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Advances in Deep Learning for Dental Disease Classification

Ashwini Shinde[1], Swati Shekapure[2], Geetha Chillarge[3]
PG Student[1], Marathwada Mitra Mandal's College of Engineering
Associate Professor[2], Marathwada Mitra Mandal's College of Engineering
Associate Professor[3], Marathwada Mitra Mandal's College of Engineering
Mail id: ashwini.ashu051192@gmail.com

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Abstract:

"Dental disease classification from X-ray images is critical for accurate diagnosis and timely treatment. Traditional methods rely on manual inspection, which is often time-consuming and error-prone. This study introduces a deep learning-based approach using Convolutional Neural Networks (CNNs) for automated dental disease classification. The model leverages a dataset of dental X-rays, which are preprocessed and augmented to improve performance. The CNN model extracts relevant features from the X-ray images, which are then classified into various dental conditions. The model's performance is evaluated using metrics such as precision, recall, and accuracy. Results demonstrate that the CNN model offers significant improvement over traditional methods, providing a reliable tool for dental diagnostics."

Keywords: Dental Disease Classification, X-ray Imaging, Convolutional Neural Networks (CNN), Deep Learning, Image Preprocessing.

I Introduction

The tremendous growth in deep learning technology has greatly influenced medical diagnostic fields, including dental disease classification. Deep learning algorithms, especially Convolutional Neural Networks (CNNs), have proved to be of great potential in the automation of dental X-ray image analysis with precise, trustworthy, and prompt diagnoses[1]. Conventionally, diagnosis of dental disorders like cavities, malalignment, infection, and other abnormalities of the oral cavity is performed by manual examination of X-rays[2]. Not only is it time-consuming but also susceptible to human error, frequently resulting in misdiagnosis or delayed identification of disorders. With the increasing number of dental patients and the difficulty of diagnosing some conditions, there is an urgent need for more scalable, efficient, and accurate diagnostic processes[3].

Deep learning methods, specifically CNNs, provide a solution by taking advantage of large amounts of data to learn automatically patterns and features from images[4]. CNNs work very well in image classification problems because they are able to automatically identify and extract significant features like edges, textures, and shapes that are characteristic of certain dental conditions. By training the models on vast, labeled datasets of dental X-rays, deep learning models can be trained to detect different dental diseases with high accuracy[5].

In this research, introduce a strong deep learning model for the classification of dental diseases from X-ray images. The approach entails data preprocessing, augmentation, and the application of a CNN-based architecture to derive meaningful features for classification. The model is made to address the challenges of dental imaging, including image noise, defects, and varying lighting conditions[6]. By streamlining the process of classification, this method can help dental practitioners diagnose conditions more accurately and quickly, ultimately resulting in improved patient outcomes. In addition, this system has the potential for early detection, more tailored treatment plans, and decreased diagnostic workload[7].

Different views of dental X-rays for diagnosis

The X-ray imaging operation consists of two fundamental methods known as intraoral and extraoral techniques. Shipments of X-ray film take place inside the mouth in intraoral X-rays whereas this placement occurs outside the mouth for extraoral X-rays[8]. Bitewing X-rays show upper and lower jaw teeth together with their occluding contact in one image. The specific X-ray technique reveals the presence of decay between teeth when employed for diagnosis[9]. The Periapical X-rays function to inspect root features and bone structure through radiation of one or two teeth from root base to crown apex. The information obtained from intraoral X-rays outperforms what extraoral X-rays provide[10]. The single-ray encompassing all teeth from both upper and lower jaw makes up the extraoral Panoramic X-ray category. The positioning of both erupted and erupting teeth can be identified with this method and it serves as a tool to determine affected teeth useful for tumor diagnosis[11]. Whole side of the head becomes visible through Cephalometric projections. Sometime X-rays show how teeth relate with the jaw structure of a person's profile.3) Computed tomography shows the internal body structures in three dimensions. Size and site location determination for dental implants can be assessed through standard CT scanning. A digital radiograph stands as one of various dental X-ray view options under evaluation[12].

