CaviScanNet: AI-Powered Cavity Detection, Segmentation, and Diagnosis with BERT Recommendations

Aruna Vipparla[1,a)] and Siva Prasanth Mysetla[2,b)], Nithin Paidi[3,c)], Sree Lakshmi Sathvika Mallempati [4,d)], Esther Rani Karnati[5,e)]

[1]*Assisstant Professor, Department of Computer Science and Engineering, NRI Institute of Technology, Agiripalli-521212, Vijayawada, Andhra Pradesh, India*

[2,3,4,5]*B. Tech Student, Department of Computer Science and Engineering, NRI Institute of Technology, Agiripalli-521212, Vijayawada, Andhra Pradesh, India*

[a)]*Corresponding Author: aruna.vipparla5@gmail.com*
[b)]*msivaprasanth5599@gmail.com*
[c)]*paidinithin2004@gmail.com*
[d)]*sree.malempati08@gmail.com*
[e)]*esther1323.com@gmail.com*

ABSTRACT. This paper introduces a deep learning-based system for dental X-ray analysis aimed at automating cavity detection, severity classification, and providing personalized recommendations. Using Mask R-CNN, the system detects cavities and segments their affected areas, while ResNet-50 classifies the severity of caries into superficial, medium, or deep categories. A fine-tuned BERT-based recommendation system then offers tailored advice based on severity and potential causes such as poor hygiene or diet. The solution reduces manual diagnostic effort, enhances accuracy, and provides actionable insights, which can be deployed via a web interface for remote accessibility and clinical integration, thus advancing dental care and early intervention.The results shows that the detection is highly accurate with 89.2% mAP (Mean Average Precision), the segmentation accuracy by DSC (Dice Similarity Coefficient) was 91.5%, the classification produced 92% validation accuracy among the superficial, medium, deep caries and recommendation had a 90% relevance score matched with dentists advice which is a one-of-a-kind feature.

KEYWORDS: Deep learning, Mask R-CNN, ResNet-50, Image segmentation, Feature Extraction, BERT-based Recommendation System, Mean Average Precision, Dice Similarity Coefficient

INTRODUCTION

Dental caries often referred to as cavities, rank among the leading oral health issues on a global scale. Their progression involves the continual destruction of tooth structures ultimately leading to pain, infections, and in extreme cases tooth loss hence a necessity for artificial replacements. The classic method for diagnosing dental caries relies heavily upon visual examination and manual interpretation of X-ray scans by the dentist. This process typically takes a considerable amount of time, is susceptible to human error, and partly depends on the expertise of the radiologist. However, recent advances in deep learning have considerably enhanced medical imaging applications such as automated detection, classification, and segmentation with great accuracy. By merging artificial intelligence (AI) within the realm of dental diagnostics, great scope for enhancing early diagnosis, reducing the load on dentists went in favor of better treatment planning for the patient.
In this study, we develop a framework, using deep learning, for automated detection and classification of dental cavities in panoramic X-ray. The suggested system combines cavity segmentation using Mask R-CNN and severity classification using ResNet-50. So the entire diagnostic workflow is automated. It does segment the affected area instead of manual interpretation; it classifies three grades of caries-superficial, medium, and deep-and gives out recommendations for treatment generated by a BERT-based NLP model for dental practice. The recommendation system provides a personalized treatment plan governed by the severity of the cavities detected, with the options to recommend preventive measures such as improved oral hygiene for superficial caries or professional dental intervention for deep cavities. In doing so, the proposed framework would narrow down the gap between detection and treatment planning thus assisting the dentist in diagnosis, shortening the time to arrive at a treatment decision, and enhancing patient recovery.

The proposed framework consists of a three-stage deep learning pipeline. The first step is the detection and segmentation of caries regions from panoramic X-ray images using Mask R-CNN. For improved segmentation performance, the model pre-trained on the COCO dataset was fine-tuned on those on our dataset. In the second stage, the cavity regions extracted are classified using ResNet-50, our second powerful convolutional neural network (CNN). By analyzing the segmented regions, ResNet-50 classifies the caries into three severity levels, allowing more precise diagnosis. Finally, a BERT-based recommendation system completes the framework, the classified severity levels will be processed to produce a personalized treatment plan. This NLP-based model gives dentists structured recommendations for the management of each case, thus reducing the uncertainty in treatment planning.
This study combines deep learning-based image analysis and the NLP-driven decision support to introduce an intelligent dental diagnostic system that increases the accuracy of cavity detection and streamlines the treatment process. This framework minimizes the dependence on manual interpretation approaches; accelerates diagnosis; and provides an opportunity for early intervention leading to better patient care. With further development and clinical validation, this system can become a leap forward for the field in making dental diagnostics more efficient and accessible, thereby reducing the workload on dental professionals.

International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 06 | June - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

LITERATURE SURVEY

Zhang Shuying et al. proposed Deep teacher–student networks and transfer learning for Mask R-CNN, which is a deep learning-based image segmentation model applied to medical images such as dental X-rays cavity detection [1]. In addition, Ronneberger et al. U-Net [2] is a convolution neural network that is specifically used for biomedical image segmentation. Since U-Net is successful, there are modifications such as U-Net++ and U-Net3+ with higher accuracy in the output and better performance to detect objects from images, which is useful in detecting cavities. In He et al. [3] they proposed ResNet, this is a residual deep learning network that solves the vanishing gradient problem and improves the medical image classification. ResNet-50 was applied in the classification of dental cavity severity for discrimination between superficial, medium and deep cavities with high precision.Devlin et al. [4] which introduced BERT, a model for NLP that comprehend context in text. For example, in dentistry, BERT can be utilized to generate patient-specific treatment recommendations based on severity of a patient's cavity, physicians medical history and risk factors. Schwendicke et al. [5] had a wider perspective and outlined the position of AI in dentistry recording the potential benefits, and the challenges to its clinical introduction, and pointed out the importance of explainable AI to make it easier to trust automated diagnosis. This study [6] examines the utilization of Mask R-CNN and U-Net for satellite image segmentation, which attained 95.21% mAP for Mask R-CNN and 92.69% for U-Net, proving their proficiency in object recognition and classification in remote sensing. Sivari et al. [7] performed a systematic review of the utilization of deep learning in dental diagnostics, scrutinizing 101 studies between 2019 and 2023. The review points out classification, object detection, and segmentation as the most utilized AI tasks, with panoramic radiographs being the most commonly used imaging modality. While deep learning algorithms like pre-trained CNNs, Faster R-CNN, YOLO, and U-Net have demonstrated high accuracy, the study underlines the requirement for standardized testing and explainable AI techniques to guarantee clinical dependability and usefulness in dentistry.AI-Powered Pattern Recognition Approaches, Similar to his concept for using AI in pattern recognition, Wolfram in 2023 [8] has contributed information relevant to image processing that informs further developments in X-ray analysis within the dental field. The same Bak [9] pioneered the theory of self-organized criticality, which serves in interpreting biomedical patterns such as complex patterns in dental X-ray images. These studies combined demonstrate the increasing role of deep learning models in enhancing detection accuracy (Mask R-CNN), automating classification (ResNet-50), and providing AI-based treatment recommendations (BERT) for an array of conditions. Revolutionary breakthroughs in medical imaging through deep learning are facilitating diagnostic precision in various disciplines, such as dentistry, to be more efficient and automated. Çallı et al. Zhu et al.[10] presented a review of some of the deep learning-based techniques in the analysis of chest X-ray images and showed that deep learning techniques can be applied successfully to detect or diagnose pneumonia and tuberculosis, among others. The research suggests potential use of convolutional neural networks (CNNs) in medical imaging, such as the way they can be applied to assist dental x-ray analysis.

