Najeeb and Islam *BMC Oral Health* (2025) 25:592
https://doi.org/10.1186/s12903-025-05989-1

BMC Oral Health

RESEARCH Open Access

Artificial intelligence (AI) in restorative dentistry: current trends and future prospects

Mariya Najeeb[1] and Shahid Islam[1*]

Abstract

Background Artificial intelligence (AI) holds immense potential in revolutionizing restorative dentistry, offering transformative solutions for diagnostic, prognostic, and treatment planning tasks. Traditional restorative dentistry faces challenges such as clinical variability, resource limitations, and the need for data-driven diagnostic accuracy. AI's ability to address these issues by providing consistent, precise, and data-driven solutions is gaining significant attention. This comprehensive literature review explores AI applications in caries detection, endodontics, dental restorations, tooth surface loss, tooth shade determination, and regenerative dentistry. While this review focuses on restorative dentistry, AI's transformative impact extends to orthodontics, prosthodontics, implantology, and dental biomaterials, showcasing its versatility across various dental specialties. Emerging trends such as AI-powered robotic systems, virtual assistants, and multi-modal data integration are paving the way for groundbreaking innovations in restorative dentistry.

Methods Methodologically, a systematic approach was employed, focusing on English-language studies published between 2020–2025(January), resulting in 63 peer-reviewed publications for analysis. Studies in caries detection, pedodontics, dental restorations, endodontics, tooth surface loss, and tooth shade determination highlighted AI trends and advancements. Inclusion criteria focused on AI applications in restorative dentistry, and publication timeframe. PRISMA guidelines were followed to ensure transparency in study selection, emphasizing on accuracy metrics and clinical relevance. The study selection process was carefully documented, and a flowchart of the stages, including identification, screening, eligibility, and inclusion, is shown in Fig. 1 to provide further clarity and reproducibility in the selection process.

Results The review identified significant advancements in AI-driven solutions across multiple domains of restorative dentistry. Notable studies demonstrated AI's ability to achieve high diagnostic accuracy, such as up to 95% accuracy in caries detection, and its capacity to improve treatment planning efficiency, thus reducing patient chair time. Predictive analytics for personalized treatments was another area where AI has shown substantial promise.

Conclusion The review discussed trends, challenges, and future research directions in AI-driven dentistry, highlighting the transformative potential of AI in optimizing dental care. Key challenges include data privacy concerns, algorithmic bias, interpretability of AI decision-making processes, and the need for standardized AI training programs in dental education. Further research should focus on integrating AI with emerging technologies like 3D printing for personalized restorations, and developing AI training programs for dental professionals.

*Correspondence:
Shahid Islam
shahidislam14@gmail.com

Full list of author information is available at the end of the article

Clinical Significance The integration of AI into restorative dentistry offers precision-driven solutions for improved patient outcomes. By enabling faster diagnostics, personalized treatment approaches, and preventive care strategies, AI can significantly enhance patient-centered care and clinical efficiency. This review contributes to advancing the understanding and implementation of AI in dental practice by synthesizing key findings, identifying trends, and addressing challenges.

Keywords Artificial intelligence, Machine learning, Deep learning, Restorative dentistry, Artificial neural networks, Caries detection

Introduction

Artificial intelligence (AI) is rapidly transforming healthcare by enhancing diagnostic accuracy, optimizing treatment plans, and improving patient outcomes. In healthcare, AI has been leveraged to streamline workflows, reduce human error, and enable precision medicine. This is particularly evident in the field of dentistry, where AI applications have become integral in diagnostic tools, treatment planning, and patient care [1]. AI's ability to analyze large datasets and identify patterns that may be missed by human clinicians makes it a valuable asset in restorative dentistry. Machine learning (ML) and deep learning (DL) techniques, which are subsets of AI, have shown significant promise in automating complex procedures and improving image analysis in fields like prosthodontics, endodontics, and pediatric dentistry. The benefits of AI in healthcare, particularly in dentistry, include increased efficiency, enhanced diagnostic accuracy, personalized treatment options, and the potential for predictive analytics that can improve long-term patient care [2–6].

Beyond restorative dentistry, AI has made significant strides in various specialized fields of dentistry. In orthodontics, AI-powered tools are revolutionizing treatment planning by enabling precise analysis of cephalometric radiographs and 3D scans, leading to optimized orthodontic outcomes. For instance, machine learning algorithms have been developed to predict tooth movement trajectories and suggest personalized treatment plans for patients undergoing orthodontic therapy [7]. Such advancements not only enhance treatment precision but also improve patient communication and satisfaction.

In prosthodontics, AI enhances the design and fabrication of dental prostheses through advanced Computer-Aided Design and Manufacturing (CAD-CAM) systems. Convolutional Neural Networks (CNNs) are employed to analyze intraoral scans and generate highly accurate digital models for crowns, bridges, and dentures [8]. These systems reduce manual errors and significantly shorten the time required for prosthesis fabrication, making them invaluable in modern dental practices.

Dental implantology has also benefited from AI, particularly in pre-surgical planning and implant placement. AI algorithms assist in identifying optimal implant sites by analyzing cone-beam computed tomography (CBCT) images, ensuring precision and reducing the risk of complications [8]. Furthermore, AI-driven simulations allow clinicians to visualize post-operative outcomes, improving patient communication and satisfaction. Recent studies have demonstrated the potential of AI to automate implant placement using robotic systems, further enhancing surgical accuracy and safety [8, 18, 39].

Finally, in the realm of dental biomaterials, AI is being used to optimize material properties and predict their performance under various conditions. Machine learning models can analyze large datasets to identify biomaterials with enhanced durability, biocompatibility, and aesthetic qualities, paving the way for next-generation restorative materials [9].

Traditional restorative dentistry, however, faces several challenges that hinder its progress. Variability in clinician expertise, resource limitations, and the subjective nature of diagnosis and treatment planning can lead to inconsistent patient outcomes. These challenges underscore the potential for AI to revolutionize the field by providing data driven, consistent, and precise solutions. AI's ability to process vast amounts of data quickly and accurately can help mitigate these issues, enabling more reliable diagnoses and treatment plans [6]. However, the implementation of AI in clinical practice is not without its challenges, including the need for standardized protocols, high quality datasets, and clinician training to ensure effective integration into dental workflows [5].

With advancements in machine learning and deep learning techniques, AI offers unprecedented capabilities in dental diagnostics, treatment planning, and patient care. This review examines AI applications in key areas such as caries detection, pedodontics, dental restorations, endodontics, and tooth shade determination. Through a systematic literature review, key methodologies, concepts, and applications of AI in dentistry are elucidated, providing insights into the transformative potential of AI-driven solutions [1–4]. The advancements in ML and DL have been widely explored for their application in dentistry, however there are still gaps in AI implementation due to the need for standardization, validation and clinician training.