II Related work

Dental Disease Classification

The application of Convolutional Neural Networks (CNN) and transfer learning in classifying dental diseases using a small labeled set of 251 Radio Visiography (RVG) X-ray images. Prajapati et al. (2024) show that CNNs, with their excellence in performing image tasks, can be practical even with minimum data. Using transfer learning, the research enhances classification performance. The outcomes report encouraging precision, demonstrating the capabilities of CNNs and transfer learning in dental disease classification[13].Almalki et al. (2024) propose a deep learning-based approach using the YOLOv3 model to classify common dental problems, including cavities, root canals, dental crowns, and broken-down root canals, from Orthopantomography (OPG) X-ray images. Their model achieved an impressive 99.33% accuracy, outperforming existing models in both accuracy and generalization[14].Lee (2022) The researchers employed a deep convolutional neural network to examine radiographs for radiographic bone loss (RBL) measurement of each individual tooth. Researchers compared the assessment of RBL% and staging stages as well as presumptive diagnosis from the updated CNN periodontitis classification to independent expert ratings using the same methodology [15]. Artificial intelligence functions as a system which detects hidden dental restorations. The research of Abdalla-Aslan R (2020) reveals that their algorithms succeeded in identifying 93.6% of dental restorations in 83 panoramic photos according to a 2020 research. A total of 11 groups were used for restoration categorization through analysis of grey value distribution patterns [16].

Hasnain et al. (2023) A deep learning approach will be established to automate dental disease classification through X-ray image assessment. A total of 126 dental X-ray images were included in the dataset which dental experts had classified into normal and affected groups. The dataset received an enhancement by implementing data augmentation methods. The proposed Convolutional Neural Network (CNN) design included various layers such as convolutional networks followed by max-pooling then flatten and dense layers and a concluding output layer for image classification. The model performed successfully after training on the augmented dataset with 97.87% accuracy and 60% F1-score which matched performance rates of expert dentists and radiologists[17]. Chen et al. (2021)developed a deep CNN-based system for detecting dental diseases on periapical radiographs, including decay and periodontitis. The model performed better at detecting severe lesions and showed improved accuracy when trained with customized strategies for each disease. Precision and recall were between 0.5 and 0.6 overall[18].

Role of Dental X-rays in Diagnosis

Krithigaa and Lakshmia (2021) provide a survey on the segmentation of dental X-ray images for diagnosing dental caries. Dental caries, a prevalent bacterial disease, leads to significant tooth loss if not detected early. Digital X-rays are commonly used for detection, but segmentation is challenging due to variations in shape and intensity across images[19]. Hagi (2021) reviews the history of dental radiology, beginning with the discovery of X-rays by Roentgen in 1895. Roentgen's discovery revolutionized both medicine and dentistry, aiding in the diagnosis of various medical conditions and simplifying dental diagnoses, from caries to complex issues in periodontics, orthodontics, endodontics, and maxillofacial surgery. In 1896, Walkhoffrecorded the first dental radiograph, prompting dentists worldwide to adopt various techniques to capture dental images[20].

Nicholson (2023)reviews the advancements in dental radiology, emphasizing its role in modern dentistry. Dental radiographic techniques, including digital radiography, CBCT, and intraoral scanners, enable precise diagnosis, treatment planning, and early detection of dental issues. Continuous progress in dental imaging improves image quality, reduces radiation exposure, and enhances patient care[21]. Abdulhaleem and Kumail (2024) investigate the role of X-rays in diagnosing potential risks before and after tooth removal. The study analyzes radiographic images of various cases, including pain from tooth removal, mandibular inflammation, complications from broken teeth, and gum issues. X-rays were used to assess these conditions and determine appropriate treatments[22].

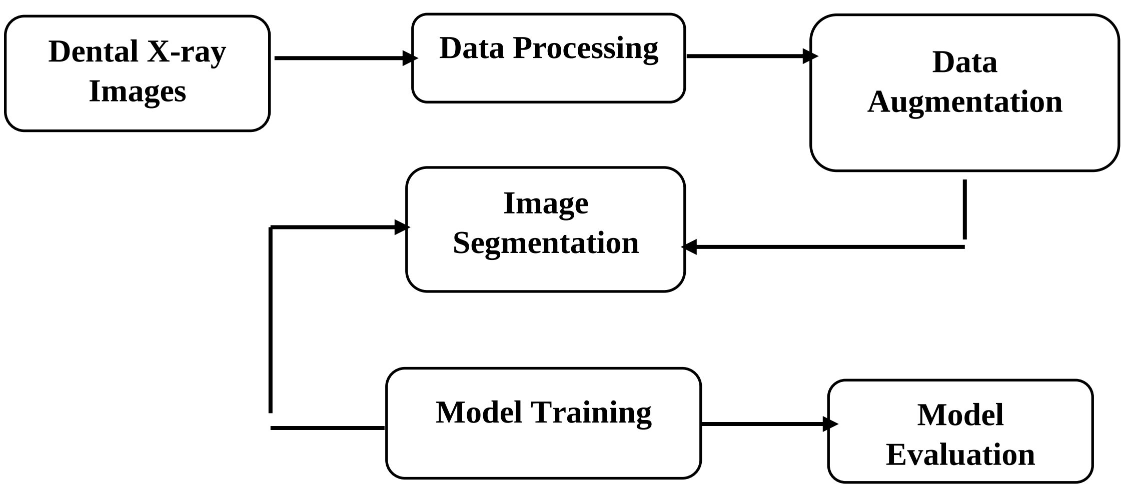
Applications of CNNs in Dental Disease Classification