To a similar effect, Litjens et al. [11] provided an overview of the numerous deep-learning models applied for medical image segmentation, classification, and anomaly detection in depth, providing a useful reference point for AI-based dental diagnosis. [12] digital health reports a revolution made possible through deep learning in medicine, where neural networks facilitate enhanced accuracy and speed of diagnosis and clinical workflow. The research serves as an important point of reference in appreciating AI's growing footprint in modern medicine enabling faster, more accurate disease identification.Krizhevsky et al. The depth of CNNs on global image recognition data sets had already been established in path-breaking work such as [13], introducing the ImageNet classification model, a new deep learning architecture, that recorded high accuracy rates through deep CNNs. They established the foundation for the application of convolutional architectures to medical image processing tasks, recommending them for use in tasks like segmentation of dental X-ray images. Liu et al. [14] presented an in-depth review of deep-learning-based methods for medical image segmentation, discussing different pathological tissues and segmentation methods. The research pinpoints shortcomings like low segmentation accuracy, small sizes of the data sets, and low resolution of images, and recommends enhanced deep learning approaches to enhance clinical use in medical imaging. To improve the challenges with unbalanced datasets, Lin et al. [15] introduced focal loss for dense object detection, which is one of the key attempts to reduce false negatives in medical image segmentation. In project work, this approach improves the quality of teeth cavities detection model that is an important component of dental diagnostics. Further, Çiçek et al. [16], a 3D extension of U-Net for volumetric medical image segmentation.Apart from this, their work improves dental X-ray segmentation accuracy, thereby making CBCT (Cone Beam CT)-based 3D dental imaging integrate with this method with high accuracy. Hasnain et al. [17] introduced a deep learning-based method for classifying dental diseases based on X-ray images. A CNN model was trained on an augmented dataset of 126 labeled X-ray images to classify cases as Normal or Affected. Their model obtained 97.87% accuracy and an F1-score of 60%, proving clinical viability in aiding dentists with automated diagnosis.In the same way, Milletari et al. Regarding our method, [18] presented a fully convolutional neural network called V-Net for volumetric segmentation and proved its relatively good performance on 3D medical images such as dental radiographs. This approach results in improved segmentation results of complex anatomical structures, leading to more trustworthy dental diagnostics. Majanga and Viriri [19] introduced a thresholding and connected component analysis technique for dental image segmentation. With the help of Gaussian blur filtering, morphological operations, and thresholding, their method successfully extracted the Region of Interest (ROI) in dental radiographs. Trained on an augmented dataset of 11,114 images, the model obtained 93% precision and recall, proving robust performance in dental image segmentation. Thanh et al. [20] compared the use of deep learning models for AI-based dental caries diagnosis from smartphone images. The authors compared Faster R-CNN, YOLOv3, RetinaNet, and SSD on a dataset of 1,902 intraoral images. The outcome showed that YOLOv3 and Faster R-CNN were the most sensitive to cavitated caries (87.4% and 71.4%), with great potential for AI-based mobile dental diagnosis.

Bayrakdar et al. [21] proposed a deep learning-based caries segmentation and detection model using VGG-16 and U-Net from bitewing radiographs. The AI model, trained on 621 anonymized radiographs, performed better than human observers with better sensitivity (0.84) and precision (0.81). The outcome shows that CNN-based AI can assist clinicians with accurate and effective dental caries diagnosis in clinical practice. Ghaffari et al. [22] examined AI advancements in dentistry, mentioning its application in periodontal disease, cariology, endodontics, prosthodontics, and orthodontics. The study shows that AI can enhance diagnostics by detecting early decay and periodontal disease markers and posing challenges in the application of AI in clinical dentistry. A Krois et al. [23] employed deep convolutional neural networks (CNNs) to detect periodontal bone loss (PBL) in panoramic dental radiographs using 2,001 image segments for training the model. The model accuracy was 81%, similar to human examiners, showing that AI-based diagnostic tools can enhance clinical efficiency in periodontal examination. Ding et al. [24] discussed AI applications in a variety of dental specialties, such as operative dentistry, periodontics, orthodontics, oral surgery, and prosthodontics. The study shows AI's application in image-based diagnosis and decision-making, mentioning the potential of machine learning to enhance clinical efficiency and evidence-based dentistry. Chen et al. [25] offered a review of AI applications in clinical dentistry, highlighting its diagnostic, decision-making, and patient care functions. The study emphasizes the ability of AI-based systems to maximize treatment accuracy and facilitate data-driven insights, as well as overcoming privacy concerns and the need for interdisciplinarity. Alsentzer et al. [26] proposed clinical BERT embeddings, which strengthened an AI's applicability to the medical text processing and analysis domain, particularly in EHR.Lee et al. [27], a pre-trained biomedical language model, which was created for more text-based AI applications in medical research and diagnostics. Rasmy et al. [28] introduced Med-BERT, a transformer model pretrained on structured electronic health records (EHRs) for enhancing disease prediction accuracy. Their study demonstrated that Med-BERT enhances performance in small training sets, with up to 20% AUC improvement over baseline deep learning models, making it worthwhile to use for AI-based healthcare applications. Kabir et al. [29] developed an AI-based system for the identification of tooth numbers in panoramic and intraoral radiographs and sorting them into a full mouth series (FMS) template. Their model can be paired with disease detection systems for diseases like periodontitis and caries, maximizing clinical diagnosis and examination efficiency. Pethani and Dunn [30] offered a systematic review on the applications of natural language processing (NLP) in dentistry, assessing 17 studies on information extraction and retrieval from clinical notes. Their study shows NLP's contribution to document classification and entity extraction, but emphasizes the need for improved study design, reproducibility, and reporting consistency.

