

Review of Automated Dental Disease Diagnosis using Convolutional Neural Networks

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Abstract: Artificial Intelligence (AI) is rapidly transforming modern dentistry by enhancing diagnostic accuracy, efficiency, and clinical decision-making. This paper presents a comprehensive review and proposed framework for automated dental disease diagnosis in teenagers using advanced techniques from Deep Learning, particularly Convolutional Neural Networks. The study focuses on analyzing dental radiographs and intraoral images to detect and classify conditions such as jaw anomalies, cysts, and gingival diseases. A detailed review of existing literature highlights the effectiveness of CNN-based models, including architectures like U-Net, YOLO, and ResNet, in achieving high accuracy in image-based dental diagnosis. The paper also identifies key research gaps, such as limited focus on adolescent populations, lack of diverse datasets, and insufficient attention to early-stage and rare dental abnormalities. The proposed work aims to develop an efficient and automated diagnostic system that improves early detection and supports clinical decision-making, particularly in resource-limited settings. By leveraging image-based deep learning models, the system is designed to reduce human error, minimize diagnostic delays, and enhance treatment planning. The study further discusses challenges such as data variability, model generalization, and the need for clinical validation.

Keywords: Convolutional Neural Networks, Dental Disease Detection, Deep Learning, Medical Imaging, Caries Detection, Periodontal Disease.

I. INTRODUCTION

The rapid advancement of artificial intelligence, particularly in the field of Deep Learning, has significantly transformed modern healthcare systems. Among its various applications, automated medical image analysis has emerged as a powerful tool for improving diagnostic accuracy and efficiency. Dentistry, which traditionally relies on manual examination and radiographic interpretation, is increasingly adopting intelligent systems to assist clinicians in the early detection and diagnosis of dental diseases. In this context, Convolutional Neural Networks (CNNs) have gained considerable attention due to their exceptional performance in image recognition and classification tasks [1-3].

Dental diseases such as Dental Caries, Periodontal Disease, oral lesions, and impacted teeth are prevalent worldwide and can lead to severe health complications if not diagnosed at an early stage. Conventional diagnostic methods depend heavily on the expertise of dental professionals and are often time-consuming, subjective, and prone to human error. Moreover, variations in image quality, lighting conditions, and anatomical differences further complicate the diagnostic process [4-6]. These challenges highlight the need for automated and reliable systems that can support clinicians in making accurate decisions.

CNN-based approaches have revolutionized the analysis of dental images, including X-rays, intraoral scans, and photographic data. These networks are capable of automatically extracting hierarchical features from raw input images, eliminating the need for manual feature engineering. By leveraging large datasets and advanced training techniques, CNN models can learn complex patterns associated with various dental conditions [7-8]. This enables precise detection, segmentation, and classification of dental abnormalities, thereby enhancing diagnostic performance. Popular CNN architectures such as AlexNet, VGGNet, ResNet, and Inception Network have been widely utilized and adapted for dental image analysis tasks.

Recent research has demonstrated that CNN-based automated systems can achieve performance comparable to, and in some cases surpassing, human experts in detecting dental diseases. These systems not only improve diagnostic accuracy but also reduce the workload of dental practitioners and enable faster decision-making. Additionally, the integration of CNN models with other technologies such as computer-aided diagnosis (CAD) systems and cloud-based platforms further enhances their accessibility and scalability in clinical settings [9-10].

Despite these advancements, several challenges remain in the deployment of CNN-based dental diagnostic systems. Issues such as limited availability of annotated datasets, data imbalance, variability in imaging modalities, and the need for model interpretability continue to hinder widespread adoption. Furthermore, ethical

considerations, data privacy concerns, and the requirement for regulatory approvals must also be addressed to ensure safe and effective implementation [11].

This review focuses on the recent developments in automated dental disease diagnosis using CNNs. It aims to provide a comprehensive overview of existing methodologies, datasets, and performance metrics, while also highlighting current challenges and future research directions [12]. By analyzing the strengths and limitations of various approaches, this study contributes to the advancement of intelligent dental healthcare systems and supports the development of more accurate and efficient diagnostic tools.