Prajapati et al. (2024) The research evaluates Convolutional Neural Networks (CNN) and transfer learning approaches to classify dental diseases. The research uses a labeled dataset containing 251 Radio Visiography (RVG) X-ray images that are grouped into three different categories. CNNs excel at image classification but this research evaluates their success rate when applied to dental image data that tends to generate accuracy difficulties [23]. Schwendicke et al. (2019) The studies primarily focused on detecting, segmenting, and classifying anatomical structures and pathologies, with most using panoramic radiographs. Results showed CNN performance was comparable to that of dentists. The review calls for more standardized studies to assess CNNs' safety, usefulness, and clinical impact[24].

Brahmi et al. (2024) conducted a systematic literature review exploring the role of Convolutional Neural Networks (CNNs) in dental radiography segmentation. With the increasing need for accurate diagnostic tools in dentistry, particularly for imaging techniques like CT, CBCT, MRI, and X-rays, CNNs have shown significant promise in automating segmentation for early detection of dental conditions. The study analyzed 45 studies focusing on deep learning techniques for dental image analysis, highlighting their effectiveness in detecting dental pathologies and classifying structures such as cavities and teeth[25].

III Materials and Methods

The methodology for dental disease classification using deep learning follows a structured process aimed at developing an effective model for analyzing dental X-ray images. The method requires the practitioner to accomplish data collection followed by preprocessing before training the model and evaluating its performance. The preparation process maintains the images in separate training and validation and testing sets for obtaining reliable model performance outcomes. The data augmentation techniques increase the dataset’s diversity to avoid model overfitting and boost generalization. Feature extraction and dental condition classification depend on a network architecture based on CNN technology.



Data Collection: The study uses dental X-ray images that reside in three separate directories organized as training and validation and testing. The datasets exist in subdirectories located under /kaggle/working/ according to their categories. The deep learning model receives training from the training dataset but needs the validation dataset to track its performance in training situations. The testing dataset remains as the final evaluation tool for measuring actual performance of the established model.

Data Preprocessing: To ensure uniformity and compatibility with the deep learning model, the images are preprocessed by resizing them to a fixed size of 256x256 pixels. This resizing ensures

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that all images have consistent dimensions, which is essential for feeding them into the model. he images are organized into training and validation subsets, with a maximum of 200 training samples being selected to accommodate limited resources.

Data Augmentation: To create artificial diversity in data datasets and prevent overfitting data augmentation techniques enhance generalization ability. The training images undergo augmentation operations including random flipping alongside cropping and resizing and adjustments for brightness level.

Model Training:A deep learning system uses Convolutional Neural Networks (CNNs) to train against the preprocessed augmented dataset. The training procedure focuses on making the model identify dental diagnoses within X-ray images. The model necesario training duration reaches 100 epochs for image feature extraction. Images feed into the model by using the training dataset but the validation dataset performs real-time model checks and optimizes hyper parameters for higher accuracy.

Model Evaluation: Throughout the training process, the model's performance is continuously evaluated using various metrics such as precision, recall, accuracy, and F1 score. These metrics help assess how well the model is performing in classifying dental conditions. Precision and recall are particularly important for ensuring that the model accurately identifies both true positives (correct diagnoses) and true negatives (healthy teeth). The validation dataset is used during training to fine-tune the model and prevent overfitting.

