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

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Abstract: A common dental ailment called periodontitis is brought on by bacterial infection of the tooth's surrounding bone. To avoid serious consequences like tooth loss, early identification and accurate treatment are essential. Dental experts have historically diagnosed periodontal disease by manually identifying and labelling the condition, a procedure that takes a great deal of skill and involves tedious, time-consuming activities. The goal of this work is to use dental imaging datasets to automatically detect and classify periodontitis by utilising sophisticated neural network architectures. By effectively analysing photos for early-stage illness detection using deep learning techniques, the suggested method lessens the need for manual inspection. Multiple optimisation tactics inside the neural networks are compared to show how they affect detection performance. Results reveal that the suggested technique provides greater accuracy, with a 2D Convolutional Neural Network model having a detection accuracy of 96.93%. This high-performance solution highlights the promise of automated systems in strengthening diagnostic precision, efficiency, and scalability for periodontitis, thereby improving patient outcomes and streamlining clinical procedures.

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

Oral ailments are the most prevalent of 300 common diseases, according to the WHO's worldwide oral health status report. Oral diseases affect more than 3.5 billion people globally [1]. One of the most widespread dental disorders, dental caries affects over 2 billion persons globally. One billion people, or roughly 30% of the population, suffer from severe periodontal disease. Thus, the two main problems in dentistry today are periodontal disease and dental caries. Periodontal disease is a serious dental condition generally caused by bacterial infection in the periodontal tissues. Poor oral hygiene practices and smoking are the primary culprits. Periodontal disease frequently manifests as bleeding or gingivitis, gum recession, sensitive teeth, foul breath, and severe periodontal disease, which can result in tooth loss. Examining the gums' colour and shape to determine whether they are red or inflamed is the first step in diagnosing periodontal disease. Next, a periodontal probe is utilised to determine the depth of the periodontal pocket to examine the level of periodontal damage. An X-ray examination is conducted to analyse the contour of the bone around the teeth, diagnose if the tooth gap is normal, and establish the existence of gum recession. The procedure of diagnosing symptoms is fairly time-consuming.

2. LITERATURE SURVEY

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

https://www.jstage.jst.go.jp/article/ieejeiss/142/5/142_557/_article/-char/ja/

ABSTRACT: One of the biggest issues affecting the quality of life for billions of people worldwide is oral health. Because there are fewer doctors than patients, diagnosis and treatment typically take longer. In order to help doctors use computer-aided diagnosis (CAD), numerous researchers proposed ways to help patients detect diseases early. Nevertheless, the majority of earlier approaches still need human intervention and are not end-to-end. The largest obstacle is that the majority of researchers do not offer a reliable method for detecting teeth prior to diagnosis. As a result, the primary goal of creating a system to support physicians is either not met or only partially met. Using the Yolov3 model as a base network in the dental panoramic radiograph, this paper suggested a detection technique to locate the tooth. The method consists of two main parts: image preprocessing and tooth localization. Firstly, because deep learning requires a huge dataset, the original image is used augmentation approach to enhance the size of the dataset as well as variety. Then, each picture is shrunk to fit the input layer of the network; however, to prevent the information loss and enhance the performance, we preserve the original ratio of the photos and alter the ratio of the input layer in the model that can fit the image ratio. Next, we feed photos into Yolov3, which is particularly tailored to meet the situation, for training. We integrate more detection heads into the backbone and concatenate the preceding head detection's result with an appropriate layer to give a more dominant outcome. The final assessment indicates an excellent result that the approach reaches 95.58% and 94.90% for precision and recall, respectively. As a consequence, our proposed approach is more reliable and practicable in the tooth localization sector, as well as beneficial to lessen the doctor's effort.

