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A Computer-Aided Model for Dental Image Diagnosis Utilizing Convolutional Neural Networks

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ABSTRACT

A Convolutional Neural Network (CNN) is an artificial neural network that is primarily utilized for the purposes of image recognition and processing, owing to its remarkable ability to recognize patterns within images. CNNs have found widespread application in diverse areas of computer vision, including but not limited to object tracking and recognition, security, and military and biomedical image analysis. CNN in orthodontic medical imaging technologies to reduce orthodontic treatment planning time, including automatic landmark search on cephalometric radiographs, cone beam computed tomography (CBCT) tooth segmentation, and CBCT tooth segmentation. This paper describes the strategy and the architecture of deep convolutional neural networks applied to DICOM datasets to distinguish between X-ray pictures with and without teeth. This work focuses on the application of the CNNs to a DICOM dataset in orthodontics as pre-processing for CNNs using fuzzy C-means clustering to construct a reasonable prediction that results in improved accuracy of this system. The aforementioned proposal has shown encouraging outcomes and visual representations, indicating that utilizing methods based on convolutional neural networks can greatly enhance the computational planning of orthodontic treatments by decreasing the time required for analysis. In many cases, this approach's analysis surpasses the accuracy of a manual orthodontist. This model achieved an accuracy exceeding 98% in applying the CNNs to differentiate between X-ray images with teeth and others with no teeth to focus any further work only on useful images which helps in diagnosis planning.

1. Introduction

According to Grand View Research, Artificial Intelligence (AI) is expected to increase by 37.3% annually from 2023 to 2030 [1]. This rapid expansion underlines the growing importance of AI

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technology in the coming years. Over the past five years, there has been a significant increase of 34.5% in the utilization of artificial intelligence in the field of dentistry [2].

Over the past 20 years, the discipline of orthodontics has embraced digital technologies, including automated dental aligner production, 3D modelling, and AI-based technologies [3].

A CNN is a powerful tool used in image processing and analysis. The present findings of medical research utilizing convolutional neural networks position this methodology as a promising computational instrument for medical professionals and the field of medicine [4]. CNN emerged as a suitable option due to their ability to learn and improve accuracy over time. CNN applies several layers to make predictions, adjusting their weights with each input data point to minimize prediction error [22]. Examples of such studies are the analysis of mammography images [5], the prediction of spontaneous preterm births [6,7] or the estimation of the healing progress of Achilles tendon [8]. AI applications have so far been limited to supervised and defined cognitive tasks, such as automated cephalometric point detection and teeth segmentation from 3D images.

New technologies are rapidly emerging in the field of dentistry. Presently, artificial intelligence and neural networks are being extensively used to aid in the diagnostic process, treatment planning, and prognosis evaluation in the field of dental radiology. Neural networks have also found use in other areas of dentistry, such as genetics, psychology, microbiology, and more. Artificial neural networks and convolutional neural networks are the most frequently utilized types [9]. Orthodontics, on the other hand, is a dental speciality that involves the recognition and "bad bites" (malocclusion) treatment. Orthodontics presents a challenge to convolutional neural networks, the use of which can help reduce the computational analysis time through more accurate segmentation and automated treatment planning [10].

1.1 Biological Background

Malocclusion or “bad bites” is defined as miss alignment between upper and lower teeth. cephalometric X-ray detection is one of the most important methods used in oral health worldwide for dental, skeletal and soft-tissue evaluation [11] as shown in Figure 1. Cephalometry has been extensively used as a method for skeletal classification in the field of orthodontic diagnosis, as well as a supportive methodology for prospective treatment planning. A good assessment helps clinicians to concentrate on which X-ray will be used in predicting the various growth patterns.

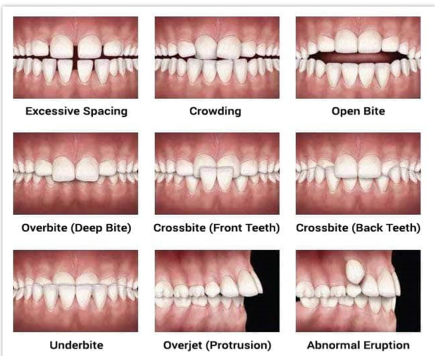


Fig. 1. Malocclusion

The AI algorithm can analyse X-ray images [12]. Within the domain of dentistry, this research represents one of the most successful uses of AI, specifically in the orthodontics field, and in compliance with medical standards.