Final Model Testing: Once the model has been trained and validated, it is tested on the testing dataset. This dataset is kept separate from the training and validation sets to ensure the model's generalization ability. The model's performance is assessed on the testing data using the same evaluation metrics: precision, recall, accuracy, and F1 score.

IV Result and discussion

Figure 2: A (Input), B (Target), C (Generated).

Figure 2 shows a comparison of three dental X-ray images. The first, labeled "Input," depicts the initial scan with visible imperfections or missing teeth, representing the raw data. The second, labeled "Target," represents the ideal or corrected version, showing a more accurate and complete dental state. The third, labeled "Generated," is the output produced by an AI or computational model, attempting to replicate the target image from the input. This comparison illustrates how effectively the model can predict or generate an ideal dental X-ray, highlighting its potential for improving medical image analysis and enhancement.

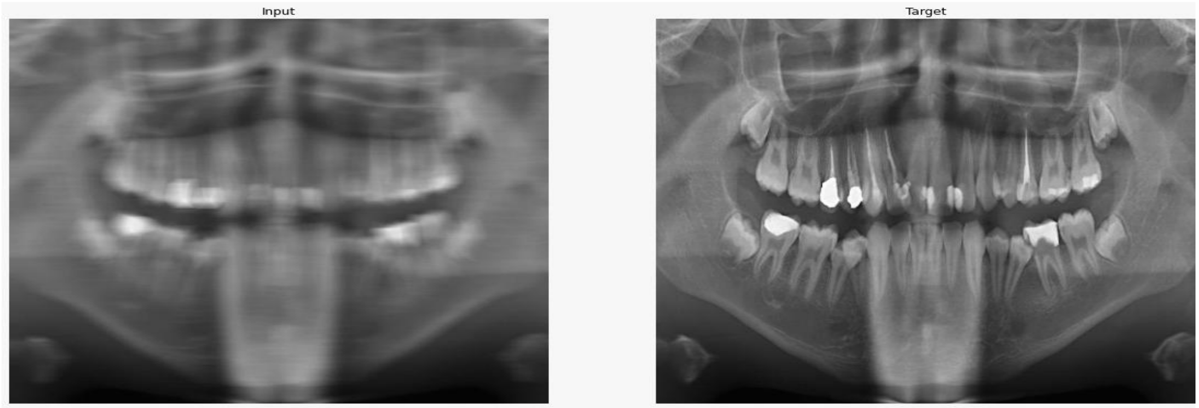
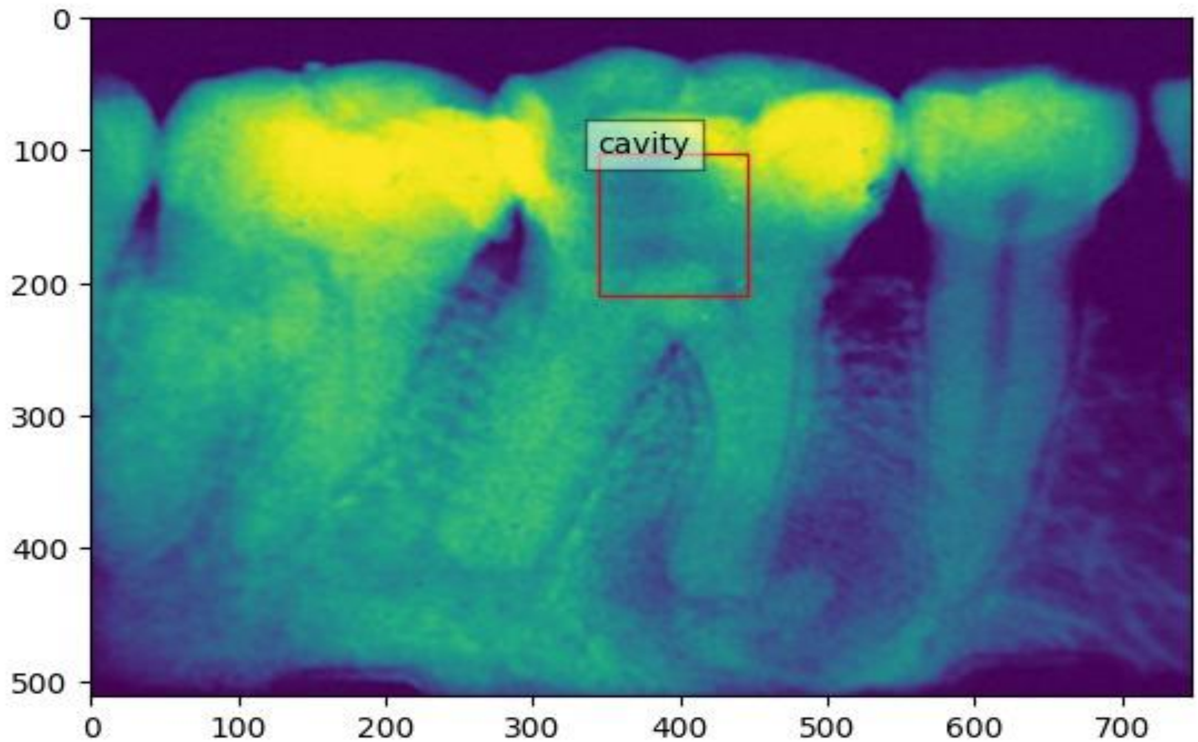