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

https://www.sciencedirect.com/science/article/abs/pii/S0933365720312616

ABSTRACT: Due to its extremely low radiation dosage, dental panoramic X-ray imaging is a widely used diagnostic technique. Automatically detecting and identifying individual teeth from panoramic X-ray pictures is a crucial need for an automated computer-aided diagnostic system in dental clinics. In this work, we introduce a spatial distance regularisation loss and propose a point-wise teeth localisation neural network. In order to automatically identify each tooth, the suggested network first conducts centre point regression for all of the anatomical teeth (i.e., 32 points). By taking into account the L2 regularisation loss of Laplacian on spatial distances, a unique distance regularisation penalty is applied to the 32 points. A multitask neural network is then used on a patch basis to localise each tooth box separately. To increase the localisation accuracy, a multitask offset training is applied to the output. Our approach locates missing teeth as well as existing teeth with success, resulting in extremely precise detection and identification. By boosting the average precision of tooth detection by 15.71 percent when compared to the best-performing method, the experimental findings show that the suggested algorithm works better than state-of-the-art techniques. The identification accuracy attained a recall score of 0.972 and a precision of 0.997. Furthermore, because the fixed 32 points were already regressed regardless of the presence of teeth, the suggested network does not need an extra identification technique.

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

https://www.mdpi.com/2306-5354/10/6/640

ABSTRACT: The hazards of dental implants are increasing along with their popularity, which is growing at a pace of around 14% annually. Inadequate cleaning can cause peri-implantitis surrounding the implant, endangering its stability and perhaps requiring retreatment. Complications including sinusitis and nerve damage are also prevalent. This study suggests a novel method for assessing the extent of periodontal damage surrounding implants utilising Periapical film (PA) in order to solve this problem. To precisely locate the implant and determine the degree of peri-implantitis damage, the system makes use of two Convolutional Neural Networks (CNN) models. With an accuracy of up to 89.31%, one CNN model can identify the implant's location in the PA. The other model, which has an accuracy of 90.45%, is in charge of determining the extent of peri-implantitis damage surrounding the implant. The method combines picture cropping based on location information collected from the first CNN with image enhancement techniques such as Histogram Equalization and Adaptive Histogram Equalization (AHE) to increase the visibility of the implant and gums. The outcome is a more precise evaluation of whether peri-implantitis has eroded to the first thread, a vital sign of implant stability. To assure the ethical and regulatory requirements of our study, this proposal has been certified by the Institutional Review Board (IRB) under number 202102023B0C503. With no current technology to analyse Peri-implantitis damage around dental implants, this CNN-based method has the potential to transform implant dentistry and enhance patient outcomes.

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

https://www.mdpi.com/2076-3417/12/11/5504

ABSTRACT: The majority of the population can readily use a mobile phone-based diagnostic tool, which could revolutionise the number of dental caries examinations. The purpose of this study was to use smartphone photos and a deep learning algorithm to diagnose the stages of smooth surface caries. Materials and techniques: 1902 images of the smooth surface of teeth taken by 695 individuals using an iPhone 7 were used as a training dataset. To identify early caries lesions and cavities, four deep learning models were tested: You Only Look Once version 3 (YOLOv3), RetinaNet, Single-Shot Multi-Box Detector (SSD), and Faster Region-Based Convolutional Neural Networks (Faster R-CNNs). A dentist's diagnosis based on an image analysis using the International Caries Classification and Management System (ICCMS) classification was the reference standard. Findings: Of the four models tested, YOLOv3 and Faster R-CNN demonstrated the highest sensitivity for cavitated caries, at 87.4% and 71.4%, respectively. These two models' sensitivity levels for visually non-cavitated (VNC) conditions were only 36.7 percent and 26%, respectively. The four models' specificity exceeded 71% for VNC and 86% for cavitated caries. Conclusion: YOLOv3 and Faster R-CNN models showed promise in the clinical use of smartphone images for dental caries diagnosis. The current study offers a first look at how AI might be applied in clinical settings after being developed in the lab.