1.2 Literature Survey

Several investigations have examined the utilization of AI in the analysis of the domain of computerized X-rays. The majority of these investigations estimate the accuracy of their AI by measuring the difference between the landmarks identified by the AI and the human gold standard. The majority of these studies evaluate the precision of their AI by gauging the deviation between the landmarks designated by the AI and the human gold standard. To automate this time-consuming and error-prone process, various researchers have used AI algorithms [13].

A comprehensive meta-analysis was conducted by Schwendicke *et al.,* to evaluate the precision of automated landmark detection among various researchers. The authors found that most of the involved studies were capable to recognize the deviation of teeth by 2 mm and the direction [14]. This information is important to define the actual clinically appropriate orthodontic considerations accuracy measured based on these landmarks [15].

To evaluate the accuracy of automatic analyses, one approach is to assess them in light of the parameters of orthodontics [16]. However, the quality of AI evaluations on this specific foundation is appraised in a few recent studies. In a recent study, Kunz *et al.,* conducted an analysis of the accuracy of their AI in terms of automated analysis, drawing on frequently used orthodontic specifications [15]. The mean deviations between the appraisals of the AI and the human gold standard were significantly less than some specific considerations. Thus, it can be postulated that the variances between the predictions of the AI and the human gold standard are either clinically unsuitable or at most, of negligible significance.

The accuracy of X-ray analysis can be improved by incorporating deep learning algorithms. Studies have shown that the application of deep learning algorithms to analysis has resulted in better performance. However, many of these studies have focused on the detection of cephalometric landmarks. Using CNNs in various phases of orthodontics starting from classifying between X-ray images to diagnosis and treatment planning to reach a precise analysis in a desirable time this work will show up how to classify between useful and un-useful X-ray images to facilitate the mission of dentists in follow-up.

The paper consists of four main sections. The second section describes the methodology of the work, including the algorithm sequence and the proposed system architecture, as well as the components of the system. The third section presents the results obtained during the work, while the fourth section outlines the conclusion of the research and suggests directions for future work.

2. Methodology

This section of the paper introduces the proposed model that was utilized for X-ray image selection, as illustrated in Figure 2.