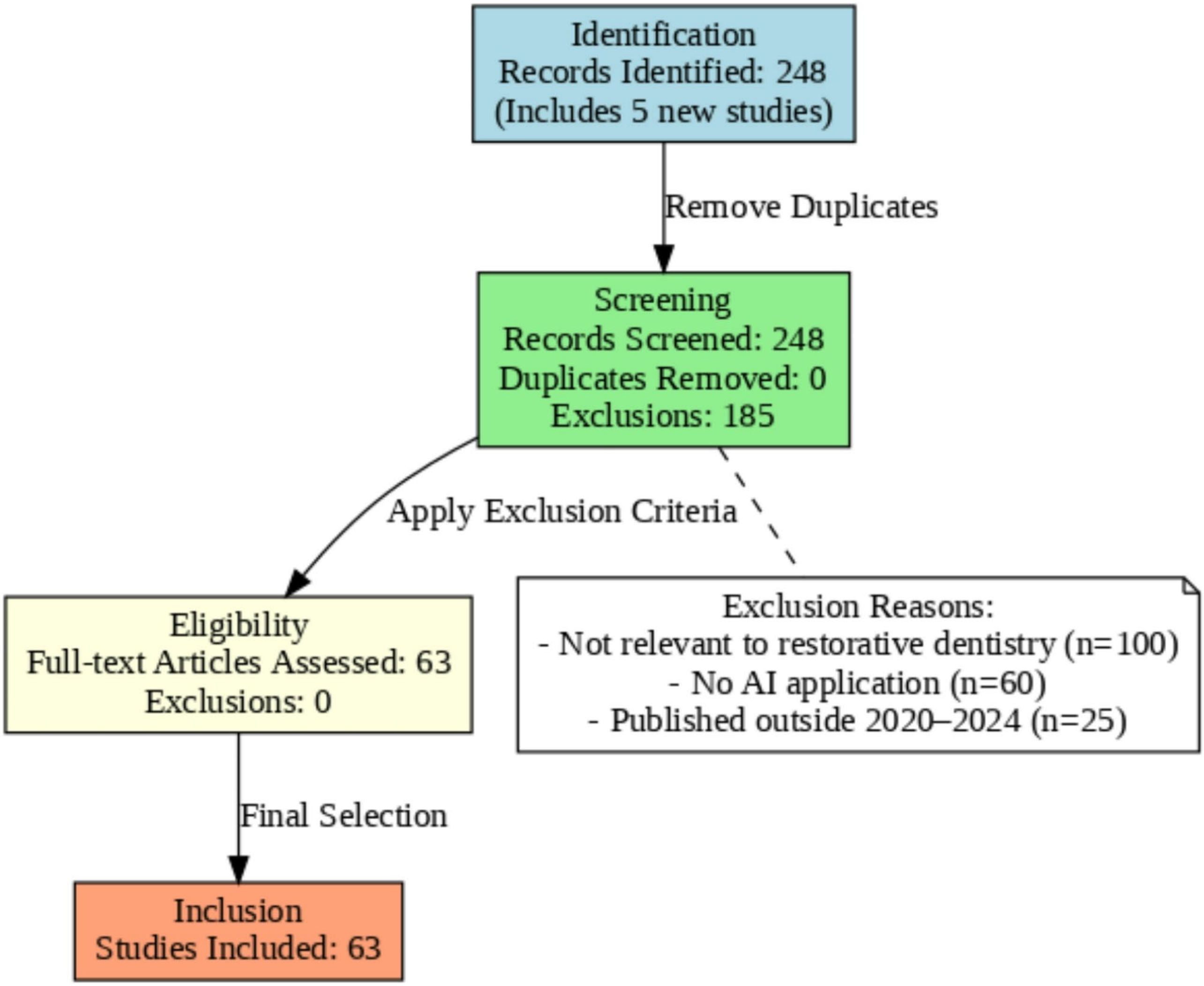

Fig. 1 PRISMA flowchart

The aim of this paper is to examine the current trends of AI applications in restorative dentistry, identify challenges, and future research directions, and contribute to the understanding and advancement of AI in dental care. The hypothesis guiding this exploration is that AI-driven solutions will significantly enhance diagnostic accuracy, treatment planning precision, and patient outcomes in restorative dentistry. By examining notable studies, trends, challenges, and future research directions, this review aims to pave the way for precision-driven, patient-centric dental care. This review synthesizes current research on AI applications in dentistry highlighting both its potential and limitations. Despite AI's remarkable contributions, challenges remain including dataset biases, ethical concerns, and the need for better validation in real world clinical settings, as AI evolves, research and collaboration among AI developers and medical professionals will be essential for successful integration of AI into mainstream dental practice.

Methodology

The methodology for this comprehensive literature review followed a systematic approach. A strategic electronic search was conducted on databases such as PubMed, Scopus, and Web of Science using the following keywords, artificial intelligence, machine learning, deep learning, restorative dentistry, endodontics, dental prosthesis, pedodontics, and caries. The search focused on English-language studies published between 2020–2025(January). The inclusion criteria required the studies that presented applications relevant to restorative dentistry. Studies that included accuracy metrics for test studies were prioritized. PRISMA guidelines were followed to document the selection process systematically. A PRISMA flowchart in Fig. 1 illustrates the