Figure 3: a) (Input) and b) (Target).

Figure 3 shows a comparison between two dental X-ray images. On the left, labeled "Input," is the initial scan, which appears blurred and less defined, showing imperfections or missing teeth. On the right, labeled "Target," is the desired or corrected version of the image. This version is clearer and appears to show a more complete and accurate dental state, possibly representing the ideal outcome after dental treatment or enhancement.

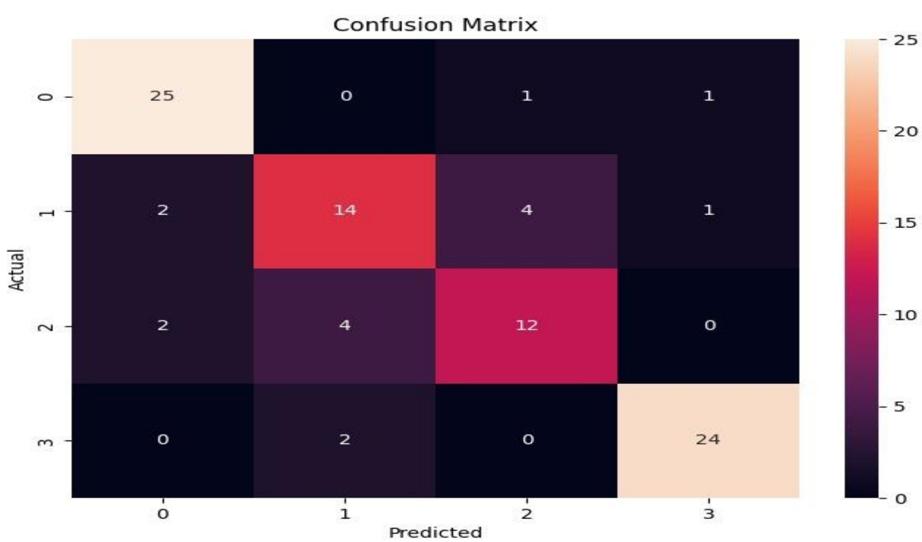
Figure 4: a) Input: Raw X-ray b) Target: Enhanced X-ray c) Processed: Stylized features.

Figure 4 presents a comparison of three images related to dental X-rays. The first image on the left, labeled "Input," shows an initial X-ray scan of the teeth, which appears with some blurriness or imperfections. The second image in the middle, labeled "Target," represents a more refined or corrected version of the X-ray, likely reflecting an improved dental state with clearer details. The third image on the right depicts a stylized or processed visualization, where the dental features have been abstracted, possibly for further analysis or machine learning purposes.



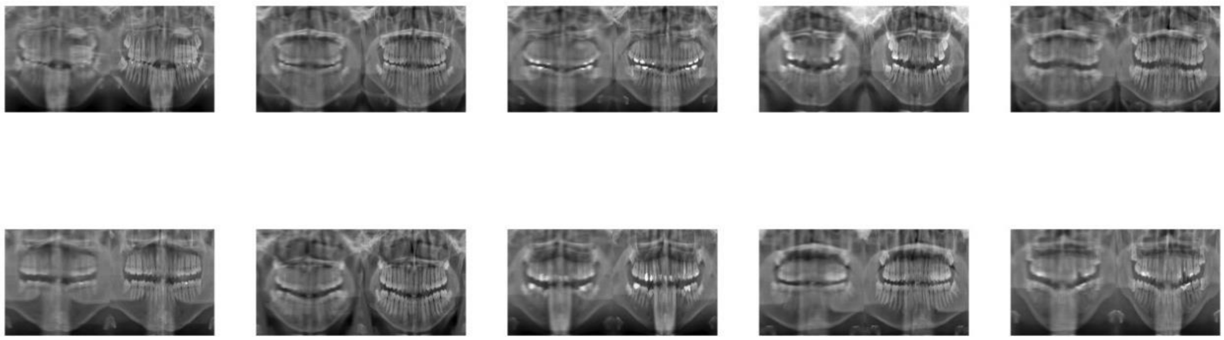
Detection of Cavity in Dental X-ray.