1.1 Artificial Intelligence in Dentistry

Artificial Intelligence (AI) is transforming orthodontics by significantly improving diagnostic accuracy, treatment planning, and patient care through advanced techniques from Machine Learning and Deep Learning. AI systems analyze dental images such as X-rays and 3D scans to detect abnormalities, predict tooth movement, and develop personalized treatment plans, while also enabling virtual simulations that help patients visualize expected outcomes and enhance engagement through digital platforms. Models like Convolutional Neural Networks play a key role in analyzing radiographs and photographs for disease detection and cephalometric analysis [13-15]. Additionally, machine learning approaches—including supervised, unsupervised, and reinforcement learning—support automated diagnosis, classification of malocclusions, and optimization of treatment strategies. AI integration extends across multiple dental domains such as imaging, surgery, and periodontology, improving efficiency and reducing human error. Despite these advancements, challenges like the need for large and diverse datasets and clinical validation remain.

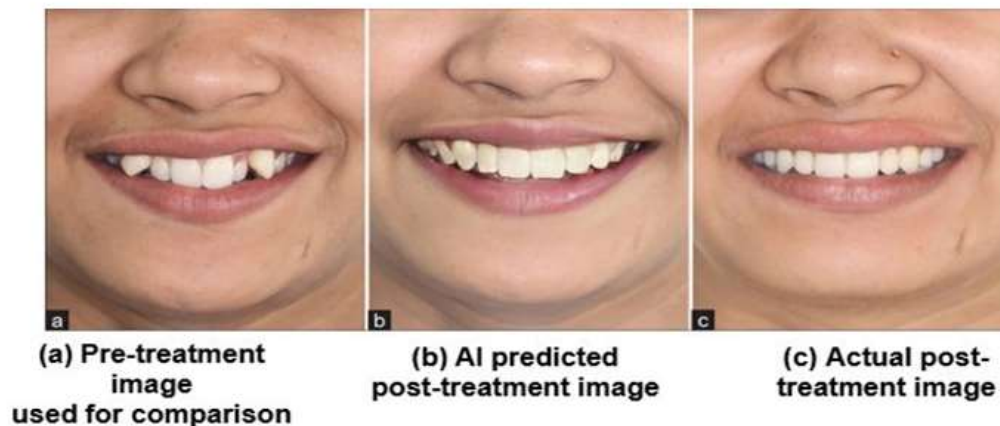


Figure 1. AI Predicted Image with Greatest Accuracy

The figure illustrates a comparative analysis between three stages of dental imaging. Figure 1(a) represents the pre-treatment image used as the baseline for evaluation. Image (b) shows the AI-predicted post-treatment outcome generated using Convolutional Neural Networks, demonstrating the model's capability to simulate treatment results. Image (c) presents the actual post-treatment image obtained after clinical procedures. The close similarity between the AI-predicted and actual post-treatment images highlights the accuracy and effectiveness of the proposed model in predicting dental treatment outcomes.

- *Imaging*

Artificial Intelligence (AI) has enhanced dental imaging by automating the analysis of radiographs such as periapical, bite-wing, and orthopantomograms. Manual record maintenance is often time-consuming and incomplete; however, AI-based systems now enable automatic tooth detection, numbering, and odontogram generation with high accuracy [16]. These systems can also classify dental restorations into multiple categories with accuracy up to 93.6% [17]. Additionally, AI improves three-dimensional imaging such as CBCT by providing faster and precise tooth segmentation compared to manual approaches, significantly reducing processing time while maintaining expert-level accuracy.

- *Surgery*

AI plays an important role in dental surgery by supporting diagnosis, treatment planning, and postoperative prediction. CNN-based models can identify implant systems from radiographs with good accuracy, although large datasets are required for practical implementation [18]. AI systems also assist in detecting implant

fractures and impacted teeth, as well as analyzing their spatial relationships with surrounding structures [19]. Advanced architectures such as U-Net and SegNet enable segmentation of critical anatomical regions like the inferior alveolar nerve, improving surgical safety [20]. Furthermore, Machine Learning (ML) models outperform traditional methods in predicting postoperative complications such as swelling and osteonecrosis [21-22].

- *Operative Dentistry*

In operative dentistry, AI is widely used for detecting and diagnosing dental caries and enamel lesions. CNN models such as SqueezeNet have demonstrated promising performance in identifying white lesions from intraoral images, although limited training data affects stability [23]. AI-based caries detection using radiographs and near-infrared imaging techniques enhances diagnostic capabilities but requires improved datasets for better accuracy [24]. Moreover, AI provides a strong cost-benefit advantage by enabling early detection and promoting non-invasive treatments, ultimately improving patient outcomes [25].