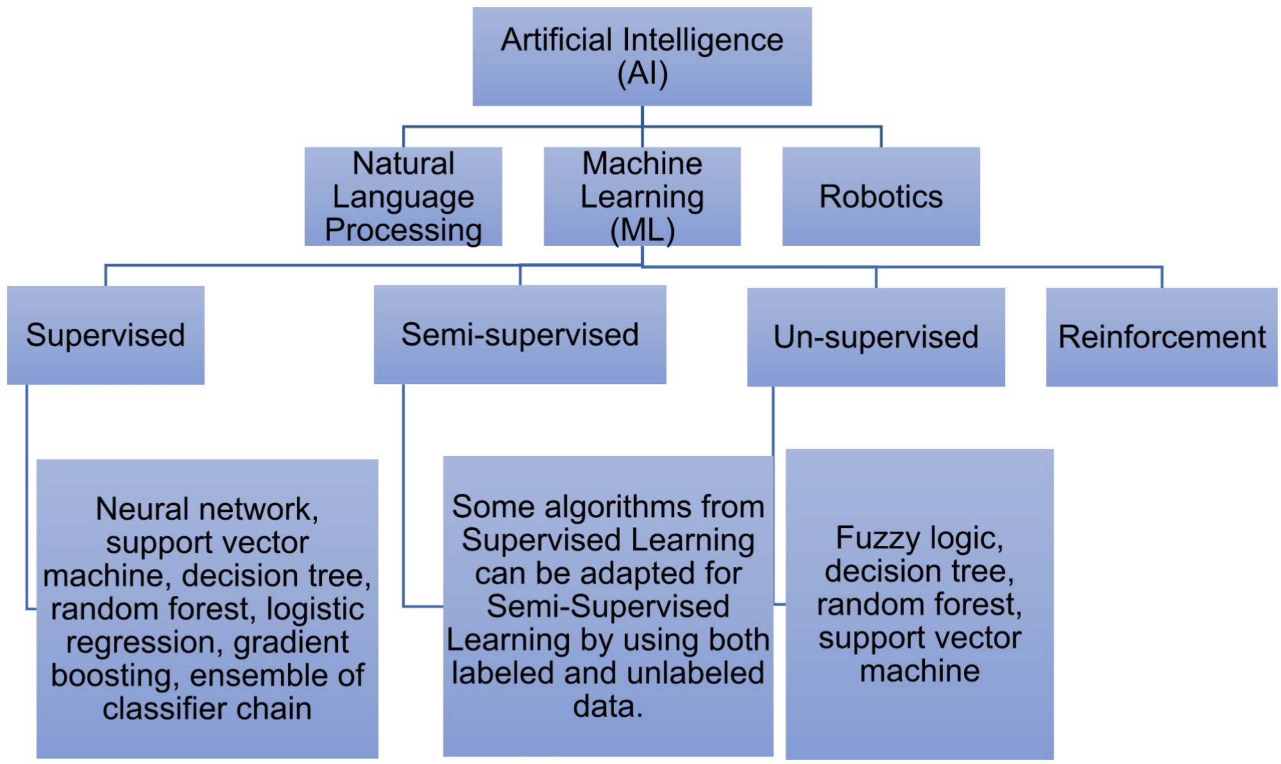

Fig. 2 Classification of AI techniques

Table 1 Overview of AI algorithms with definitions

Convolutional Neural Networks (CNN)	**A class of deep neural networks, specialized in feature extraction and classification from raw images through layers including convolution, pooling, and fully connected layers [51]**
Recurrent Neural Networks (RNN)	RNNs process sequential data, using loops for variable-length inputs in tasks like text or speech. With parameters shared across moments, RNNs predict the next moment or produce results based on processed input data [53]
Region-Based Convolutional Neural Networks (R-CNN)	An algorithm designed for object detection and localization through region proposal and classification, with improved precision by restoring edges and addressing cropping-induced distortions, especially in varied image sizes and cluttered environments [53]
Back-Propagation Neural Networks (BPNN)	A type of neural network which employs the backpropagation training algorithm and incorporates modifications to enhance training performance [54]
Feedforward Neural Networks (FFNN)	A type of neural network where information moves in one direction, from the input layer through hidden layers to the output layer [55]
Gradient Boosting (GB)	An ensemble learning technique that combines the predictions of multiple weak models (typically decision trees) to create a stronger predictive model [6]
Extreme Gradient Boosting (XGB)	A machine learning algorithm employing a Gradient Boosting approach, constructing short decision trees and sequentially correcting errors until a predefined set of trees is achieved; designed for accelerated training and enhanced performance [56]
Decision Tree (DT)	A decision tree is depicted as a flowchart-style structure where internal nodes represent attribute tests, branches signify the outcomes of these tests, and leaf nodes correspond to class labels [6]
Random Forest (RF)	An ensemble learning method that constructs a multitude of decision trees during training and outputs the mode of the classes for classification tasks [6]
Fuzzy Logic (FL)	A mathematical framework for dealing with uncertainty, where variables can have values between true and false [6]
Logistic Regression (LR)	A classification model, which uses a statistical method for classification of linear and binary problems, to predict an outcome [57]
Support Vector Machine (SVM)	A supervised machine learning algorithm that can be used for classification or regression tasks [6]
Ensemble of Classifier Chains (ECC)	An ensemble learning method, in which the classifier chains procedure is iteratively employed with randomly generated orders. Each iteration takes into account the predictions of the previous ones. The final decision is determined by combining these results using the voting method [58]

identification, screening, eligibility, and inclusion stages, providing transparency and reproducibility in study selection.

Initially, 248 studies were selected based on titles, and after applying exclusion criteria and carefully assessing abstracts, 63 studies remained for further analysis. Data collection involved these 63 studies, with 34 of them identified as test studies. Extracted information from the test studies included author, year, aspect, AI models, dataset size, and accuracy. Notably, the 34 test studies were a subset of the final 63, representing a focused set for detailed analysis to demonstrate the reliability of statements and discuss their accuracies. A quality assessment was conducted to evaluate the rigor of the studies.

The thematic organization facilitated the structured exploration of 34 literatures on AI concepts, definitions, applications, limitations, and enhancements. Critical analysis within each theme addressed biases, dataset issues, and identified research gaps. Synthesis and comparison across studies aimed to uncover commonalities, differences, and emerging trends. Discussions delved into the reliability and robustness of AI applications, ethical considerations, and potential future directions.

In summary, the review initially considered 248 studies, ultimately including 63 in the final analysis.

Key concepts of artificial intelligence

Artificial Intelligence (AI) is a dynamic field within computer science, defined as the ability of a machine to perform tasks that typically require human intelligence [5]. This involves simulating and modeling human brain functions to support learning, reasoning, problem-solving, decision-making, visual perception, and speech recognition [5, 6]. Machine Learning (ML), a category within AI, involves training algorithms to learn from data and make predictions or decisions [5, 7]. It enables machines to enhance their performance without explicit programming, relying on the ability to learn and adapt based on the information provided [8]. ML includes application-oriented methods within the broader scope of AI, such as supervised, semi-supervised, unsupervised, and reinforcement learning. Figure 2 provides a comprehensive classification of AI techniques, outlining branches like Machine Learning and its specific methodologies. The subtypes of these ML techniques, represented by specific algorithms, are further defined in Table 1.