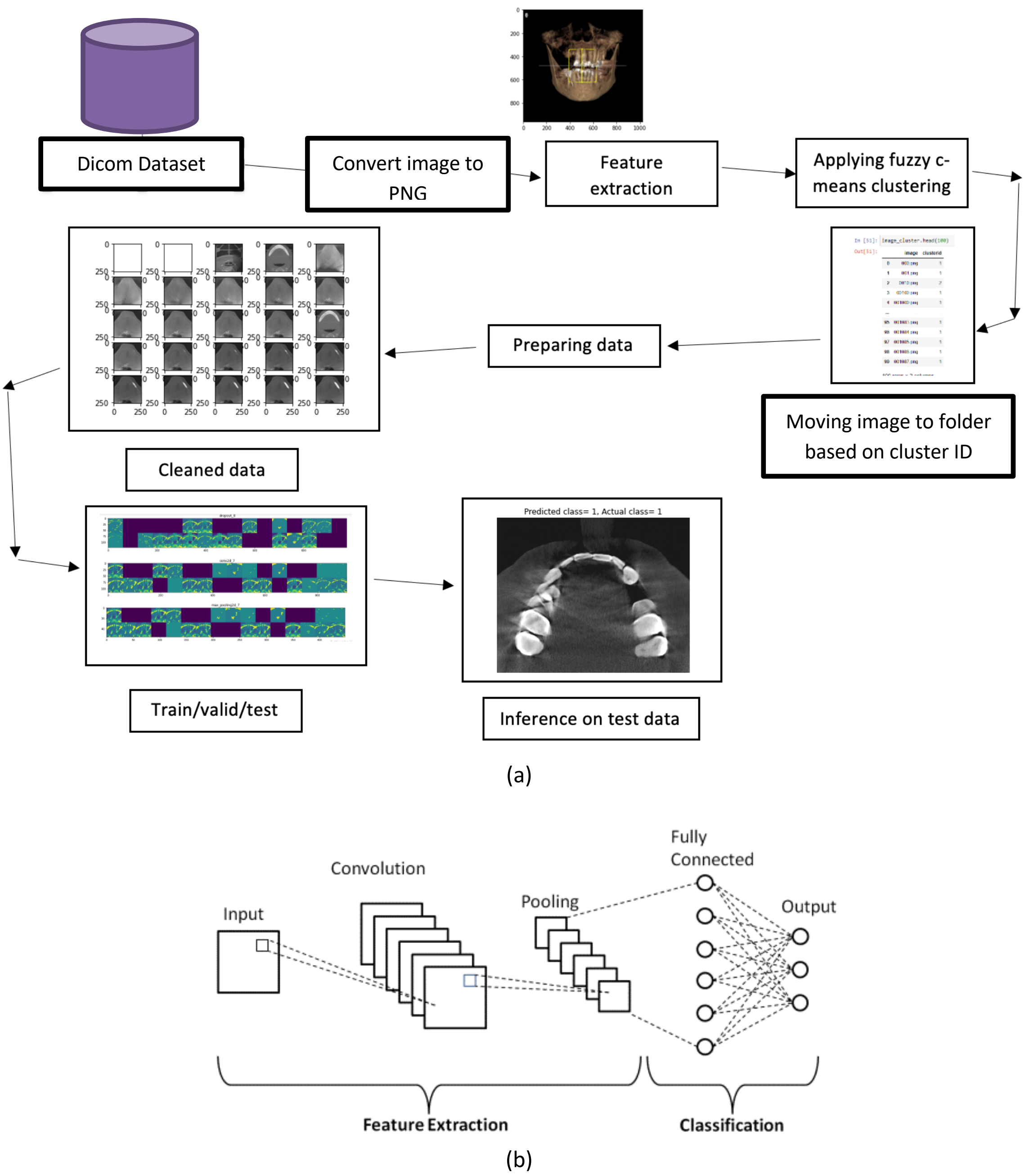


Fig. 2. (a) Proposed model, (b) CNN proposed architecture

The proposed system for detecting the images with teeth and others with no teeth is illustrated in Figure 2. The stages include image processing, which involves grayscale conversion and removing the background to facilitate the application of fuzzy C-means and feature extraction. Finally, in image preparation, the data is ready to be clustered. This Model diagram of predicted and actual class for clean dataset separated into train and valid and test.

2.1 Image Pre-Processing

To reduce complexity, the image is first transformed to grayscale. This is done by reducing the 3D pixel value (RGB) to a 1D value. Grayscale conversion is helpful for many tasks, such as edge detection, that do not require 3D pixels. Then removing the background to be ready for feature extraction and fuzzy C-means clustering

2.2 Feature Extraction

A CNN is comprised of two fundamental components, namely feature extraction and classification. Feature extraction comprises five convolution layers with kernel size of 2*2 with dropout of 0.25, three activation layers, two ReLU and one sigmoid, max-pooling is part of every layer to take out a single representation of all features convolved. The process of mining features entails converting unrefined data into digitalized features that can be processed while maintaining the information contained in the primary dataset, thus resulting in a more fluent representation of the data. This approach yields superior results compared to the direct application of machine learning to the raw data [17]. This model depends on the inception V3 function that was done during clustering.