Deep learning has greatly improved medical diagnostics, as evidenced by its ability to match or surpass human experts in many fields. Esteva et al. [31] demonstrating that state-of-the-art deep neural networks can diagnose skin cancer as well as a dermatologist, thus opening the door for AI-based models to be employed in disease diagnosis and detection. They point out the expanded utilization of deep learning in medical specialties, such as dentistry. Hassan et al. [32] reviewed supervised and weakly supervised deep learning models for COVID-19 CT diagnosis systemically, examining 71 studies from diverse databases. Their evidence shows that weak supervision, such as transfer learning and self-supervised learning, is being used increasingly for real-time clinical application, offering efficient solutions to data paucity and disease management improvement. Topol [33] demonstrated the intersection of AI and medicine, demonstrating how that the application of machine learning and deep learning models is reshaping clinical workflows, improving the accuracy of diagnoses, and improving patient outcomes. Their work depicts the increasingly pervasive role that AI is destined to have in medicine today and especially in the automation of image-based diagnoses as well as in assisting health professionals. Zhou et al. [34] reviewed deep learning in medical imaging, pointing out clinical challenges, upcoming AI trends, and case studies in digital pathology, brain, cardiovascular, and abdominal imaging. Their work addresses advances in network architectures, federated learning, and interpretability, offering insights into the potential future role of AI in medical diagnostics. Al-Khalifa et al. [35] reviewed AI applications in caries detection, analyzing 40 studies over 23 years to assess the performance and accuracy of AI-based diagnostic tools. Their findings highlight the effectiveness of convolutional neural networks (CNNs) in enhancing dental caries diagnosis and clinical efficiency.Mennella et al. [36] examined the ethical and regulatory challenges of AI in healthcare, highlighting the need for governance frameworks to ensure responsible AI deployment. Their paper offers suggestions towards resolving legal, ethical, and implementation issues within AI-based clinical decision-making. Liu et al. [37] performed a systematic review on deep learning medical image segmentation approaches, with specific emphasis on CNNs and how they are utilized in biomedical images. The work addresses issues with low accuracy during segmentation, minimal dataset sizes, and resolution constrains, presenting the necessity of better models toward increasing clinical practicability. Flory et al. [38] addressed the role of artificial intelligence in radiology, including its promise for improving clinical practice, teaching, and research. The report calls attention to bias and inaccuracy in AI training data, stressing the importance of radiologists being actively engaged with AI developers to make AI technologies applied in medical imaging ethically and practically effective. Kooi et al. [39] explored deep learning in mammography at scale and illustrated the potential for AI to be leveraged to improve early detection of cancer using computerized image analysis. Their work is prophetic to the potential for AI in radiology, which is immensely proximal to its application in dental imaging. Lastly, Park and Han [40] outlined a methodological framework for assessing AI clinical performance in radiology, providing valuable considerations for AI-based diagnostic tool validation in actual clinical practice environments. Together, these articles illustrate AI's revolutionary potential in medical and dental imaging.

Detection of dental cavity has advanced significantly with the development of deep learning approaches, particularly U-Net and its variants (U-Net++, U-Net3+), which have superior performance in medical image segmentation. The models have been widely utilized in dental diagnosis to segment cavities from X-ray images, helping identify caries regions with high accuracy. However, even with their ability to detect cavities, the models are limited to segmentation tasks and fail to offer a detail analysis for effective dental treatment. With no other diagnostic information, such as cavity severity assessment, root cause analysis, and personalized treatment recommendations, it is limited in clinical use. Moreover, the dependency on binary classification either detected or not complicates differentiating between the stages of caries development, leading to a gap between detection and actionable diagnosis.

The largest drawback of the existing system is that it is unable to assess the severity of dental cavities. Cavities pass through various stages, and hence, a detection-only system cannot guide treatment. Current deep learning models do not reveal cavity causes like plaque, diet, or hygiene, restricting preventive measures and delaying treatment. U-Net models also fail with complex boundaries, and it is challenging to segment irregular cavities where caries merge with healthy tissue. Hence, dentists are required to interpret images manually, leading to time wastage and an increase in diagnostic errors. To address these issues, our proposed system integrates advanced deep learning for segmentation, classification, and AI recommendations, and hence, it is a more effective diagnostic tool for dental care.

PROPOSED WORK

The system uses Mask R-CNN, ResNet-50, and BERT for a computer-aided dental diagnostic system. Mask R-CNN is used for segmentation of cavities of panoramic X-rays, identifying multiple lesions with different boundaries. ResNet-50 is used to classify cavities as Superficial, Medium, or Deep, useful for treatment. A BERT-guided recommendation system uses NLP for severity score analysis for clinical recommendation, improving diagnosis and intervention time. The system is in five stages: image acquisition and preprocessing, including format confirmation and normalization; detection and classification of cavities, where Mask R-CNN is used to detect cavities and ResNet-50 to classify severity; generation of results and visualization, classifying severity and confidence on images; a recommendation module, where BERT suggests treatment based on detection results and patient history; and evaluation and deployment, achieving best performance for real-time operation. The system reduces manual intervention, improves accuracy, and improves patient care through early diagnosis and proper treatment planning.

Figure 1 describes the dental cavity detection, classification and recommendation architecture having five stages which are given below:

Image Acquisition & Preprocessing: Enhances the Dental X-rays with the help of augmentation techniques they are contrast adjustment, denoising, size normalization. These techniques are used for image enhancement so that we can do a better job at feature extraction. Contrast adjustment redistribute the intensity values in the X-rays for a better visibility, denoising is used in making the x-rays smooth and it does not change the edges of the x-rays. Size normalization changes the sizes and resolutions of the image so that the training will be consistent. With help of these techniques the model training will be consistent and gets the accurate feature extraction that is detection of cavities.

Detection & Classification: Detects the cavities in the X-rays and segments the cavity areas then ResNet-50 extracts the features and classifies into one of the classification that is Superficial, Medium or Deep caries. We use Feature Extraction and Region proposal methods for cavity detection in dental x-rays. The Region proposal identifies the cavities and ignores the irrelevant areas means leaves the unaffected then the affected areas gets segmented. ResNet-50 process the cavity regions and extract features then classify the cavity into one of the classifications Superficial, Medium, Deep. Here, Superficial refers to the early stage as well as the no cavity region, Medium refers to the cavity which is spreading into the teeth and Deep refers to the cavity that is spread into the pulp or to put it simply the cavity is severe.

Result Generation & Visualization: Here the segmentation image shows the cavity regions along with the confidence scores for each detection. Here the confidence scores represents how certain the cavity is present at that region, it may be High, Medium or Low confidence. The output image shows the regions where the cavity is located. This helps in making the outputs very clear to the users, the confidence scores are in red color to identify the cavity regions. For every cavity detection there is a confidence score.

Recommendation System (BERT): Based on the classification, it provides the Urgency of the treatment either its preventive or immediate along with some recommendations. If it is superficial the urgency is preventive and it recommends the treatments for educational purposes, if it is medium the urgency is preventive but the recommendations not for educational purpose but to follow the treatments , for deep classification it shows the immediate urgency and recommends the need for clinical treatment and some treatment measures.