In supervised learning, the algorithm is trained on a labeled dataset where input data is paired with corresponding output data, aiming to learn a function that maps input to output for making predictions on new, unseen data [10]. Unsupervised learning, on the other hand, involves training the algorithm on an unlabeled dataset to uncover underlying data structures, such as clusters, without predefined output information [10]. Semi-supervised learning is a machine learning paradigm that utilizes a combination of labeled and unlabeled data in the training set, where labeled data with meaningful tags guides the algorithm in learning to label previously unlabeled data, enhancing predictions. Reinforcement learning is a computational approach that involves learning from experience through trial and error, aiming to determine optimal actions in an environment by maximizing cumulative rewards over time, commonly applied in robotics [10].

Deep Learning, a specialized subset within ML, uses deep neural networks to autonomously learn hierarchical patterns and representations from raw data, eliminating the reliance on manual feature engineering [5]. The algorithm is processed similarly to the brain and hence

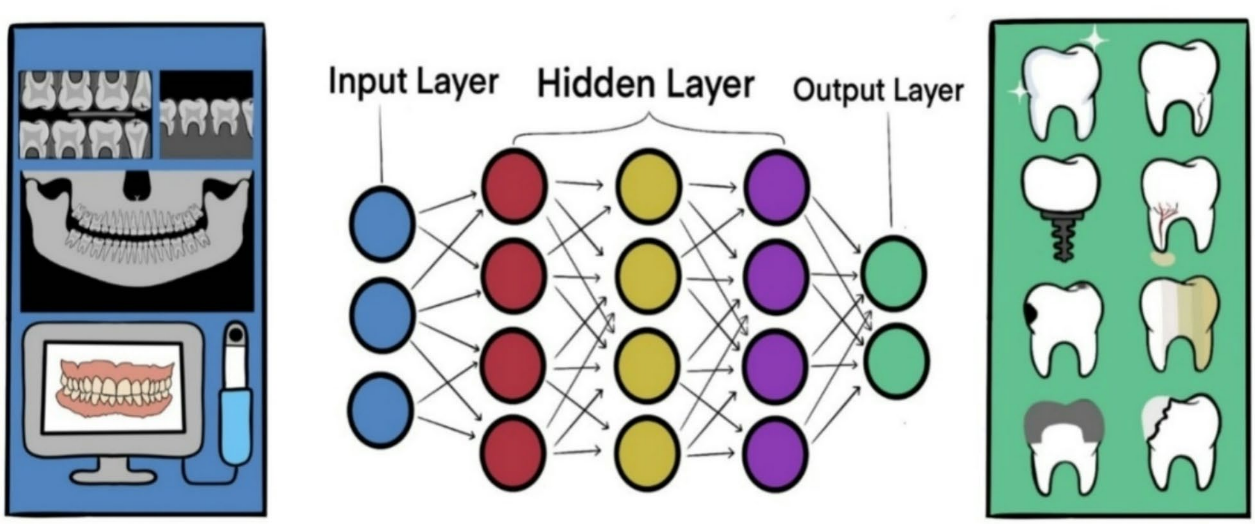

Fig. 3 Neural network structure

referred to as a neural network (NN) [11]. The structure of deep neural networks, characterized by multiple layers of interconnected nodes (neurons), enables the model to capture intricate features and relationships in the data [6, 8, 12]. The neural network's architecture involves distinct layers: the Input layer, which receives raw input data; the Hidden layer, engaging in complex tasks to process information and derive meaningful output. This output serves as input for the subsequent layer, forming a cascading chain of information processing. The Output layer determines the final output by aligning the number of neurons with dataset classes for conclusive results [6].

A visual depiction of deep neural network structures is presented in Fig. 3, illustrating the flow of information through layers and the complexity of feature extraction. Various inputs, including OPG, periapical, bitewing radiographs, intraoral scans, and smartphone photographs, capture the nuanced details of oral health. These inputs seamlessly feed into the neural network, visually represented by interconnected spheres. Each sphere, or neuron, processes information and transmits it through the network, resembling the cognitive processes of the human brain. As data progresses through hidden layers, it autonomously learns hierarchical patterns, discerning features essential for dental analysis. AI performance in pediatric dental panoramic radiographs has been used for detecting caries, missing teeth and endodontic lesions. It is notable to address a preciously underexplored age group highlighting the potential of AI in automating radiograph analysis [4].

The output layer functions as a dental oracle, with each sphere corresponding to a specific tooth condition. This visual representation is depicted on eight different teeth, each showcasing the ability of the structure to detect diverse dental conditions. It transcends beyond a mere neural network; it emerges as an intelligent dental interpreter.

Similar to how a dentist derives insights from diverse radiographic inputs and clinical images, the deep learning structure discerns patterns, contributing to the automated diagnosis of dental conditions. It stands as a virtual dental expert, seamlessly understanding and classifying conditions across diverse dental scenarios. This architecture is particularly effective in addressing complex tasks such as image and speech recognition, natural language processing, and scenarios involving high-dimensional data [13].

AI applications in restorative dentistry

AI improves precision and efficiency by enabling predictive modeling and automation in clinical workflows involved in restorative dentistry by influencing diagnostic processes such as treatment planning, image analysis, prosthodontics and biomaterials research [1].

In restorative dentistry, AI serves as a transformative force, reshaping both clinical and administrative tasks with unparalleled efficiency. On the administrative front, AI seamlessly handles appointments, maintains accurate records, and offers personalized treatment reminders, streamlining operational workflows [5]. In diagnostics, AI, empowered by Convolutional Neural Networks (CNNs), excels in early detection of complex oral health issues, facilitating timely interventions and cost-effective treatments [6, 8, 14].

AI's influence extends to precise tooth numbering and charting, enhancing the accuracy of patient records and treatment planning [15]. In one study, tooth detection and numbering using CNN on periapical radiographic images, achieved an impressive accuracy of 98.67%, providing valuable insights into precise tooth localization [16]. This not only enhances diagnostic workflows but also allows for more accurate treatment planning and patient-specific care.

AI's capabilities also play a crucial role in prognosis prediction, providing valuable insights into individual tooth health. For example, a study used AI models such as gradient boosting, decision tree, and random forest to predict tooth prognosis, offering insight into potential risks or complications before proceeding with treatment. This allows clinicians to make more informed decisions about which restorative procedures to prioritize based on predicted outcomes [17].

Moreover, AI's capabilities in segmentation further enhance its role in restorative dentistry. Research focused on the automatic segmentation of various objects on orthopantomographs (OPGs) using DL. Their study achieved impressive segmentation accuracies across different aspects, including tooth segmentation, dental caries, dental restorations, crown–bridge restorations, dental implants, root canal fillings, and residual roots [18]. This level of precision plays a critical role in dental diagnostics, enabling clinicians to identify and target areas requiring intervention more effectively. This additional dimension highlights how AI's multifaceted capabilities contribute to a comprehensive approach in optimizing oral health standards. AI emerges as an indispensable ally, harmonizing cutting-edge technology with healthcare expertise to elevate the standards of optimal oral health. AI's ability to analyze and segment complex images quickly and accurately complements the clinician's expertise by offering real-time insights, thus enhancing the overall decision-making process.