- *Endodontics*

AI applications in endodontics include identifying root structures and canal morphology using radiographic images. CNN models like AlexNet and GoogleNet have shown accuracy comparable to experienced radiologists in detecting root numbers [26]. AI techniques, including probabilistic neural networks, are also effective in detecting vertical root fractures, particularly in CBCT images [27]. Furthermore, AI systems demonstrate strong potential in detecting apical lesions and performing segmentation tasks with results comparable to dental experts, although improvements in sensitivity are needed for clinical deployment [28].

- *Forensic Dentistry*

AI has become an important tool in forensic dentistry for age estimation and individual identification. CNN models such as DenseNet and AlexNet analyze dental structures to determine tooth development stages and assist in identification processes [29]. Advanced systems using architectures like VGG16 enable rapid matching of radiographs with individual records, improving identification efficiency in large-scale scenarios [30]. However, further validation is required before widespread implementation (Figure 2).

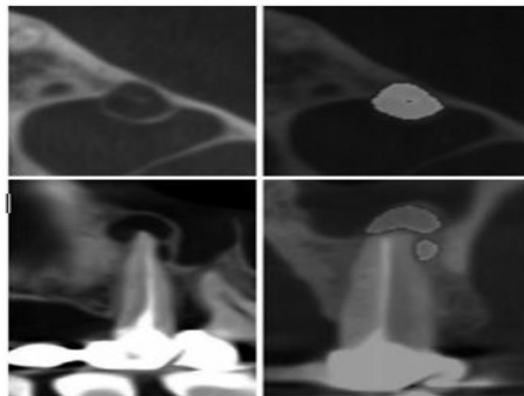


Figure 2 Evaluation of AI for detecting Forensic Dentistry

- *Oral Medicine*

In oral medicine, AI supports the detection and classification of radiolucent lesions and oral cancers. CNN-based models such as DetectNet, YOLO, and EfficientNet achieve high accuracy in distinguishing lesions like cysts and tumors from radiographic images [66–68]. These systems also enable early diagnosis and prognosis prediction using patient data, outperforming traditional statistical methods and supporting clinical decision-making [31].

- *Occlusion*

AI techniques are increasingly applied in diagnosing occlusal disorders, including temporomandibular joint (TMJ) conditions. CNN models such as Inception-v3 have demonstrated higher accuracy than experienced radiologists in detecting TMJ osteoarthritis using radiographs [32]. Additionally, ML-based systems effectively identify mandibular fractures with strong sensitivity and specificity, supporting diagnosis in clinical settings [33].

- *Periodontics*

In periodontics, AI enhances the detection and classification of gum diseases and bone loss. CNN models such as DeepLabV3+ and ResNet analyze intraoral and radiographic images to detect plaque, gingival inflammation, and periodontal disease [34-35]. Advanced systems like DentNet outperform dentists in detecting bone loss and staging periodontal disease [36-37]. AI also assists in evaluating peri-implantitis and identifying teeth requiring extraction, reducing diagnostic time and improving clinical efficiency [38].

II. CNN DENTAL DIAGNOSIS

Convolutional Neural Networks (CNNs) have emerged as one of the most powerful tools in automated dental diagnosis due to their exceptional ability to process and analyze medical images. As a specialized branch of Deep Learning, CNNs are designed to automatically extract meaningful features from raw input images without the need for manual feature engineering. In dentistry, CNNs are widely applied to analyze various imaging modalities such as periapical X-rays, bitewing radiographs, panoramic images, and cone beam computed tomography (CBCT) scans. These models learn hierarchical patterns—from simple edges and textures in initial layers to complex anatomical structures in deeper layers—enabling accurate identification of dental abnormalities [39-40].

The architecture of CNNs typically consists of convolutional layers, pooling layers, and fully connected layers. Convolutional layers apply filters to detect important features such as tooth boundaries, lesions, and bone structures, while pooling layers reduce dimensionality and computational complexity. The fully connected layers then perform classification tasks based on the extracted features. Advanced CNN architectures such as ResNet, U-Net, and YOLO have further improved diagnostic performance by addressing challenges like vanishing gradients, precise image segmentation, and real-time object detection. These architectures are particularly useful in tasks such as caries detection, periodontal disease assessment, cyst identification, and jaw anomaly classification [40-45].