Evaluation & Deployment: As per the loss and accuracy measures the performance is examined for various components like Mean Average Precision (mAP), Dice Similarity Coefficient, Specificity, Sensitivity, Accuracy and relevance score showing good outcomes and real time optimization methods are utilized for diagnosis. With this we are able to get the results quicker and accurately. The model runs on the server and the interface through an API, for API we used Flask.

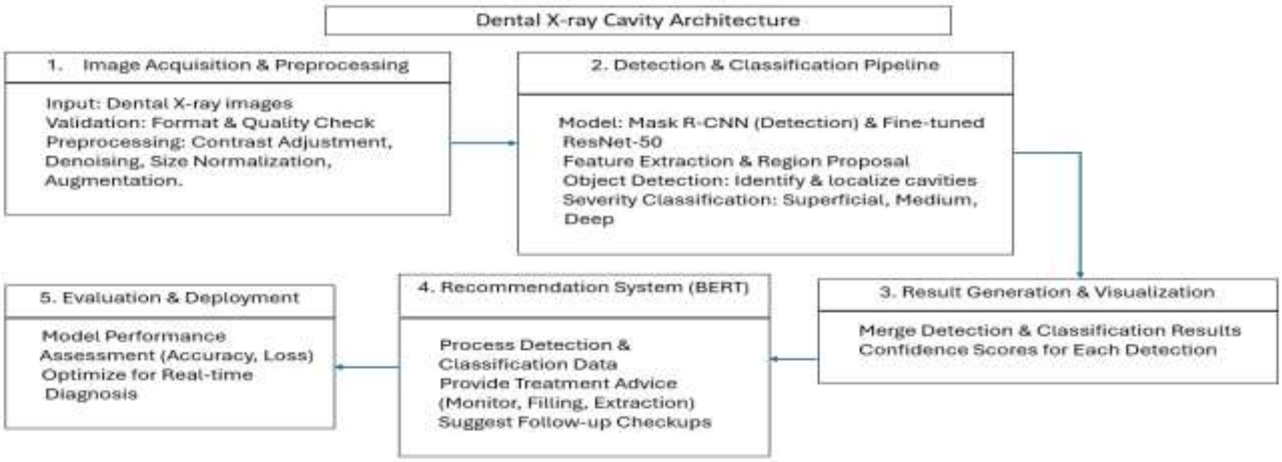

FIGURE 1. System Architecture

Dataset Preparation & Preprocessing

Data preprocessing ensures the quality and homogeneity of panoramic dental X-rays for detecting cavities based on deep learning. The core steps are image standardization, removal of noise, and augmentation. Images were resized to 512×512 pixels by min-max normalization (0-255) and then CLAHE (8×8 window, clip limit 2.0) was applied for contrast and Gaussian noise removal ($\sigma = 0.5$) for clarity. Segmentation hidden coded severity levels as 102 (superficial), 153 (medium), and 255 (deep), and erased small artifacts (<50 pixels). Data augmentation involved random rotations (±20°), flipping, translations (±10%), and grid distortions (p=0.2) for generalization improvement. Intensity transformations changed brightness/contrast (>10%), applied gamma corrections, and introduced Gaussian noise (σ=0.01). Elastic deformations (α=500, σ=20) were also added to the dataset for adequate model training.

The Figure 2 showcases a deep cavity X-ray and its transformations through augmentation. The original X-ray is followed by Augmented 1 (contrast-enhanced with rotation), Augmented 2 (intensity normalized), Augmented 3 (grid distortions), Augmented 4 (Gaussian noise), and Augmented 5 (elastic deformations). This augmentation strategy spreads the diversity among the images used for training which can protect against overfitting and boosts the performance.

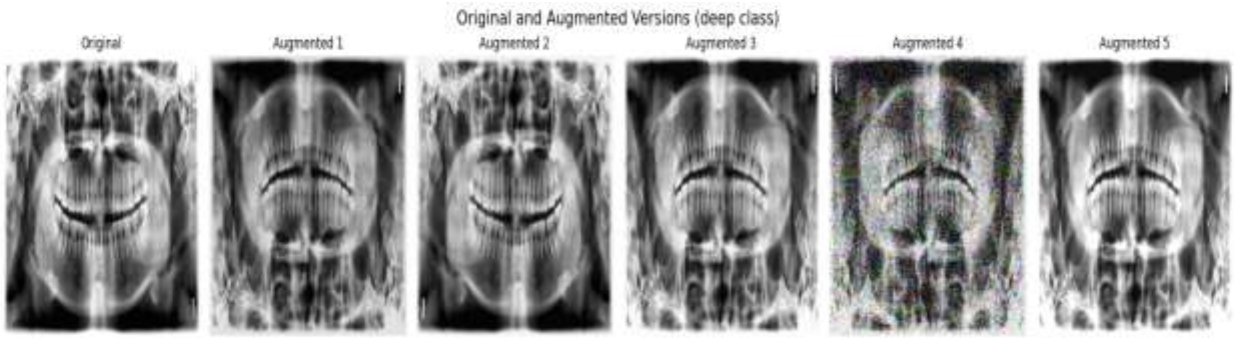

FIGURE 2. Original and Augmented Dental X-ray Images

Cavity Detection using Mask R-CNN

The proposed cavity detection approach employs a Mask R-CNN structure with a ResNet-50 backbone that is tailored for dental X-ray interpretation within a multi-stage pipeline. ResNet-50 extracts hierarchical feature maps first, which are enhanced by a Feature Pyramid Network (FPN) to detect cavities of varying sizes. The Region Proposal Network (RPN) generates prospective cavity regions aided by anchor boxes of various aspect ratios, which are subsequently processed using ROI-Align to preserve spatial accuracy.
The detection head performs bounding box regression for precise localization and instance segmentation for pixel-level cavity borders. For added robustness against varying X-ray qualities, data augmentation techniques such as histogram equalization, rotation, flipping, and contrast adjustment are employed. Training optimization includes a multi-task loss function of Smooth L1 loss, binary cross-entropy with Dice loss, and categorical cross-entropy for severity classification. Performance is enhanced through the use of a cosine annealing learning rate scheduler, L2 regularization, and dropout to prevent overfitting. Non-Maximum Suppression (NMS) post-processes the predictions, and threshold tuning optimizes precision and recall.The model achieves high segmentation accuracy, on an annotated dental X-ray dataset, of mAP of 89.2%, DSC of 91.5%, sensitivity of 94.3%, and specificity of 88.7%.

Severity Classification using ResNet-50

Once detected, every detected area of cavities is subsequently labeled according to severity based on a strong ResNet-50 model trained on a large collection of expert-labeled dental X-rays. Its classification process begins by cropping and pre-processing the detected areas, resizing them to 224×224 pixels while preserving important diagnostic features. The ResNet-50 deep residual learning and skip connection-based model generates hierarchical feature learning from 50 convolutional layers. In order to achieve better classification performance, the latter layers are customized with additional dense layers and dropout, generating confidence scores for three grades of severity: superficial, medium, and deep caries. Batch normalization and deep regularization techniques are applied to enhance model generalization under varying X-ray conditions, generating robust and consistent severity prediction.