AI models have been shown to outperform human clinicians in certain diagnostic scenarios, particularly in tasks that require high-speed processing of large datasets, such as analyzing radiographs or detecting subtle

Table 2 Accuracy of AI models across various aspects and datasets

Article	Aspect	AI Models	Dataset	Accuracy	Rating	Interpretation
[16]	Tooth Detection and Numbering	CNN	1,686 Periapical radiographic images	98.67%	***	High accuracy in tooth detection and numbering using CNN on a dataset of Periapical radiographic images.
[17]	Diagnosis of Tooth Prognosis	GB, DT, RF	2359 teeth from 94 cases	GB: 68.96%, DT: 84.13%, RF: 83.12%	**	Moderate accuracy in diagnosing tooth prognosis using ensemble models (GB, DT, RF) on a dataset of teeth from 94 cases. Decision Tree exhibits the highest accuracy among the models.
[18]	Segmentation of Teeth on OPGs	DL	7696 panoramic images	Tooth Segmentation: 95%, Caries, Restorations, Implants, RCT, Residual Roots: 99%	***	High accuracy in segmentation of teeth on OPGs using DL on a large dataset of panoramic images, with all segmentation tasks achieving near-perfect accuracy.
[20]	Caries Detection	CNN	150,000 annotated intraoral images	93.40%	***	High accuracy in detecting medical image via segmentation whilst maintaining high stability in image capturing.
[21]	Caries Detection	CNN	2,417 OCT and radiographic images	92.50%	***	High accuracy in caries detection using CNN on a diverse dataset of OCT and radiographic images.
[22]	Caries Detection and Classification	CNN	1,160 panoramic films	98.60%	***	Excellent accuracy in both caries detection and classification using CNN on panoramic films.
[23]	Smartphone-based Occlusal Caries Detection	SVM	587 images of unrestored extracted molars and premolars	83.33-92.37%	***	SVM demonstrated high accuracy in recognizing carious lesions on occlusal surfaces from smartphone images.
[24]	Smartphone-based Early Occlusal Caries Detection	SVM, RF, KNN, GB, LR	587 images of unrestored extracted teeth using a smartphone	Detection: 87.39%, Classification: 88.76%	***	SVM and other models achieved high accuracy in early occlusal caries detection from smartphone images.
[25]	Caries Detection	CNN	3686 bitewing images	80%	**	Moderate accuracy in caries detection using CNN on a substantial dataset of bitewing images.
[26]	Caries Detection	CNN	748 OCT images	95.21%	***	CNN achieved high accuracy in caries detection on OCT images, indicating robust performance. Other models also contributed positively to the study.
[27]	Diagnosis of Deep Caries and Pulpitis	CNN	844 periapical images	82-86%	**	Moderate to high accuracy in diagnosing deep caries and pulpitis using various CNN models on periapical images.
[28]	Diagnosis of Interproximal Caries Lesions	CNN	1,000 bitewing images	94.59%	***	High accuracy in diagnosing interproximal caries lesions using CNN on a dataset of bitewing images.
[29]	Multi-stage Caries Lesion Segmentation	CNN	1159 oral panoramic images	80.71-93.61%	***	High accuracy in segmenting multi-stage caries lesions using various CNN models on oral panoramic images.
[30]	Caries Classification	CNN	400 panoramic images	87%	**	Moderate accuracy in classifying dental caries using CNN on panoramic images.
[31]	Distal Caries Prediction in Mandibular Second Molars	LR, RF, ANN, SVM, XGB	2642 panoramic images	LR: 81%, RF: 83%, ANN: 80%, SVM: 81%, XGB: 81%	**	Moderate accuracy in predicting distal caries using various machine learning models on panoramic images.
[34]	Classification of Early Childhood Caries	ECC	Information on clinical, demographic, behavioral, and parent-reported oral health of 6,404 children aged 3–5 collected	58-67%	*	Low to moderate accuracy in classifying early childhood caries using ECC on diverse information sources.

Table 2 (continued)

Article	Aspect	AI Models	Dataset	Accuracy	Rating	Interpretation
[35]	Prediction of Early Childhood Caries	LR, RF, GB	Survey data of 4195 children aged 1–5 years	23.2-24.5%	*	Low accuracy in predicting early childhood caries using various machine learning models on survey data.
[32]	Detection of Caries and Dental Restorations	CNN	350 bitewing images	80.25-98.44%	***	High accuracy was achieved, with CNN demonstrating the best performance in caries and restoration detection, respectively, with dataset of bitewing images.
[36]	Tooth Segmentation	CNN	500 teeth from 175 CBCT scans	Without filling: 100%, with filling: 99–100%	***	High accuracy in automatic tooth segmentation using CNN on a dataset of teeth from CBCT scans, showcasing perfect accuracy in the control group and near-perfect accuracy in the experimental group.
[37]	Detection of Implants and RCT-treated Teeth	R-CNN	350 panoramic images	Implants: 92.21-99.89%, treated teeth: 97.13-99.71%	***	High accuracy in detecting implants and RCT treated teeth using R-CNN on a dataset of panoramic images.
[38]	3D-CNN for Partial Dental Crown Generation	3D-CNN	120 tooth preparations using intraoral scans	60%	*	Low accuracy in generating partial dental crowns using 3D-CNN on a limited dataset of tooth preparations.
[39]	Detection of Tooth Region for Correct Implant Placement	CNN	500 CBCT images	52.50-79.17%	**	Moderate accuracy in detecting tooth region for correct implant placement using CNN on a dataset of CBCT images.
[40]	Classification of Dental Arches	CNN	1184 images of dental arches	99.5-99.7%	***	High accuracy in classifying dental arches using CNN on a diverse dataset of dental arch images.
[42]	Prediction of post-operative pain following RCT	BPNN	300 cases of RCT	95.60%	***	High accuracy in predicting post-operative pain following RCT using BPNN on a substantial dataset of RCT cases.
[43]	Detection of Dental Apical Lesions	CNN	476 periapical images, 411 normal, 65 with apical lesion	92.75%	***	High accuracy in detecting dental apical lesions using CNN on a diverse dataset of periapical images.
[44]	Periapical Lesion Categorization using PAI scoring	CNN	3,990 periapical root areas from 1950 periapical images	86.30%	**	Moderate accuracy in categorizing periapical lesions based on the PAI scoring system using CNN on a large dataset of periapical images.
[45]	Prediction of Endodontic Microsurgery Prognosis	GB, RF	234 teeth from 178 CBCT images	GB: 80%, RF: 80%	**	Moderate accuracy in predicting endodontic microsurgery prognosis using GB and RF on a dataset of teeth from CBCT images.
[46]	Classification of Periapical Lesions	CNN	1000 CBCT images	68-70%	**	Moderate accuracy in classifying periapical lesions using CNN on a dataset of CBCT images.
[47]	Detection of Unobturated MB2 Canals	CNN	102 CBCT images	84%	**	Moderate accuracy in detecting unobturated MB2 canals using CNN on a dataset of CBCT images.
[64]	Apical Lesion Segmentation on Panoramic Radiographs	DeepLabv3+	260 Panormic radiographs	~90%	***	High accuracy in detecting and segmenting apical lesions on panoramic radiographs, indicating strong potential for clinical diagnostic support.
[65]	Detection of Periapical lesion	CNN	30 Periapical and Panoramic radiographs	89.6%	**	The study compares AI-based radiographic interpretation with traditional methods in detecting periapical periodontitis, showing that the AI approach achieves a comparable diagnostic accuracy.
[66]	Automated Root Canal Segmentation on CBCT in Single-rooted Teeth	CNN	69 CBCT scans	DSC: 89–93%	***	The AI tool demonstrated highly accurate segmentation of root canals with Dice similarity coefficients ranging from 89–93% and a marked reduction in segmentation time compared to manual methods (AI: ~42 s vs. Manual: ~2262 s).