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

https://www.mdpi.com/1424-8220/21/21/7049

ABSTRACT: In today's world, apical lesions—the broad name for chronic infectious diseases—are extremely prevalent dental conditions that can be brought on by a number of different circumstances. The most common endodontic therapy now in use is patient-taken X-ray photos with the lesion area manually annotated, which takes time. Additionally, because of the various shooting angles or dosages, the important elements in certain photos could not be seen. Repetitive tasks should be automated to speed up and streamline the diagnosis process. This would free up dentists' time to concentrate on technical and medical diagnosis, treatment, dental hygiene, and medical communication. This paper suggests and develops a lesion area analysis model based on convolutional neural networks (CNN) in order to achieve the automated diagnosis. The database created by dentists who supplied the useful clinical data has been authorised by the Institutional Review Board (IRB) with application number 202002030B0 for the creation of a standardised database for clinical application. In this work, a Gaussian high-pass filter is used to preprocess the picture data. The X-ray picture is then divided into many separate tooth sample images using an iterative thresholding technique. The CNN migration learning model is trained using the collection of individual tooth pictures that make up the image database. The model is trained and validated using 70% of the picture database, with the remaining 30% being utilised for testing and determining the model's correctness. The suggested CNN model has a practical diagnostic accuracy of 92.5%. The automated diagnosis of the apical lesion was successfully made possible by the suggested model.

3. METHODOLOGY

i) Proposed Work:

The proposed system introduces an automated approach for detecting and classifying periodontal disease using deep learning, with a focus on increasing diagnostic accuracy and clinical efficiency. A 2D Convolutional Neural Network (CNN2D) is implemented to learn and extract intricate features from bitewing radiograph images, enabling precise identification of periodontal issues. To further enhance the model's learning efficiency, both ADAM and ADAMAX optimizers are applied and compared, targeting faster convergence and better handling of high-dimensional data.

As an extension, the system integrates the CNN2D model with a Flask-based web application to support real-time image analysis and user interaction. This web interface enables seamless uploading and processing of dental images, allowing users and dental professionals to receive instant diagnostic feedback. The lightweight nature of Flask ensures quick deployment and flexible integration of machine learning models, supporting remote diagnostics and easy accessibility.

ii) System Architecture:

The architecture of the proposed system is built around a deep learning pipeline that processes bitewing radiograph images to detect periodontal disease. Initially, dental X-ray images are collected and preprocessed through techniques such as resizing, normalization, and contrast enhancement to ensure uniformity and improve feature visibility. These preprocessed images are then passed to a 2D Convolutional Neural Network (CNN2D), which automatically extracts relevant spatial features such as bone loss patterns, tooth alignment, and tissue structure. The CNN is trained using labeled data, and optimization algorithms like ADAM and ADAMAX are employed to improve convergence speed and accuracy during model training. The trained model can classify whether the input image indicates a healthy condition or signs of periodontitis.

To enable real-time interaction, the trained CNN2D model is deployed using a Flask-based web application. This lightweight front-end allows users, including dentists and technicians, to upload dental images via a web browser. Once uploaded, the system processes the image through the CNN model and returns the diagnostic output almost instantly. This integration of machine learning with a web framework not only enhances accessibility but also facilitates seamless deployment in clinical environments. Furthermore, the modular design supports future upgrades, such as incorporating additional disease categories or linking with electronic health record (EHR) systems for comprehensive patient management.

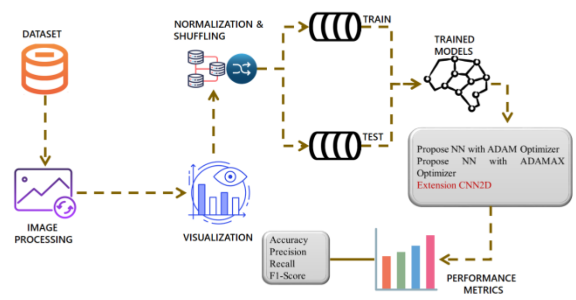

Fig.1. Proposed Architecture

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**

One deep learning method that adjusts learning rates during training is the Neural Network with ADAM optimiser. By automatically modifying weights for the best convergence, it effectively trains the model to categorise dental pictures. By reducing the loss function, the ADAM optimiser helps this system learn to detect periodontitis from photos more quickly and reliably, which enhances the classification model's overall performance and accuracy.

b) NN with ADAMAX Optimizer

An expansion of ADAM, neural networks with the ADAMAX optimiser provide improved performance when handling sparse input. This approach uses dental photos to train the neural network, which can handle bigger models more steadily. By preventing overfitting and facilitating faster convergence, the ADAMAX optimiser enhances the model's capacity to generalise and precisely identify periodontitis across various image datasets while guaranteeing effective learning during training.

c) Extension CNN2D

Convolutional neural networks like the CNN2D model are perfect for image classification problems because they can extract information from two-dimensional pictures. This algorithm analyses dental pictures to automatically identify and categorise periodontal disease. In order to provide effective pattern identification and detection, the 2D convolutional layers collect important spatial characteristics from the pictures. By learning hierarchical features for improved disease diagnosis in dental imaging, it significantly contributes to increasing the model's accuracy.