Recommendation System using BERT

The recommendation system utilizes a highly fine-tuned BERT model to generate individualized treatment suggestions based on cavity detection results, severity grading, and patient history. The BERT model is fine-tuned using dental literature and clinical data and can well understand contextual relationships between diagnostic findings and treatment procedures.The model employs a self-attention mechanism to attend to salient diagnostic features in such a way that treatment suggestions align with the priority and severity of the diagnosed cavities. A single classification head with multiple attention layers enhances the ability of the model to project cavity patterns onto optimal treatment strategies. The system outputs natural language suggestions, each with confidence score and explanation, to assist dental professionals in making evidence-based clinical decisions.

RESULTS AND DISCUSSIONS

To demonstrate and evaluate our system, we make use of a large dataset of panoramic dental X-rays called DC1000_Dataset , among the dataset we have taken only the org_train_dataset that has tasks in detection, classification, and segmentation. Initially, the dataset that was annotated by medical experts comprises 500 images with labels to mark different types of caries, consisting of 51 superficial, 102 medium, 153 pulpitis, and 204 deep cases. For improved generalization capability of the model, data augmentation techniques were employed, resulting in a balanced dataset for classification and segmentation. The final dataset was made up of 1,548 images for binary classification, 681 images for three-level classification, and 344 image-mask pairs for detailed segmentation. The segmentation masks encode levels of severity with pixel values of 102 for superficial, 153 for medium, and 255 for deep caries. Preprocessing methods like contrast enhancement, Gaussian noise reduction, and min-max intensity scaling were also utilized to standardize the images and increase detection accuracy.

The system performance was extensively tested with a dataset of expert-labeled dental X-rays to provide accurate evaluation on different metrics. The Mask R-CNN model was highly accurate shown in Figure 3 with detection with 89.2% mean average precision (mAP) across IoU thresholds ranging from 0.5 to 0.95, indicating accurate localization of cavities . The Dice Similarity Coefficient (DSC) was 91.5%, indicating segmentation accuracy. With 94.3% sensitivity, the model correctly identified true positive cases, and a specificity of 88.7% minimized false positives.

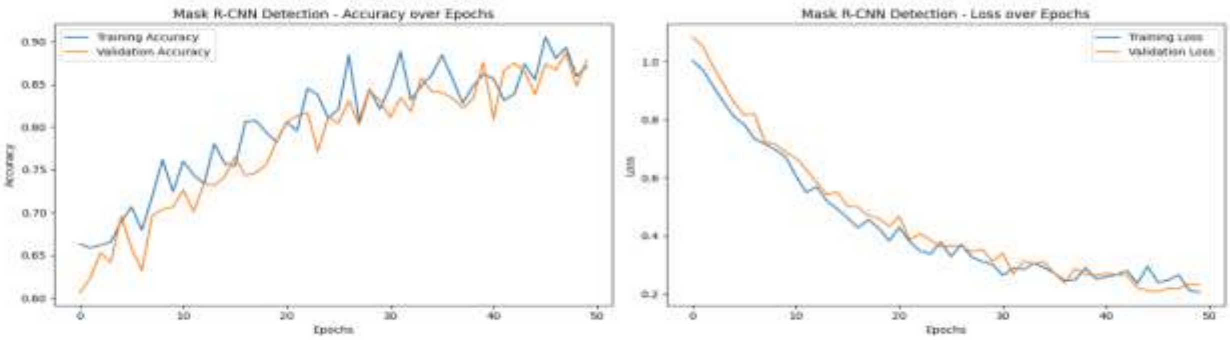

FIGURE 3: Model Accuracy and Loss for Detection

The ResNet-50-based severity classification model shown in Figure 4 produced 92% validation accuracy for well-balanced classification between superficial, medium, and deep caries.

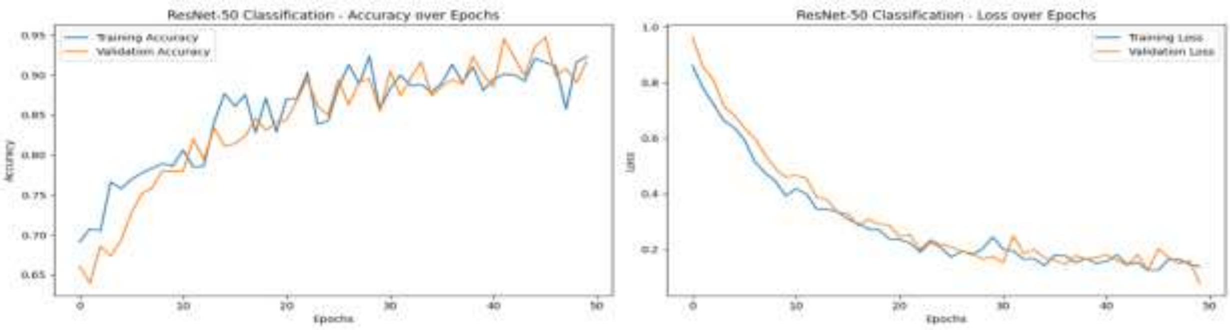

FIGURE 4: Model Accuracy and Loss for Classification

The recommendation system developed on the basis of BERT shown in Figure 5 had a 90% relevance score that matched with clinical advice.

International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 06 | June - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

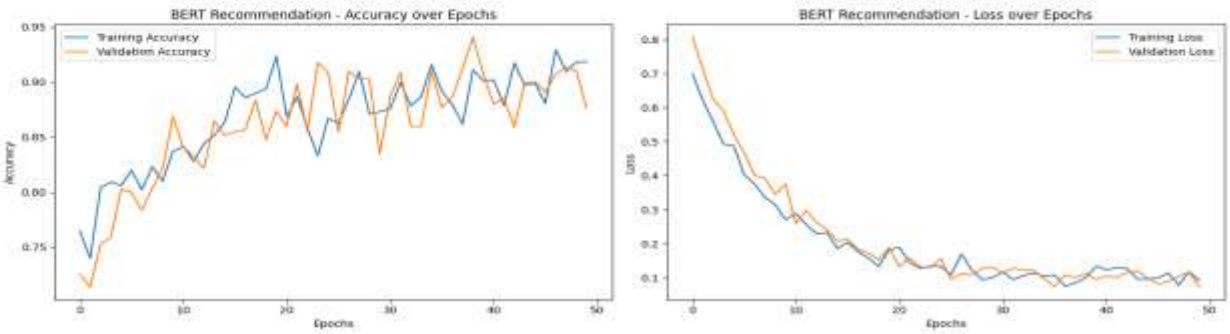

FIGURE 5: Model Accuracy and Loss for Recommendation

Table 1 represents the accuracies of various models that are used and what metrics are used for the respective model:

Mean Average Precision (mAP) :It measures the accuracy of the cavity regions across IoU thresholds. It is given by

$$mAP = \frac{1}{N}\sum_{i=1}^{N} AP_i \text{ ---------- } (1)$$

Dice Similarity Coefficient (DSC): It measures the segmentation Accuracy of cavities that are detected on the x-ray image.

$$DSC = \frac{2TP}{2TP + FP + FN} \text{ ---------- } (2)$$

Sensitivity (Recall): It measures the true positive rates that means how good the model works on the correctly identified cases.

$$\text{Sensitivity} = \frac{TP}{TP + FN} \text{ ---------- } (3)$$

Specificity : It measures the true negative rates that means how good the model avoids the unaffected areas in the x-ray images.