Table 2 (continued)

Article	Aspect	AI Models	Dataset	Accuracy	Rating	Interpretation
[67]	Automated detection and labeling of posterior teeth in dental bitewing X-rays	YOLO (Object Detection)	3000 adult digital bitewing radiographs	**Tooth Detection**: Precision 0.99, Recall 0.995, mAP 0.99 **Tooth Numbering**: Precision 0.963, Recall 0.965, mAP 0.963	***	The YOLO-based system accurately detects and labels posterior teeth in bitewing radiographs, achieving high precision, recall, and mean average precision. With rapid inference times (303 ms on CPU; 9.1 ms on GPU), it offers significant clinical workflow improvements.
[68]	Automated segmentation of the pulp cavity system in mandibular molars on CBCT images	CNN	66 CBCT scans	DSC: 88% ± 7% for first molars; 90% ± 6% for second molars;	***	The AI-driven tool demonstrated high accuracy and significant time efficiency in segmenting the pulp cavity system. It provided comparable performance for both first and second molars while markedly reducing segmentation time compared to manual methods.

***: Represents high accuracy or performance, with a range above 90%

**: Indicates moderate accuracy or performance, within the range of 70–90%

*: Signifies low to moderate accuracy or performance, below 70%

patterns in images. For instance, AI-powered systems can analyze periapical radiographs with greater accuracy and speed, which could significantly reduce diagnostic time in busy clinical settings and enable earlier intervention. One study found that CNNs achieved an accuracy of 98.67% in tooth detection and numbering, which is higher than the average accuracy of human clinicians [12]. Such AI systems complement clinicians by offering a second opinion or assisting in complicated diagnostic scenarios, where human expertise may still be required for a final diagnosis or treatment plan.

Table 2 compiles the findings of recent studies on dental AI applications, summarizing the aspects studied, AI models employed, datasets utilized, reported accuracy percentages, ratings, and interpretations. This table provides a succinct overview of the key findings from the studies discussed in this section. It's important to note that while these reported accuracy percentages offer valuable insights, factors such as sample size, methodology, and dataset diversity may influence the generalizability and reliability of the findings. Furthermore, we will delve into specific trends and noteworthy findings from the table in later sections of this paper, providing a comprehensive analysis of the current state of AI applications in dentistry.

Caries

Recent studies highlight significant strides in caries detection through machine learning algorithms, specifically Convolutional Neural Networks (CNNs). These algorithms show promising results in analyzing intraoral digital images [11, 19]. Their effectiveness is particularly notable in identifying non-cavitated lesions and interproximal carious lesions, areas that often pose challenges for dentists due to limited visibility and may go undiagnosed, especially in their early stages [15]. The enhanced overall accuracy not only supports dentists in making accurate diagnoses but also facilitates the implementation of non-invasive, cost-effective treatments like fluoride varnish through early detection, offering advantages for both the dentist and the patient.

Various studies demonstrate the efficacy of AI techniques in caries detection, with notable accuracy percentages. For instance, a study employed an AI-assisted caries detection system using intraoral images, applying CNN for feature extraction and segmentation, demonstrating high accuracy and validating the potential for clinical integration, particularly in early caries detection and diagnosis [20]. Another study reached high accuracy with CNN on panoramic films [22]. A study employed a Support Vector Machine (SVM) for recognizing carious lesions on occlusal surfaces using smartphone images, achieving notable accuracies for differentiating caries groups [23]. In another study, various machine learning models, including SVM, Random Forests, and Logistic Regression, were applied for early occlusal caries detection, resulting in high detection and classification accuracies [24]. Additionally, a study focused on caries detection using a CNN with high accuracy in identifying caries in bitewing images [25]. A recent study by Huang YP et al. demonstrated the efficacy of deep learning algorithms in caries detection using Optical Coherence Tomography (OCT). Their CNN-based model achieved an impressive accuracy of 95.21%, underscoring the potential of OCT as a non-invasive imaging modality for early caries diagnosis. This advancement highlights the versatility of AI in leveraging diverse imaging techniques to enhance diagnostic precision [26]. These studies collectively underline the versatility and accuracy of machine learning models in enhancing dental diagnostics and caries detection across varied datasets and imaging modalities. These advancements play a crucial role in identifying and diagnosing caries with high precision.

In a study, researchers delved into deep caries and pulpitis diagnosis using CNN on periapical images [27]. Another study significantly contributed by diagnosing interproximal caries lesions with CNN on bitewing images, achieving an impressive accuracy of 94.59% [28]. The segmentation of multi-stage caries lesions has also been a significant focus, with researchers contributing significantly to this area, utilizing various CNN models on panoramic images [29, 64]. Furthermore, assessing the classification accuracy of dental caries is crucial, as highlighted by a study [30].