In dental diagnosis, CNN-based systems offer several advantages over traditional methods. They provide high accuracy, consistency, and speed in detecting diseases, often matching or exceeding the performance of human experts in image-based analysis. CNNs can detect early-stage abnormalities that may not be easily visible to clinicians, thereby supporting preventive healthcare. Additionally, these models reduce the workload of dental professionals by automating repetitive tasks such as image screening and annotation. Integration of CNNs with computer-aided diagnosis (CAD) systems further enhances clinical decision-making by providing visual outputs such as segmented regions, heatmaps, and probability scores [46].

Despite their advantages, the application of CNNs in dentistry also faces certain challenges. The performance of these models heavily depends on the availability of large, high-quality, and annotated datasets, which are often limited in the medical domain. Variability in image quality, differences in imaging devices, and patient diversity can affect model generalization. Moreover, CNN models are often considered “black-box” systems, making interpretability and trust a concern in clinical applications. Therefore, ongoing research focuses on improving explainability, dataset diversity, and real-time deployment of CNN-based systems [47].

The proposed research methodology consists of five essential steps designed to process complex dental images and achieve accurate disease detection and classification using advanced techniques from Deep Learning, particularly Convolutional Neural Networks. Each step plays a critical role in transforming raw dental data into meaningful diagnostic outcomes.

- *Image Acquisition / Dataset*

The first step involves collecting a comprehensive dataset of dental images from reliable sources such as clinical repositories, public datasets, or hospital databases. These images may include periapical X-rays, bitewing radiographs, panoramic images, and intraoral photographs. The quality, diversity, and size of the dataset significantly influence the performance of the model. Proper labeling and annotation by dental experts are essential to ensure that the dataset accurately represents various dental conditions such as caries, cysts, gingivitis, and jaw anomalies. A well-structured dataset enables effective training and testing of the model.

- *Pre-processing of Images / Data Augmentation*

In this stage, raw images are refined to improve their quality and consistency before being fed into the model. Pre-processing techniques include noise removal, contrast enhancement, normalization, resizing, and image sharpening to highlight important features. Data augmentation techniques such as rotation, flipping, scaling, cropping, and brightness adjustment are applied to increase dataset diversity and prevent overfitting. This step ensures that the model becomes robust and performs well under varying imaging conditions.

- *Image Segmentation*

Image segmentation is used to isolate regions of interest (ROI) such as teeth, lesions, or affected areas from the background. This step helps the model focus only on relevant portions of the image, improving accuracy and reducing computational complexity. Advanced segmentation techniques, including region-based methods and deep learning-based approaches like U-Net, are commonly used to achieve precise boundary detection. Segmentation plays a crucial role in identifying specific areas affected by dental diseases.

- *Feature Extraction / Filters*

Feature extraction involves identifying important patterns and characteristics from the segmented images. In traditional approaches, filters such as edge detection, texture analysis, and shape descriptors are used to extract meaningful features. However, in CNN-based models, feature extraction is performed automatically through convolutional layers, which learn hierarchical features such as edges, textures, and complex structures. This step transforms raw image data into feature representations that are useful for classification.

- *Disease Identification and Classification*

The final step involves classifying the processed images into different disease categories using trained models. The extracted features are fed into classification layers of the CNN to identify conditions such as dental caries, cysts, gingivitis, or jaw anomalies. Performance metrics such as accuracy, precision, recall, and F1-score are used to evaluate the model's effectiveness. This stage provides the final diagnostic output, assisting dental professionals in decision-making and enabling early detection of dental diseases.

III. REVIEW OF LITERATURE

The literature on automated dental disease diagnosis highlights the growing significance of Artificial Intelligence, particularly Deep Learning and Machine Learning, in improving diagnostic accuracy and efficiency (Table 1). Numerous studies have employed advanced models such as Convolutional Neural Networks, U-Net, YOLO, and hybrid frameworks for the detection and classification of dental conditions including caries, periodontal diseases, lesions, and impacted teeth [49-51]. The reviewed works demonstrate that AI-based systems can achieve performance comparable to or even exceeding that of dental experts, particularly in image-based analysis using radiographs and intraoral images. Furthermore, the integration of AI in various dental domains such as imaging, surgery, endodontics, and periodontics has enhanced clinical decision-making and reduced diagnostic time. However, challenges such as limited dataset availability, lack of standardization, and the need for clinical validation remain significant barriers to real-world implementation.