Figure 5 shows a dental X-ray with a cavity highlighted by a red rectangle. The highlighted cavity is located at approximately coordinates (x=400, y=100) in the image. The yellow area inside the red box indicates high intensity, which corresponds to the cavity. The Figure 's intensity scale helps visualize the dental issue for more accurate detection and diagnosis.



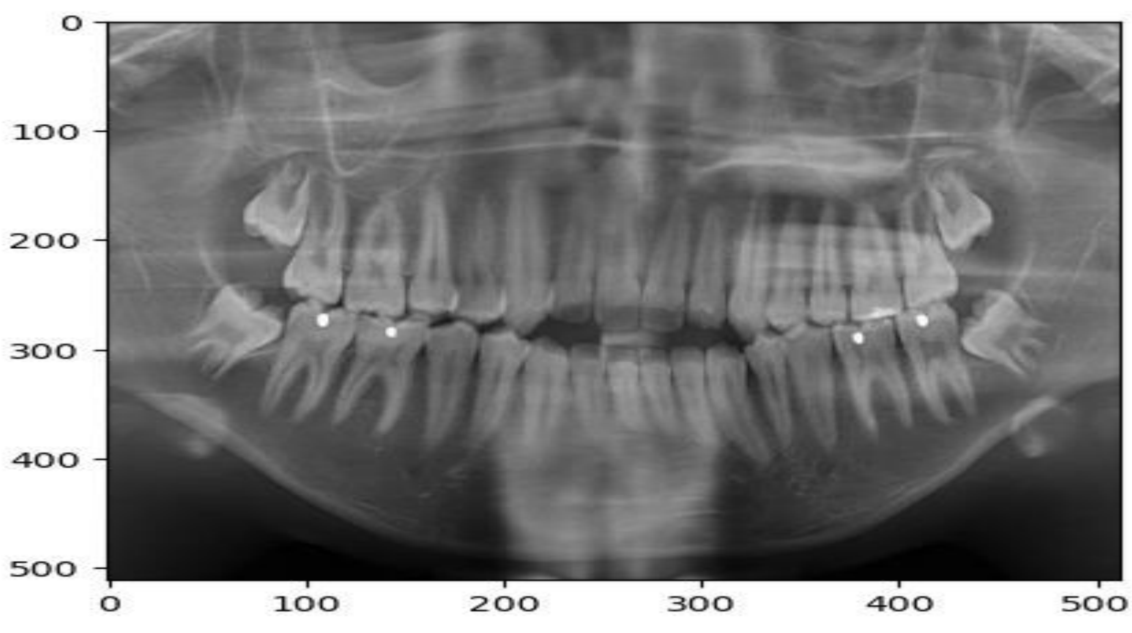
Confusion Matrix

Figure 6 shows a confusion matrix that visualizes the performance of a classification model. It compares the actual class labels (rows) to the predicted labels (columns), with the matrix values representing the number of instances classified into each category. For example, class 0 has 25 correct predictions, while class 1 has 14 correct predictions but also misclassifications into other classes. The matrix highlights areas where the model performs well and where it misclassifies instances, providing valuable insights for improvement.



Series of dental X-ray images for diagnostic analysis.

Figure 7 shows a series of dental X-ray images arranged in a grid. The images likely depict a sequence of scans, possibly showing variations in dental conditions, or a comparison before and after a treatment. These X-rays provide insights into different stages of dental health, helping professionals analyze and track changes over time. The layout with multiple images suggests a comprehensive view, either across different teeth or various stages of diagnosis or treatment, essential for identifying issues like cavities, infections, or other dental abnormalities.