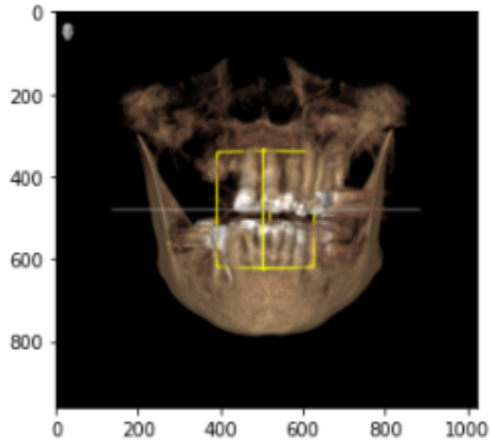


Fig. 3 Sample of feature extraction

2.3 Fuzzy C-Means Clustering

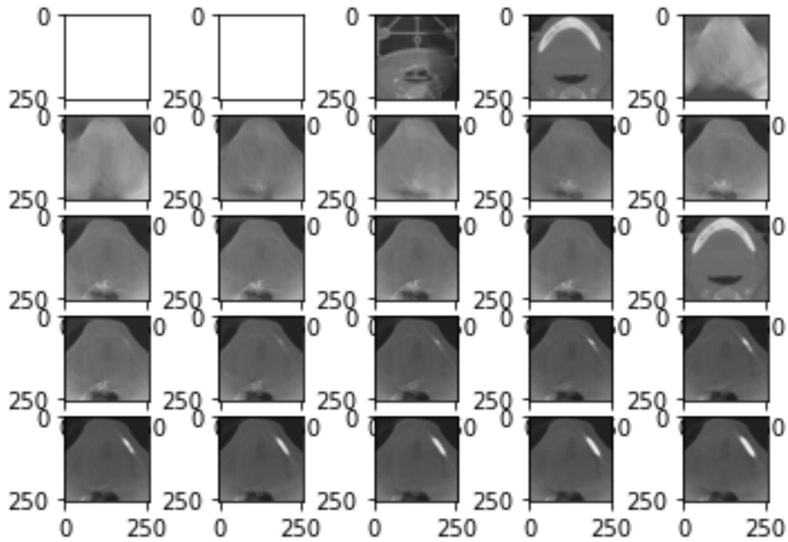
Fuzzy C-means clustering is a prevalent method for clustering that employs an unsupervised technique, necessitating no labelled response for the given input data. Typically, specialists commence by obtaining information about the structure of the dataset. This approach enables one piece of data to belong to two or more clusters, utilizing multi-valued logic derived from fuzzy set theory. Combining the feature extraction in CNNs with fuzzy C-means clustering enhances the result while preparing the data to classify the cleaned data and then moved them into folders. This stage is a pre-preparation for the next one which includes splitting images into train, valid and test.

2.4 Train Valid Test

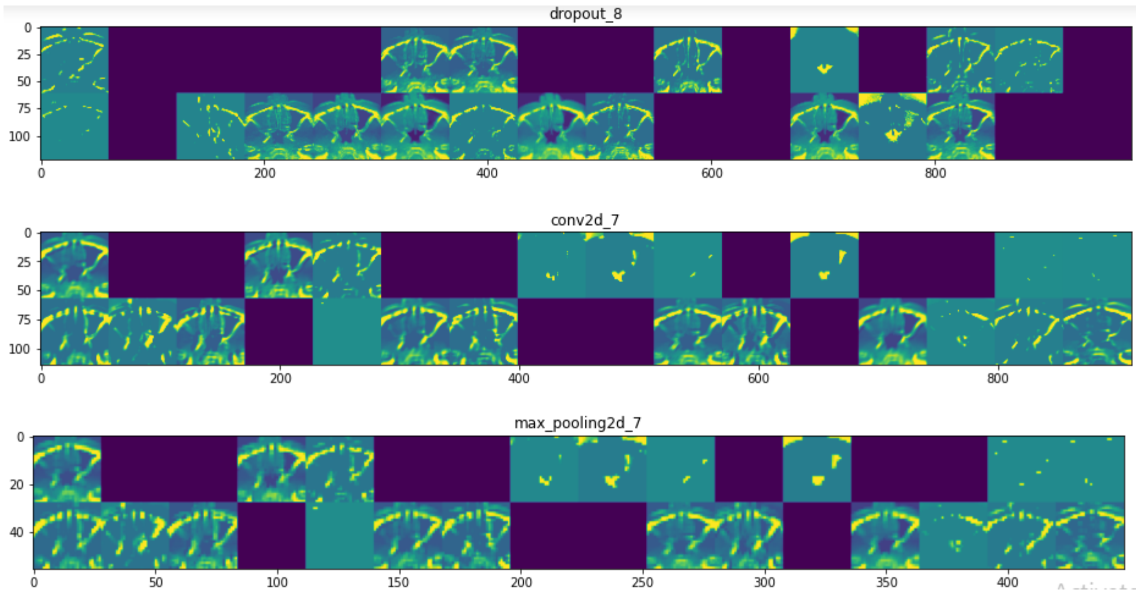
The best practice in machine learning is to randomize the data split into three groups for unbiased evaluation.

i. Training Set: to train the model.
ii. Validation Set: for unbiased evaluation of the model.
iii. Test Set: used for the final evaluation of the model.

