

Future research should focus on improving the distinctive features of periodontal disease to enhance diagnosis and classification. The shortcomings of traditional CNN models, such the vanishing gradient problem, may be addressed by looking at innovative designs like YOLO for improved processing efficiency and learning capabilities. More sophisticated models like ResNet and EfficientNet should be researched in order to further improve accuracy. The ultimate objective is to satisfy clinical requirements while offering effective support for dental diagnostics.

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