Predictive models for caries risk and exposure have been explored by researchers focusing on predicting distal caries in mandibular second molars associated with impacted third molars, employing logistic regression (LR), random forest (RF), artificial neural network (ANN), support vector machine (SVM), and extreme gradient boosting (XGB) on panoramic images with accuracies ranging from 80 to 83% [31]. Another study concentrated on caries detection using CNNs on bitewing images, demonstrating high accuracies [32].

Pedodontics

In addition to traditional diagnostic scenarios, AI has found application in the field of pedodontics, where the field of dentistry is continually evolving. Current trends in pedodontics include the utilization of customized AI-driven appliances for orthodontic tooth movement, AI-enabled pain control, and the integration of 4D goggles and virtual reality for effective behavior modification [33]. These technological advancements signify the dynamic nature of dental technology and its commitment to improving patient outcomes.

The mentioned AI applications are particularly relevant in pedodontics, where specialized studies addressing early childhood caries have been explored. For instance, one study applied Ensemble of Classifier Chains (ECC) for automatic classification of early childhood caries using clinical, demographic, behavioral, and parent-reported oral health status information. This approach achieved accuracies in the range of 58–67%, showcasing the potential for AI to integrate diverse data sources for enhanced classification [34]. Lastly, utilizing logistic regression, random forest, and gradient boosting machine for the prediction of early childhood caries using survey data of young children yielded accuracy rates ranging from 23.2 to 24.5% [35]. These studies collectively highlight the diverse applications of AI in caries detection, diagnosis, risk assessment, and classification within pedodontics and the broader dental landscape.

Dental restorations

AI revolutionizes dentistry by demonstrating exceptional accuracy in detecting diverse dental restorations, including veneers, inlays, onlays, composite resin fillings, gold and amalgam fillings, crowns, and bridges. Studies utilizing CNN models showcase impressive accuracy in the detection of dental restorations and implants. One study showcased the effectiveness of CNN models in detecting dental restorations across bitewing images [32]. Another study utilized a Convolutional Neural Network (CNN) for automated tooth segmentation, achieving remarkable accuracy rates of 100% for the control group (teeth without filling) and 99–100% for the experimental group (teeth with filling) [36]. Moving beyond restorations, AI has proven instrumental in the precise detection of dental implants. In a study, implant detection using R-CNN on panoramic images yielded remarkable accuracy [37]. Al-Sarem M et al. explored the use of pretrained deep learning models for detecting tooth regions to ensure accurate implant placement. Their study achieved accuracies ranging from 52.50 to 79.17% on CBCT images, highlighting the potential of AI in optimizing pre-surgical planning for dental implants [39]. These findings underscore the transformative potential of AI in enhancing diagnostic capabilities across various dental applications.

The integration of AI significantly enhances the Computer-Aided Design and Computer-Aided Manufacturing (CAD-CAM) process in restorative dentistry [15, 33]. CNNs analyze intraoral 3D scans in the scanning phase, prioritizing dental structures and minimizing interference from soft tissues. This precise data is then utilized in the CAD phase, where AI crafts detailed digital models for various restorations. Farook TH et al. (2024) developed and validated a 3D-CNN model for generating partial dental crowns (PDC) using intraoral scans. Although the model achieved an accuracy range of 60%, it underscores the potential of AI in automating precision modeling for dental restorations. Further refinements in dataset size and variability could enhance its applicability in clinical settings [38].

One study focused on detecting the tooth region for correctly placing the implant, employing various CNN models [39]. Another study conducted a classification of dental arches using a CNN. The accuracy achieved was remarkably high, with 99.50% for the maxilla and 99.70% for the mandible [40]. Moreover, Alsolamy et al. (2024) utilized a YOLObased object detection model to automate the detection and labeling of posterior teeth in dental bitewing radiographs, achieving nearperfect precision (0.99) and recall (0.995) with rapid inference times, thereby enhancing the efficiency of clinical charting [67]. This emphasizes the role of AI in precise classification tasks within restorative dentistry.

The seamless integration of these studies reinforces the narrative of AI's significant contributions to restorative dentistry, from precision modeling to accurate implant placement and detailed classification of dental arches. Each study enriches the discussion by providing real-world examples of AI applications in the field.

Endodontics

In endodontics, AI serves as a supplementary diagnostic tool, refining precision through Decision Support Systems, particularly leveraging Artificial Neural Networks (ANNs). AI aids in locating the minor apical foramen, enhancing accuracy in working length determination, and improving the identification of root fractures, periapical lesions, and unique canal configurations [11, 15, 33]. AI applications in endodontics includes radiographic interpretation, diagnosis and treatment planning via image analysis, identifying root morphology, periapical lesions and vertical root fractures with high precision by incorporating machine learning, deep learning and neural networks in endodontic workflows, this can be achieved by outlining the development process of AI models for clinical use [41].

Recent studies demonstrate the impact of AI in endodontics, achieving high accuracy percentages in identifying periapical lesions, predicting post-operative pain after Root Canal Treatment (RCT), detecting unobturated canals, and classifying periapical lesions. One study predicted post-operative pain after Root Canal Treatment (RCT) with a BPNN, achieving 95.60% accuracy [42]. Another study employed a CNN ensemble for Apical Lesion Detection, reporting 92.75% accuracy [43]. Categorizing periapical lesions using a CNN resulted in 86.30% accuracy [44]. Predicting endodontic microsurgery prognosis with GB and RF models, both achieved a high accuracy [45].

Ketenci Çay et al. (2025) applied the DeepLabv3 + method to panoramic radiographs for apical lesion segmentation, achieving an accuracy of approximately 90%, which highlights the potential of advanced deep learning frameworks for robust endodontic diagnostics [64]. Similarly, Nagareddy et al. (2024) compared AI-based radiographic interpretation with traditional methods in detecting periapical periodontitis, reporting an accuracy of 89.6% on a combined set of periapical and panoramic radiographs, thereby underscoring the viability of AI as an alternative diagnostic tool in endodontics [65].

Classifying periapical lesions using CNNs resulted in competitive accuracy rates, achieving 68% and 70% [46] A study conducted to detect unobturated MB2 canals with a CNN model, reached high accuracy [47]. Another study investigated RCT treated teeth detection with R-CNN models, reporting accuracies ranging from 97.13 to 99.71% on panoramic images [37].

SantosJunior et al. (2024) developed an AI-powered tool for automated root canal segmentation in single-rooted teeth using CBCT, achieving Dice similarity coefficients of 89–93% and markedly reducing segmentation time compared to manual methods, thereby streamlining endodontic workflows [66]. Similarly, Slim et al. (2024) demonstrated that a CNNbased system could accurately segment the pulp cavity system in mandibular molars on CBCT images, achieving Dice similarity coefficients of 88% for first molars and 90% for second molars, with a significant reduction in segmentation time compared to manual approaches [68].