In this step create a predicted class and an actual class to be prepared for the final step in classifying the dataset.



(a)



(b)

Fig. 4. (a) Process of train/valid/test, (b) Train/valid/test

2.5 Inference on Test Data

Inference is the process of utilizing the acquired knowledge obtained from a neural network model that has undergone training to deduce a conclusive outcome. Hence, when an unknown dataset is introduced to a trained neural network, the accuracy of the forecast is determined by the neural network's predictive precision. Creating a prediction class and an actual class to get the final result of X-ray images with teeth and others with no teeth taking 1 and 0 consecutive.

Fig. 5. Inference on tested data

3. Results

Experiments have been carried out on a rich benchmark dataset of size 1510 images. Performance measurements have been applied to calculate the efficiency of the proposed model. The benchmark dataset is subdivided into training data, validation and testing dataset. This section demonstrates the experimental results, it begins with a description of the experimental environment followed by the dataset classification and its result, ending this section with a comparison between recent research and another comparison to show the importance of AI classification and classical one.

3.1 Experimental Environment

A novel algorithm was verified within a distinctive environment consisting of three DICOM datasets, totalling 1510 images with diverse properties. The implementation of a comprehensive range of diverse images was employed to accomplish the goal of evaluating the paramount importance that lies in the algorithm's ability to be both efficient and durable. This experiment was done on Windows 10 using Jupyter Notebook Anaconda 3.

3.2 Dataset

A dataset consisting of 2D and 3D X-rays; this dataset was collected from the DigiScan Dental and maxillofacial imaging centre in Alexandria, Egypt. This model begins with the usage of 2D scans. X-rays are in DICOM format. The total number of X-rays is 1510 images in which the classification will be mentioned as class 1 which is the images with no teeth and class 2 with teeth. Class 2 consist of the maxilla about the mandible being in harmony, they are in a normal relationship and the maxilla is prognathism or the mandible is retrognathism or both (and vice versa).

3.3 Results of Data Classifying

The proposed algorithm adopted CNNs concerning the three main stages of train, valid and test. 2D CNNs utilize 2D convolutional kernels for the purpose of predicting a segmentation map for a singular slice. The forecast for a complete image's segmentation maps is achieved by sequentially predicting each slice by moving in two directions. The 2D convolutional kernels can leverage context across the height and width of the slice to make predictions.

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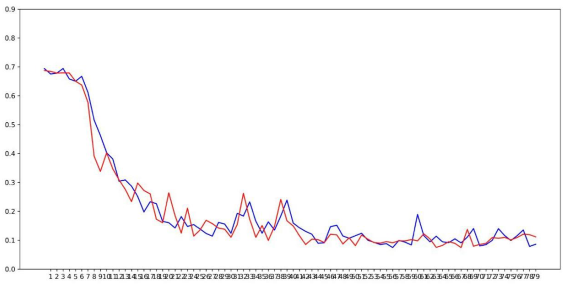
In most cases, the outcome of a neural network produces a predicted value for the relevant output factor or probabilities for different values of the related output factor, and a decision is reached based on these values.