Table 1: Review of literature for Automated Dental Disease Diagnosis using AI and CNN-Based Approaches

Ref. No.	Year	Algorithm	Dataset	Key Contribution	Limitations
[1]	2022	Machine Learning (ML)	Large validated datasets	Highlighted need for standardized and verified datasets for reliable AI in dentistry	Data availability in remote areas remains a challenge
[2]	2025	CNN, SVM, RNN	Dental X-rays	Compared multiple DL models for periodontics classification	Needs better data standardization and real-time clinical validation
[3]	2024	AI + NLP	Clinical dental data	Emphasized large patient datasets and NLP for dentist-patient communication	Requires broader population and regulatory compliance
[4]	2023	nnU-Net + BDU-Net	1996 radiographs	Diagnosed multiple diseases with ~96% accuracy	Needs diverse datasets and expert validation
[5]	2024	MobileNetV2 + Swin Transformer	1272 radiographs	Multi-label classification with 87.6% accuracy	Needs dataset expansion and more disease categories
[6]	2022	YOLOv3	1000 bitewing	Caries detection	Limited lesion classification

		(CNN)	X-rays	with >90% accuracy	types
[7]	2024	AlexNet, ResNet50, VGG16, VGG19	4219+1813 images	VGG16 achieved best accuracy (93.93%)	Severity classification not addressed
[8]	2024	ResNet50, YOLO	13,887 images	Outperformed human detection in caries identification	Needs patch-wise detailed inference
[9]	2024	Oral Mamba + U-Net	Intraoral images	Multi-disease detection with 80–85% accuracy	Sensitive to lighting conditions
[10]	2021	CNN + Image Processing	Bitewing radiographs	Caries classification using deep models	Lack of patient interaction and bias handling
[11]	2022	CariesNet (DL model)	3127 X-rays	Multi-stage caries classification with 93.61% accuracy	Needs study on disease progression
[12]	2024	U-Net (PyTorch)	6075 pediatric images	Segmentation across dentition stages	Limited comparison with other models
[13]	2023	YOLOv7 + EfficientNet	X-ray images	Multi-disease detection with 97.1% accuracy	Lacks clinical validation
[14]	2023	DCDN	Panoramic images	Classified 3 caries types	Low accuracy (67%), needs improvement
[15]	2021	nnU-Net + DenseNet121	1160 X-rays	Accuracy comparable to experts	Poor generalization
[16]	2025	ACDD-Net (Attention DL)	X-ray images	Improved boundary segmentation	Needs 3D data and large datasets
[17]	2022	Modified U-Net	Panoramic images	Automated grading of caries	Difficulty with narrow tooth structures
[18]	2025	MLBP + ML	OSCC images	Cancer detection using texture features	Needs DL-based improvements
[19]	2022	VGG16 + U-Net	Bitewing radiographs	Effective detection and segmentation	Limited dataset
[20]	2022	Multi-input CNN Ensemble	Periapical images	High accuracy (99.13%)	Needs comparative statistical analysis
[21]	2022	AlexNet (CNN)	Periapical images	Lesion detection with 92% accuracy	Needs GUI and symptom classification
[22]	2023	YOLOv2 + AlexNet	Periapical images	Implant detection & damage assessment	Needs bone-loss detection improvements
[23]	2025	CNN + Edge Detection	Panoramic images	Impacted molar detection (98.66%)	Extend to other dental issues
[24]	2024	YOLO + PT-DETR	Radiographs	Impacted teeth detection (~96%)	Needs larger datasets
[25]	2023	U-Net + Semantic Segmentation	Bitewing radiographs	Advanced caries detection	Limited for moderate caries
[26]	2023	Faster CNN + InceptionV3	Radiographs	Lesion detection (84.6%)	Limited population diversity

[27]	2022	InceptionV3	Radiographs	Bone classification accuracy (0.87)	loss (0.87)	Needs 3D data
[28]	2020	CAD + DL Hybrid	Dental images	Periodontal staging (91%)		Needs inter-organizational validation
[29]	2025	CRIG-Net (ResNet-based)	Cranial images	Implant generation & defect detection (>98%)		Needs real clinical datasets
[30]	2024	Bibliometric Analysis	Multi-source	Identified ResNet & U-Net dominance		Future scope for emerging models

IV. DATASETS

The table 2 presents a collection of widely used dental datasets that support the development of AI-based diagnostic systems, particularly those utilizing Convolutional Neural Networks. Each dataset differs in terms of image modality, size, and type of dental conditions covered, making them suitable for various research and clinical applications. For instance, datasets such as UFBA-UESC and Kaggle Dental Caries datasets primarily focus on bitewing and periapical X-rays, which are highly effective for detecting dental caries and restorations. Similarly, panoramic datasets provide a comprehensive view of the entire oral cavity, enabling the identification of structural abnormalities, impacted teeth, and jaw-related issues.