4. EXPERIMENTAL RESULTS

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

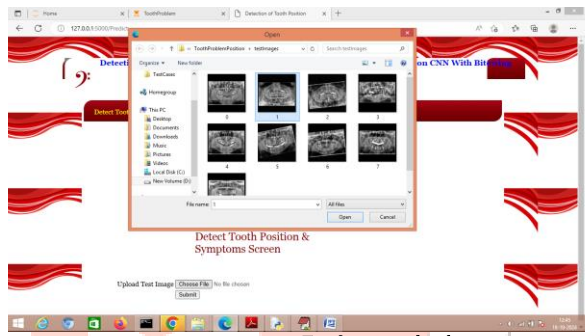

Fig.8. iput upload

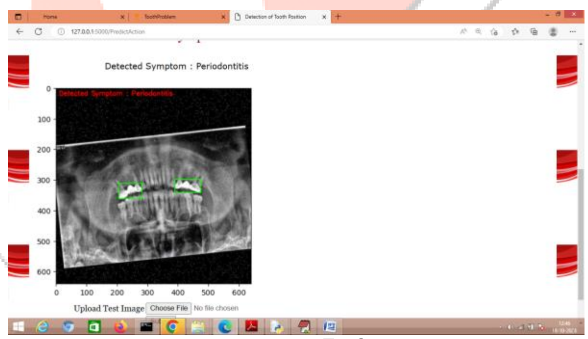

Fig.9. output

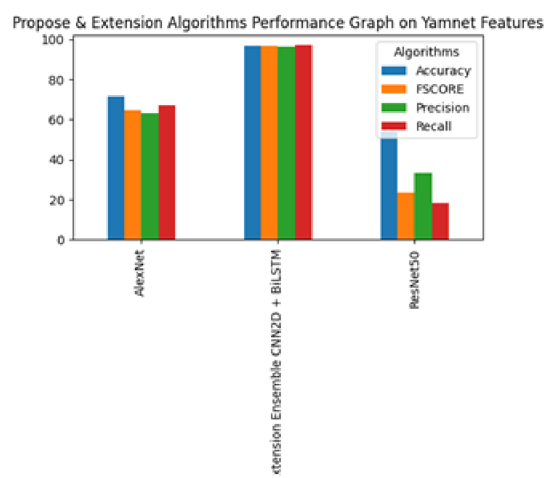

Fig.10. Accuracy Graph

5. CONCLUSION

Through the use of dental imaging datasets and a strong deep learning-based methodology, this work effectively tackles the difficulties associated with automating the identification of periodontitis. The method provides an effective and scalable alternative for the early identification of periodontal disease by drastically reducing the dependence on manual diagnosis through the use of sophisticated neural network architectures. With an astounding accuracy of 96.93%, the 2D Convolutional Neural Network (CNN2D) outperformed the other models that were investigated. This outcome demonstrates the model's exceptional capacity to extract complex information and provide accurate classifications of periodontal diseases. The suggested technique improves accuracy and decreases the time and skill needed for manual labelling by simplifying the diagnostic procedure. The results highlight how automated deep learning frameworks have the potential to revolutionise dental diagnostics, especially in intricate situations like tooth location, opening the door to better patient outcomes and more effective clinical procedures.

6. FUTURE SCOPE

Enhancing the unique characteristics of periodontal disease should be the goal of future research in order to improve diagnosis and classification. Investigating cutting-edge designs like YOLO for enhanced computing efficiency and learning capabilities might help address the drawbacks of conventional CNN models, such as the vanishing gradient problem. To further increase accuracy, more complex models like ResNet and EfficientNet should be studied. The ultimate goal is to provide efficient assistance for dental diagnostics while meeting clinical requirements.

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