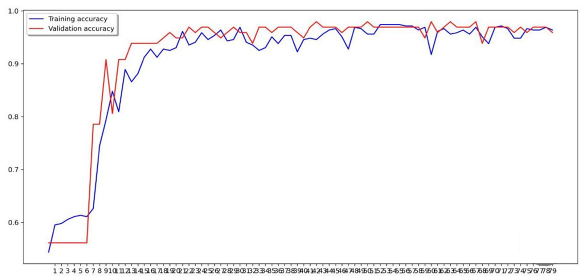
Fig. 6. The result after applying CNNs

3.4 Comparison between Different Performance Measures

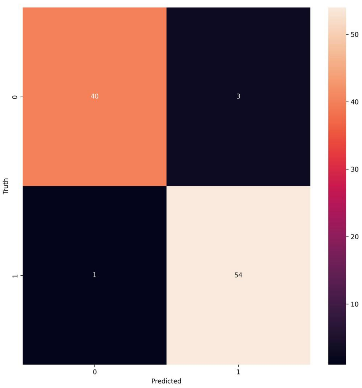
This section shows the performance measure of the proposed model which appears in Graph 1(a) and identifies the training loos and the validation loss which are slight and Graph 1(b) highlights the validation and training accuracy that increased during execution to reach 97.8%. Those measures are the indicators of a reasonable result with good performance. This model also represents a confusion matrix in graph 2 as shown below the counts of predicted and truth values that help in the calculation of precision, recall and f-score. Table 1 below this work demonstrates a comparison between different performance measures for each class.



Graph 1(a): Training and validation loss



Graph 1(b): Training and validation accuracy



Graph 2: Confusion matrix

Table 1
Performance measures

	Precision	Recall	f1-score	Support
No-teeth	0.98	0.93	0.95	43
Teeth	0.95	0.98	0.96	55
Accuracy			0.96	98
Macro avg	0.96	0.96	09.6	98
Weighted avg	0.96	0.96	09.6	98

3.5 Comparison between This Proposed Model and Recent Ones

Table 2 provides a comparison between the proposed model and other recent models that use CNN method and morphological pre-processing for X-ray image analysis. The table includes models tested on various datasets and a large number of images under different conditions.

Table 2
Comparison between the proposal model and other models in the literature

Authors	Method	Accuracy
J. H. Lee [18]	CNN	89%
Yu *et al.,* [19]	CNN	93.3%
Chang H. *et al.,* [20]	CNN	93%
Kurt Bayrakdar S. [21]	CNN	95.3%
This proposed model	CNN	98%

This study demonstrated the potential accuracy and efficiency of a CNN algorithm for detecting teeth. This highlights the effectiveness of deep learning techniques in dental image analysis and shows an improvement of the accuracy rate by over 5% when tested on different datasets.

3.6 Comparison between AI Classifying and Classical Classifying

Table 3 highlights the importance of AI diagnostics in the form of a comparison between classical diagnostics and artificial ones [2]. This comparison depends on some very useful criteria in diagnostic and treatment planning such as time, decision making and accuracy.

Table 3
The importance of AI diagnostics in the form of a comparison between classical diagnostics and artificial ones

Criteria	AI Diagnostics	Classical Diagnostics
Time	AI systems can process massive amounts of data in a matter of minutes, assisting in decision-making and freeing up doctors' time for other vital activities.	Traditional diagnostics rely on doctors studying patient scans and making a final judgement using manual, time-consuming techniques.
Decision Making and analysis	AI orthodontics solutions can easily learn and recognise patterns, analyse photos, and make choices because of limitless storage and huge processing power.	Human practitioners cannot analyse all data fast and accurately because of limited processing and recollection ability.
Accuracy	In contrast to human professionals who face weariness, distraction, sadness, and a variety of other psychological challenges, AI systems can deliver factual remedies based on thousands of sources.	Human error is an unavoidable component of traditional diagnosis in both severe and mild medical diseases. Major diagnostic errors account for 10-20% of patient death in the United States.

4. Conclusions

In this paper, CNN's little dependence on pre-processing, decreasing the needs of human effort to develop its functionalities, pre-processing and feature extraction in image analysis are very useful in this work. The clustering techniques such as Fuzzy C-means clustering are very effective for class prediction. Automatic systems help doctors locate images with teeth and others without teeth in two separate classes. Orthodontists spend a significant amount of time analysing and diagnosing X-ray images, which is a laborious and time-consuming process. This is due to the complexity of the images, which require manual detection by orthodontists. An average accuracy exceeding 97% has been achieved by this model, indicating its effectiveness in positively diagnosing and predicting periodontal compromised teeth. This high level of accuracy leads to the next phase, which involves the development of universal intelligence-based neural networks. These advanced computer systems, equipped with sophisticated algorithms, aim to assist orthodontic diagnostics and treatment management. By leveraging the power of artificial intelligence, these systems can provide orthodontists with the most suitable treatment plans, leading to better treatments and reliable outcomes.

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