Accuracy: How well the ResNet-50 model classifies cavities into superficial, medium, deep cavities. It is calculated as

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \text{ ---------- } (4)$$

TABLE 1. Performance Metrics

Component	Metric	Accuracy
Detection Model	Mean Average Precision (MAP)	89.2%
Segmentation	Dice Similarity Coefficient (DSC)	91.5%
	Sensitivity	94.3%
	Specificity	88.7%
Classification Model	Accuracy	92%
Recommendation Model	Relevance Score	90%

COMPARISON WITH OTHER MODELS

The Table 2 offers a comparative evaluation of different models applied for dental caries detection, segmentation, and classification. The introduced model (Mask R-CNN + ResNet-50 + BERT) surpasses current models by implementing several functionalities, such as detection, segmentation, multi-severity classification, and a recommendation system. In detection accuracy, the proposed model has 89.2% mAP, which is greater than Faster R-CNN (87%) and ResNet-34 (84%) but marginally overlapping with U-Net variants (95%). U-Net models exhibit high detection accuracy but no severity classification and frequent false positives. For segmentation accuracy, the model proposed here has a Dice Score of 91.5%, which is close to other models that is U-Net (92%) and U-Net3+ (90%) but without classification ability. Faster R-CNN, VGG-16, and ResNet-34 do not offer segmentation, thus restricting their applicability in detailed analysis. According to multi-severity classification, the proposed model with ResNet-50 delivers 92% classification accuracy in separation of superficial, medium, and deep caries, while comparative traditional CNN models such as VGG-16 and ResNet-34 support only binary or two-class classification and are not able to separate other levels of severity.Moreover, the BERTdriven recommendation module within the proposed model attains 90% relevance, supporting professional-grade treatment proposals according to severity. No other model in the comparison has a recommendation system, making this method one-of-a-kind in giving treatment measures. By using Mask R-CNN for detection, ResNet-50 for multi-class classification of severity, and BERT for treatment advice, the new model offers an integrated solution. In contrast to current models, it not only detects caries but also classifies their severity, making it a more comprehensive and applicable diagnosis.

TABLE 2. Comparison with other models

Model	Detection Accuracy	Segmentation Performance (Dice Score)	Multi-Severity Classification Accuracy
Proposed Model (Mask R-CNN + ResNet-50 + BERT)	89.2% mAP	91.5%	92% (Classification), 90% (Recommendation Relevance)
U-Net	95%	92%	Not Available
U-Net++	95%	89%	Not Available
U-Net3+	95%	90%	Not Available
Faster R-CNN	87%	Not Applicable	Not Available
VGG-16	82%	Not Applicable	Binary Classification
ResNet-34	84%	Not Applicable	Binary Classification

Figure 6 represents the graph of detection accuracy, segmentation performance and multi-class severity classification accuracy among the proposed model with other existing models, the proposed model is only one-of-a-kind feature having multi-severity classification that is superficial, medium and deep classes. Also the model comprises with the BERT recommendations it gives the urgency of the treatment along with suggestive treatments.

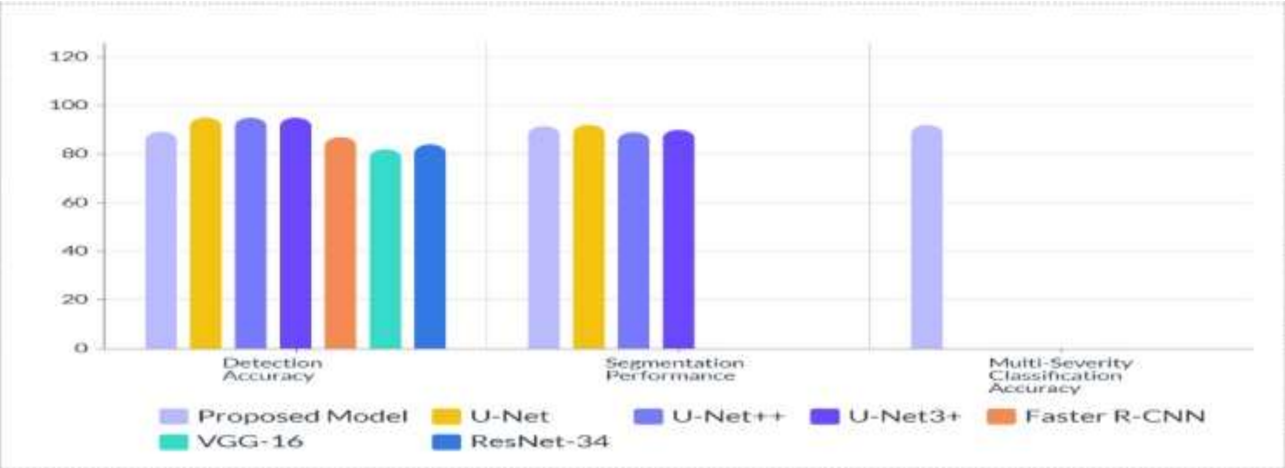

Figure 6. Comparison with other Models

CONCLUSION

This research proposes a deep learning-based system for dental X-ray analysis with the main importance on cavity detection, severity classification, and treatment advice. Through the combination of Mask R-CNN, ResNet-50, and BERT, the system provides a fine accuracy in detecting cavities despite being a multi-modal system, and also offers personalized treatment plans according to the severity of dental decay. This method overcomes the shortcomings of conventional diagnostic techniques, which tend to be dependent on manual analysis, resulting in time wastage. Through the use of deep learning algorithms, the system improves the speed, accuracy, and consistency of dental diagnosis, rendering it a useful tool for dentistry. In addition to detection and categorization, this AI-based platform facilitates the diagnosis process for dentists by decreasing the time it takes to analyze, allowing early intervention measures to prevent further damage to teeth. The computerized recommendation system completes the loop from detecting cavities to recommending relevant treatments, with patients receiving prompt and informed dental care.