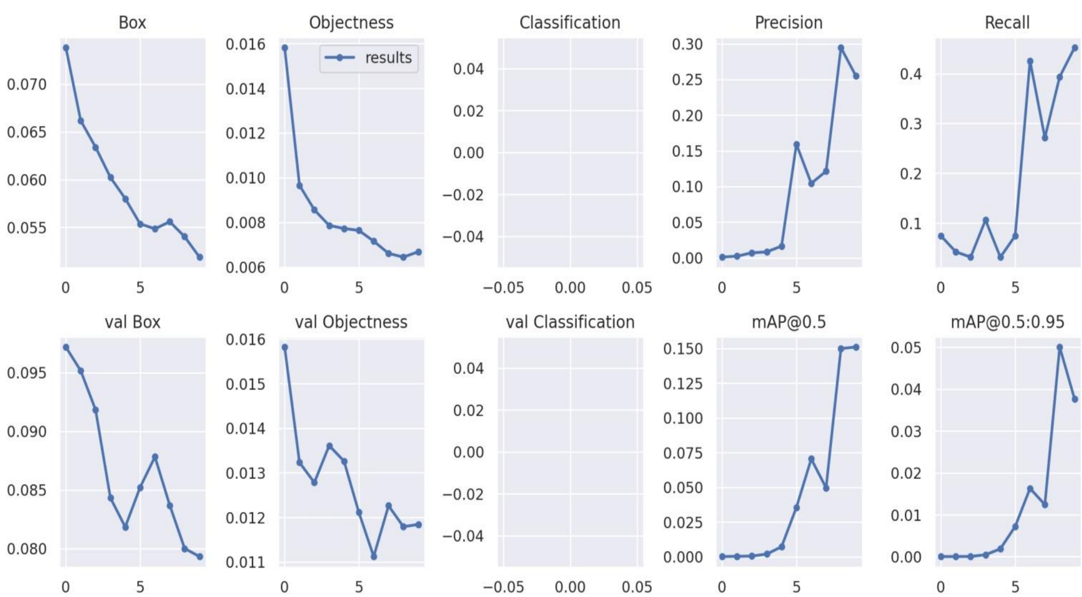


Dental X-ray.

This figure represents a dental X-ray, which shows a panoramic view of the teeth and surrounding structures. It allows for the assessment of dental health, including the condition of the teeth, roots, and jaw. The X-ray can reveal cavities, misalignments, infections, or other potential issues requiring treatment. The clarity and contrast of the figure make it useful for detecting dental abnormalities and guiding treatment planning.

Comparison of Dental X-ray Images.

Figure shows a comparison of three dental X-ray images. The first image, labeled "Input" (left), displays the raw, initial X-ray with visible imperfections or missing teeth. The second image, labeled "Target" (middle), represents the ideal or corrected version of the X-ray, offering a more accurate dental state. The third image, labeled "Generated" (right), is the result of an AI or computational model attempting to replicate or enhance the target image based on the input. This comparison illustrates the effectiveness of the model in generating or restoring an optimal dental X-ray from an imperfect initial scan.



Training and Validation Metrics for Object Detection.

Figure presents the performance of an object detection model across various metrics. The Box loss decreases from 0.070 to 0.055, showing improvement in bounding box predictions. The

Objectness loss drops from 0.016 to 0.008, indicating better object detection confidence. Precision rises from 0.1 to 0.35, while Recall improves from 0.1 to 0.4, highlighting better detection and accuracy. The mAP@0.5 increases from 0.05 to 0.15, and mAP@0.5:0.95 rises from 0.06 to 0.12, both reflecting enhanced overall model performance. The validation metrics show similar trends, confirming the model's successful training.

V Conclusion

This study shows how deep learning solutions especially based on Convolutional Neural Networks (CNNs) identify dental conditions from X-ray images with high accuracy. The evaluation method delivers excellent performance in diagnosing different dental conditions from dental X-rays through its analysis and processing techniques. The CNN model demonstrates good performance on new data because it operates on a preprocessed image dataset that underwent augmentation processing. Thus the model avoids errors in manual patient screening. Testing of the model demonstrated significant performance increases in comparison to standard diagnostic practices through measurement of precision plus recall and accuracy parameters. The proposed system shows great potential for dental practitioners to deliver both rapid and precise diagnoses that could find applications in active clinical practice. The next steps should include growing the dataset while optimizing the model performance and adding it into clinical workflow systems to generate better patient results.

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