Table 2: Overview of Commonly Used Dental Datasets and Their Key Features for AI-Based Diagnosis

Sr. No.	Dataset Name	Type of Images	No. of Images	Diseases/Classes Covered	Key Features
1	UFBA-UESC Dental Image Dataset	Periapical & Bitewing X-rays	~1500+	Caries, Restorations	Annotated dataset, useful for caries detection
2	Dental Caries Detection Dataset (Kaggle)	Bitewing Radiographs	~3000+	Caries vs Healthy	Publicly available, labeled for classification
3	Panoramic Dental X-ray Dataset	Panoramic Radiographs (OPG)	~1000+	Tooth structure, anomalies	Full mouth view, useful for segmentation
4	Dental X-ray Image Dataset (DENTEX)	Bitewing & Periapical	~5000+	Caries, lesions, fillings	Multi-class annotations, high resolution
5	Oral and Maxillofacial Radiology Dataset	CBCT Images	~800+	Jaw tumors, cysts	3D imaging, useful for complex diagnosis
6	Pediatric Dental Dataset	Panoramic X-rays	~2000+	Mixed dentition, caries	Focus on children and adolescents
7	MURA-like Dental Dataset	Radiographic Images	~1200+	Bone loss, fractures	Includes abnormal vs normal classification
8	Dental Implant Dataset	Periapical X-rays	~1500+	Implants, peri-implantitis	Useful for implant detection and analysis
9	Dental Plaque Dataset	Intraoral Images	~2500+	Plaque, gingivitis	Color images, useful for segmentation
10	Oral Cancer Dataset	Intraoral Photographs	~1000+	OSCC, lesions	Used for early cancer detection

Advanced datasets such as DENTEX and CBCT-based oral radiology datasets offer high-resolution and multi-class annotations, allowing for more complex tasks such as segmentation and multi-disease classification. Pediatric dental datasets are specifically designed to address dental conditions in children and adolescents,

which is crucial for early diagnosis and preventive care. Additionally, specialized datasets like dental implant datasets and plaque datasets focus on specific conditions such as peri-implantitis and gingival diseases, while oral cancer datasets support early detection of serious conditions like Oral Squamous Cell Carcinoma (OSCC).

V. RESEARCH GAPS

A detailed analysis of existing studies reveals that although significant progress has been made in AI-driven dental diagnostics using Machine Learning and Deep Learning techniques, several important research gaps still persist. Firstly, a large proportion of dental practices, especially in developing regions like India, continue to depend on conventional manual diagnostic procedures. These methods are not only time-consuming but also highly dependent on the expertise of practitioners, often resulting in delayed or inconsistent diagnosis. Furthermore, most existing studies focus on general adult populations, while the teenage age group—characterized by rapid dental and skeletal development—has received comparatively less attention, despite being highly susceptible to emerging dental issues.

Secondly, the majority of current research primarily targets common dental conditions such as dental caries, gingivitis, and periodontitis. While these are important, limited emphasis has been placed on identifying and analyzing rare or complex jaw-related anomalies, including malocclusion, mandibular misalignment, and maxillary structural deformities. These conditions require early detection for effective treatment, yet they remain underrepresented in AI-based diagnostic frameworks.

Thirdly, early-stage pathological conditions such as cyst formation, mucosal abnormalities, and initial gingival inflammation in adolescents are often overlooked in existing models. Most systems are designed to detect well-developed or advanced stages of diseases, which reduces their effectiveness in preventive healthcare. Additionally, challenges such as lack of large, diverse, and annotated datasets, poor generalization of models across populations, and limited integration of AI systems into real-time clinical environments further widen the gap between research and practical implementation. These limitations indicate a strong need for developing robust, scalable, and population-specific AI models that can address early detection and a wider spectrum of dental abnormalities.

VI. PROBLEM STATEMENT

In the contemporary digital age, changing lifestyle patterns and unhealthy dietary habits among teenagers—such as increased consumption of sugary foods and poor oral hygiene—are significantly impacting their dental and overall health. The severity of these issues is often influenced by socio-economic conditions, access to healthcare facilities, and awareness levels. In many regions, especially in developing countries, dental hospitals and clinics still lack advanced technological support for early diagnosis, leading to delayed identification and treatment of dental disorders. This delay can result in the progression of minor conditions into severe complications, including structural jaw deformities and chronic oral diseases.