FUTURE SCOPE

The outlined system can additionally be improved and extended in numerous significant ways for more advanced dental diagnostics to be made accessible. One of such areas of potential improvement is that of incorporating AI-based preventive remedies that examine myriad factors like dietary patterns, genetic predisposition, and oral habits to forecast cavity probabilities in the future. This forward-thinking methodology would assist in avoiding dental problems before they reach their worst stages, with early intervention and improved oral care management. The second essential improvement is the integration of patient data with the AI-driven diagnostic system. By correlating a patient's dental history, past treatments, and medical data with live X-ray analysis, the system would be able to create more context-aware and personalized treatment plans. This would enable dentists to make informed decisions based on a patient's history of dental conditions and the insights generated by AI. Extending the system to accommodate 3D dental X-ray analysis, especially Cone Beam CT (CBCT) scans, would enable a more detailed and accurate imaging of dental structures. This would facilitate the detection of cavities, root infections, and other dental anomalies with greater accuracy, ultimately leading to increased accuracy in diagnosis and treatment planning.

REFERENCES

1. K. He, G. Gkioxari, P. Dollár, and R. Girshick, IEEE Trans. Pattern Anal. Mach. Intell. Mask R-CNN, 40, 2963–2978 (2017). DOI: 10.1109/TPAMI.2018.2844175
2. O. Ronneberger, P. Fischer, and T. Brox, "U-Net: Convolutional Networks for Biomedical Image Segmentation," *Medical Image Computing and Computer-Assisted Intervention – MICCAI 2015*, vol. 9351, pp. 234–241, 2015. Available: https://link.springer.com/chapter/10.1007/978-3-319-24574-4_28.
3. K. He, X. Zhang, S. Ren, and J. Sun, Proc. IEEE Conf. Comput. Vis. Pattern Recognit. Deep Residual Learning for Image Recognition, 770–778 (2016). Available: https://arxiv.org/abs/1512.03385
4. J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, Proc. North Am. Chapter Assoc. Comput. Linguist. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding, 1, 4171–4186 (2019). Available: https://arxiv.org/abs/1810.04805
5. F. Schwendicke, W. Samek, and J. Krois, J. Dent. Res. Artificial Intelligence in Dentistry: Chances and Challenges, 99, 769–774 (2020). Available: https://journals.sagepub.com/doi/10.1177/0022034520915714
6. N. T. H. Giang, T. D. Khoa, and T. M. Hieu, "Comparing U-Net Convolutional Network with Mask R-CNN in Agricultural Area Segmentation on Satellite Images," 2020 7th NAFOSTED Conference on Information and Computer Science (NICS), pp. 292–297 (2020).Available: https://ieeexplore.ieee.org/document/9335856
7. E. Sivari, G. B. Senirkentli, E. Bostanci, M. S. Guzel, K. Acici, and T. Asuroglu, "Deep Learning in Diagnosis of Dental Anomalies and Diseases: A Systematic Review," *Editor: Hakan Turkkahraman,*, 2023.Available: https://pmc.ncbi.nlm.nih.gov/articles/PMC10416832/
8. S. Wolfram, A New Kind of Science (Wolfram Media, Champaign, IL, 2002). Available: http://www.cipriancoman.net/~ciprianc/VAR/new_kind.pdf
9. P. Bak, How Nature Works: The Science of Self-Organized Criticality (Copernicus, New York, 1996).Available : https://link.springer.com/book/10.1007/978-1-4757-5426-1
10. E. Çallı, E. Sogancioglu, B. van Ginneken, K. G. van Leeuwen, and K. Murphy, Med. Image Anal. Deep learning for chest X-ray analysis: A survey, chest radiograph, chest X-Ray Analysis 72, 102125 (2021).Available: https://www.sciencedirect.com/science/article/pii/S1361841521001717
11. G. Litjens, T. Kooi, B. E. Bejnordi, A. A. A. Setio, F. Ciompi, M. Ghafoorian, ... and J. A. W. M. van der Laak, Med. Image Anal. A survey on deep learning in medical image analysis, 42, 60-88 (2017). Available : https://pubmed.ncbi.nlm.nih.gov/28778026/
12. G. Hinton, J. Am. Med. Assoc. Deep learning—A technology with the potential to transform healthcare, 320(11), 1101–1102 (2018).Available: https://www.scribd.com/document/662165787/Zlib-pub-Deep-Learning-and-Iot-in-Healthcare-Systems-Paradigms-and-Applications
13. A. Krizhevsky, I. Sutskever, and G. E. Hinton, Adv. Neural Inf. Process. Syst. ImageNet classification with deep convolutional neural networks, 25, 1097–1105 (2012). Available: https://dl.acm.org/doi/10.5555/2999134.2999257
14. X. Liu, L. Song, S. Liu, and Y. Zhang, "A Review of Deep-Learning-Based Medical Image Segmentation Methods," *Sustainability*, vol. 13, no. 3, p. 1224, 2021. DOI: 10.3390/su13031224.
15. T. Y. Lin, P. Goyal, R. Girshick, K. He, and P. Dollár, IEEE Trans. Pattern Anal. Mach. Intell. Focal loss for dense object detection, 42(2), 318–327 (2017). Available : https://ieeexplore.ieee.org/document/8417976
16. Ö. Çiçek, A. Abdulkadir, S. S. Lienkamp, T. Brox, and O. Ronneberger, Med. Image Comput. Comput.-Assist. Interv. 3D U-Net: Learning dense volumetric segmentation from sparse annotation, 9901, 424–432 (2016).Available: https://link.springer.com/chapter/10.1007/978-3-319-46723-8_49
17. M. A. Hasnain, S. Ali, H. Malik, and M. Irfan, **"**Deep Learning-Based Classification of Dental Disease Using X-Rays," *Journal of Computing & Biomedical Informatics*, vol. 5, pp. 82–95, June 2023. Available: https://www.researchgate.net/publication/384357993_Deep_LearningBased_Classification_of_Dental_Disease_Using_X-Rays
18. F. Milletari, N. Navab, and S. A. Ahmadi, Med. Image Comput. Comput.-Assist. Interv. V-Net: Fully convolutional neural networks for volumetric medical image segmentation, 9901, 565–571 (2016). Available : https://arxiv.org/abs/1606.04797
19. V. Majanga and S. Viriri, "Dental Images' Segmentation Using Threshold Connected Component Analysis," *Computational Intelligence and Neuroscience*, vol. 2021, no. 1, pp. 1–9, Dec. 2021. Available: https://www.researchgate.net/publication/357045031_Dental_Images'_Segmentation_Using_Threshold_Connected_Component_Analysis