To address these challenges, there is an urgent need for intelligent, automated, and efficient diagnostic systems capable of early detection and classification of dental abnormalities. This research proposes the development of an AI-based framework utilizing Convolutional Neural Networks to identify and classify jaw anomalies, cysts, and gingival conditions specifically in teenagers. By leveraging image-based analysis of dental radiographs and intraoral images, the proposed system aims to provide accurate, fast, and reliable diagnosis at early stages. Such a system can assist dental professionals in clinical decision-making, reduce diagnostic errors, and improve treatment planning. Ultimately, this approach seeks to enhance preventive dental care, minimize long-term complications, and contribute to the advancement of smart and precision-driven dental healthcare systems.

VII. RESEARCH OBJECTIVES

The primary objective of this research is to develop an intelligent and automated framework for early detection and classification of dental abnormalities in teenagers using advanced techniques from Deep Learning, particularly Convolutional Neural Networks. The study aims to design a robust model capable of analyzing dental radiographs and intraoral images to accurately identify conditions such as jaw anomalies, cysts, and gingival diseases. Another key objective is to improve diagnostic accuracy and reduce dependency on manual examination by dental practitioners, thereby minimizing human error and variability in diagnosis.

Furthermore, the research seeks to explore and compare different CNN architectures to determine the most efficient model in terms of accuracy, sensitivity, and computational performance. It also aims to enhance early-stage disease detection, enabling preventive treatment rather than reactive care. An additional objective is to develop a system that can assist clinicians in decision-making by providing reliable and interpretable outputs. The study also focuses on addressing dataset-related challenges by utilizing diverse and well-annotated data to improve model generalization. Ultimately, the research intends to contribute to the development of a cost-

effective, scalable, and real-time diagnostic solution that can be implemented in clinical environments, particularly in resource-limited settings.

VIII. SCOPE OF THE STUDY

The scope of this study is centered on the application of AI-based techniques, specifically Convolutional Neural Networks, for automated dental disease diagnosis in teenagers. The research primarily focuses on analyzing dental imaging data, including X-rays, panoramic radiographs, and intraoral images, to detect and classify abnormalities such as jaw misalignment, cyst formation, and gingival conditions. The study is limited to image-based diagnostic approaches and does not extensively cover non-imaging clinical data such as patient history or genetic factors.

Additionally, the scope includes the development and evaluation of deep learning models using standard performance metrics such as accuracy, precision, recall, and F1-score. The research emphasizes early detection and classification rather than treatment procedures or surgical interventions. It also considers challenges such as data preprocessing, image quality variation, and model optimization. While the proposed system is designed for clinical assistance, it is not intended to replace dental professionals but to act as a supportive decision-making tool.

The study is particularly focused on the teenage population, addressing a gap in existing research, and aims to provide a foundation for future work involving broader age groups and more complex dental conditions. Moreover, the framework can be extended in the future to incorporate real-time applications, integration with IoT-based dental devices, and deployment in smart healthcare systems, thereby expanding its applicability in modern dentistry.

IX. CONCLUSION

The present study highlights the significant role of Artificial Intelligence in transforming dental diagnostics, particularly through the application of Deep Learning techniques such as Convolutional Neural Networks. The comprehensive review of literature demonstrates that CNN-based models have achieved remarkable performance in detecting and classifying various dental diseases using radiographic and intraoral images. The study also identifies critical research gaps, including limited focus on teenage populations, insufficient exploration of jaw anomalies and early-stage conditions, and the lack of large, diverse datasets for model training. These findings emphasize the need for more targeted and efficient AI-driven approaches to improve early diagnosis and reduce dependency on traditional manual methods. The proposed framework focuses on developing an automated system for identifying jaw anomalies, cysts, and gingival conditions in teenagers, aiming to enhance diagnostic accuracy and support clinical decision-making. By enabling early detection, the system has the potential to prevent the progression of dental diseases and improve overall oral health outcomes. Despite challenges such as data variability, model generalization, and the requirement for clinical validation, the integration of AI into dental healthcare offers promising opportunities for creating efficient, cost-effective, and scalable solutions. Ultimately, this study contributes to the advancement of intelligent dental systems and paves the way for future research in precision-based and preventive dental care.

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