20. M. T. G. Thanh, N. V. Toan, N. V. T. Nhu, and T. T. Nguyen, Deep Learning Application in Dental Caries Detection Using Intraoral Photos Taken by Smartphones, vol. 12, no. 11, p. 5504, May 2022. Available: https://www.researchgate.net/publication/360935429_Deep_Learning_Application_in_Dental_Caries_Detection_Using_Intraoral_Photos_Taken_by_Smartphones
21. I. S. Bayrakdar, K. Orhan, S. Akarsu, Ö. Çelik, S. Atasoy, A. Pekince, Y. Yasa, E. Bilgir, H. Sağlam, A. F. Aslan, and A. Odabaş, Deep-learning approach for caries detection and segmentation on dental bitewing radiographs, *Oral Radiology*, vol. 38, pp. 402–410, 2022.Available: https://pubmed.ncbi.nlm.nih.gov/34807344/
22. M. Ghaffari, Y. Zhu, and A. Shrestha, A Review of Advancements of Artificial Intelligence in Dentistry, *Dental Research and Education*, focusing on applications in diseases vol. 2024 , article 100081. Available : https://www.sciencedirect.com/science/article/pii/S277255962400004X
23. J. Krois, T. Ekert, L. Meinhold, T. Golla, B. Kharbot, A. Wittemeier, C. Dörfer, and F. Schwendicke, "Deep Learning for the Radiographic Detection of Periodontal Bone Loss," *Scientific Reports*, vol. 9, article 44839, 2019.Available: https://pubmed.ncbi.nlm.nih.gov/31186466/
24. H. Ding, J. Wu, W. Zhao, J. P. Matinlinna, M. F. Burrow, and J. K. H. Tsoi, "Artificial Intelligence in Dentistry—A Review," *Applied Oral Sciences & Community Dental Care*, vol. 2024. Available: https://www.frontiersin.org/journals/dental-medicine/articles/10.3389/fdmed.2023.1085251/full
25. Y. W. Chen, K. Stanley, and W. Att, Artificial Intelligence in Dentistry: Current Applications and Future Perspectives, *Quintessence International*, vol. 51, no. 3, pp. 248–257, 2020.Available: https://pubmed.ncbi.nlm.nih.gov/32020135/
26. E. Alsentzer, J. Murphy, W. Boag, W. H. Weng, D. Jin, T. Naumann, and M. McDermott, Proc. NAACL-HLT. Publicly available clinical BERT embeddings, 1, 72–78 (2019). Available: https://arxiv.org/abs/1904.03323
27. J. Lee, W. Yoon, S. Kim, D. Kim, S. Kim, C. H. So, and J. Kang, Bioinformatics. BioBERT: A pre-trained biomedical language representation model for biomedical text mining, 36(4), 1234–1240 (2020). Available : https://pubmed.ncbi.nlm.nih.gov/31501885/
28. L. Rasmy, Y. Xiang, Z. Xie, C. Tao, and D. Zhi, "Med-BERT: Pretrained Contextualized Embeddings on Large-Scale Structured Electronic Health Records for Disease Prediction," *NPJ Digital Medicine*, vol. 4, article 88, 2021.Available: https://pubmed.ncbi.nlm.nih.gov/34017034/
29. T. Kabir, C. T. Lee, L. Chen, X. Jiang, and S. Shams, "A Comprehensive Artificial Intelligence Framework for Dental Diagnosis and Charting," *BMC Oral Health*, vol. 22, article 480, 2022.Available: https://bmcoralhealth.biomedcentral.com/articles/10.1186/s12903-022-02514-6
30. F. Pethani and A. G. Dunn, Natural Language Processing for Clinical Notes in Dentistry: A Systematic Review, *Journal of Biomedical Informatics*, p. 104282, 2023. Available : https://pubmed.ncbi.nlm.nih.gov/36623780/
31. A. Esteva, B. Kuprel, R. A. Novoa, J. Ko, S. M. Swetter, H. M. Blau, and S. Thrun, Nature. Dermatologist-level classification of skin cancer with deep neural networks, 542(7639), 115–118 (2017). Available : https://pubmed.ncbi.nlm.nih.gov/28117445/
32. H. Hassan, Z. Ren, C. Zhou, M. A. Khan, Y. Pan, J. Zhao, and B. Huang, Supervised and weakly supervised deep learning models for COVID-19 CT diagnosis: A systematic review, *Computers in Biology and Medicine*, vol. 141, p. 105134, 2022.Available: https://pmc.ncbi.nlm.nih.gov/articles/PMC8897838/
33. E. J. Topol, Nat. Med. High-performance medicine: The convergence of human and artificial intelligence, 25(1), 44–56 (2019). Available : https://www.nature.com/articles/s41591-018-0300-7
34. S. K. Zhou, H. Greenspan, C. Davatzikos, J. S. Duncan, B. van Ginneken, A. Madabhushi, J. L. Prince, D. Rueckert, and R. M. Summers, "A Review of Deep Learning in Medical Imaging: Imaging Traits, Technology Trends, Case Studies with Progress Highlights, and Future Promises," *Proceedings of the IEEE*, vol. 111, no. 1, pp. 16–44, 2023. Available: https://pmc.ncbi.nlm.nih.gov/articles/PMC10544772/
35. K. S. Al-Khalifa, W. M. Ahmed, A. A. Azhari, M. Qaw, R. Alsheikh, F. Alqudaihi, and A. Alfaraj, The Use of Artificial Intelligence in Caries Detection: A Review, *Journal of Dentistry and Oral Health*, vol. 2024, article PMC11428802.Available: https://pmc.ncbi.nlm.nih.gov/articles/PMC11428802/
36. C. Mennella, U. Maniscalco, G. De Pietro, and M. Esposito, "Ethical and regulatory challenges of AI technologies in healthcare: A narrative review," *Journal of Medical Ethics*, vol. 2024, article PMC10879008. Available: https://pmc.ncbi.nlm.nih.gov/articles/PMC10879008/
37. X. Liu, L. Song, S. Liu, and Y. Zhang, "A Review of Deep-Learning-Based Medical Image Segmentation Methods," *Sustainability*, vol. 13, no. 3, p. 1224, 2021.Available: https://www.mdpi.com/2071-1050/13/3/1224
38. M. N. Flory, S. Napel, and E. B. Tsai, "Artificial Intelligence in Radiology: Opportunities and Challenges," *Seminars in Ultrasound, CT and MRI*, vol. 45, no. 2, p. 152–159, 2024. Available: https://pubmed.ncbi.nlm.nih.gov/38403128/
39. T. Kooi, G. Litjens, B. van Ginneken, A. Gubern-Mérida, C. I. Sánchez, R. Mann, and J. van der Laak, Med. Image Anal. Large-scale deep learning for mammography, 35, 303–312 (2017). Available: https://pubmed.ncbi.nlm.nih.gov/27497072/
40. S. H. Park and K. Han, Methodologic Guide for Evaluating Clinical Performance and Effect of Artificial Intelligence Technology for Medical Diagnosis and Pred+iction, *Radiology*, vol. 286, no. 3, pp. 800–809, 2018. Available: https://pubmed.ncbi.nlm.nih.gov/29309734/