These studies showcase the evolving landscape of AI applications in endodontics, contributing to precision advancement in various aspects of the field.

Other applications in restorative dentistry

Tooth surface loss

Tooth Surface Loss (TSL), characterized by irreversible loss of hard dental tissue, poses a prevalent issue. Artificial Neural Networks (ANNs) employ detailed analyses of contributing factors to predict TSL accurately. AI proposes personalized preventive treatment plans for patients at high risk of TSL, emphasizing the necessity of preventive measures [15]. Utilizing ML to evaluate sculpted teeth morphology can improve the precision and consistency of dental restoration. A workflow comprising of data collection, scanning, mathematical modeling and ML-based assessment reported an accuracy of 70–75% in judging hand-carved dental morphology to assist dental technicians in learning and refining their skills [2].

Tooth shade

Advancements in AI, particularly Convolutional Neural Networks (CNNs), significantly impact restorative dentistry by extracting spatial features from intraoral photographs. This ensures precise determination of tooth shade and accurate matching to natural tooth colors [6, 15]. Back-Propagation Neural Networks (BPNN) and Fuzzy Logic (FL) contribute to adaptability across diverse datasets, capturing and accounting for variability in tooth shades [6]. Technological advancements in digital shade matching for fixed prosthodontics, spectrophotometry, digital photography and AI-driven algorithms have been utilized by incorporating AI and ML. These methods enhanced accuracy and consistency of color reproduction in prosthetic restorations. AI integration further improves precision by recognizing subtle variations in teeth color [3].

Despite these advancements, it is noteworthy that AI-related studies focusing on tooth shade determination and non-carious tooth surface loss from the years 2020–2023 are currently lacking in the literature. This reveals a research gap that warrants attention and exploration in future studies. These methods collectively advance AI capabilities in restorative dentistry, contributing to accurate and comprehensive tooth shade analysis.

Potential future applications

Furthermore, AI extends its capabilities to predict the viability of dental pulp stem cells, offering valuable insights into regenerative dentistry [15]. While these applications may not be as directly tiedint to the core of restorative dentistry, they contribute to improved overall efficiency and patient care in dental practices. As we look ahead, the anticipated impact of AI in restorative dentistry reveals significant and promising advancements, particularly through the integration of AI-powered virtual assistants and chatbots [5]. These innovations could enhance the patient experience, improve communication, and streamline dental workflows.

Recent research underscores the potential for AI to extend beyond diagnostics and treatment planning into patient education. A study emphasized the need for enhanced oral health education among pregnant women. Integrating AI-driven educational tools, such as chatbots or personalized learning platforms, could address these gaps effectively, improving patient compliance and outcomes. Puleio F et al. (2024) reviewed the clinical, research, and educational applications of ChatGPT in dentistry. Their findings underscored the potential of AI-driven chatbots to enhance patient education, streamline administrative workflows, and support dental professionals in decision-making processes. Such applications align with the broader vision of precision-driven, patient-centric care in restorative dentistry [48].

Looking forward, the future of restorative dentistry holds promise for groundbreaking developments in robotic AI applications, potentially automating tooth preparation and filling procedures [5]. While current prototypes provide glimpses into this innovative domain, careful consideration of the ethical implications is paramount. The realization of fully automated robotic systems remains an ongoing exploration within restorative dentistry, prompting a delicate balance between technological progress and ethical considerations. The ongoing exploration of fully automated robotic systems in restorative dentistry underscores the need for careful consideration of patient safety, regulatory approval, and clinician collaboration.

Reliability

The reliability of AI in restorative dentistry is substantiated by commendable diagnostic accuracy, precision in treatment planning, predictive analytics capabilities, and streamlining of operational workflows. Numerous studies affirm the efficacy of AI algorithms in detecting oral health abnormalities, often outperforming human experts. AI's ability to analyze patient data over time and predict potential issues contributes to proactive and personalized care. The technology enhances the precision of treatment plans and optimizes administrative processes, reducing errors and improving overall efficiency. Validation through clinical trials and real-world implementations further underscores AI's reliability, positioning it as a valuable tool in advancing the field of restorative dentistry.

Limitations and collaborative solutions

While the transformative benefits of AI in dentistry are evident, acknowledging and mitigating potential challenges is imperative. One significant limitation lies in the need for extensive and diverse datasets to ensure robust AI models [5, 6, 8, 14, 19, 49]. The lack of standardized datasets hampers the generalizability and reliability of AI applications, particularly in restorative dentistry. For instance, AI models trained on datasets from specific populations may fail to perform accurately when applied to other ethnic groups or age demographics [50]. Collaborative efforts to pool data globally can address this necessity, allowing AI models to be trained on representative datasets and mitigating biases. This approach enhances generalizability across diverse populations, ethnicities, and dental conditions, ultimately improving its applicability in diverse clinical settings.

Another limitation involves ethical considerations, particularly in the areas of data privacy, security, and the interpretability of AI decision-making processes [5, 6, 8, 14, 19, 49, 59]. Recent studies in 2024 have highlighted growing concerns about patient data confidentiality and the potential misuse of sensitive health information [48, 59]. Overcoming these challenges is essential for accelerating research and ensuring that AI applications remain transparent and accountable. Collaborative data sharing can mitigate data scarcity, but it must be done with careful adherence to privacy regulations such as GDPR and HIPAA, as well as the establishment of clear guidelines and frameworks for responsible data sharing [49, 59].

Moreover, the need for ongoing validation, transparency, and updates to AI applications is paramount, especially given the moderate performance of machine learning models in areas such as assessing the morphology of sculpted teeth [1, 12]. A recent study emphasized the importance of continuous model refinement to address evolving clinical needs and reduce generalizability limitations [48]. Further improvements are necessary in dataset size and variability to ensure that AI models remain relevant and effective in real-world scenarios. This ensures alignment with the evolving landscape of dental practices, maximizing positive impacts while mitigating potential risks.

Additionally, relying on static image analysis limits the applicability of AI in dynamic clinical scenarios, necessitating further advancements in multi-modal data integration [2]. A recent study explored the use of AI in combining imaging data with clinical notes and patient history, demonstrating improved diagnostic accuracy and treatment planning efficiency [13]. Such innovations highlight the potential of AI to move beyond static analyses and provide holistic solutions for patient care.

Ethical concerns related to data privacy and security, as well as the interpretability of AI decision-making processes, must be addressed. Regulatory challenges emphasize the need for clinician-AI collaboration to validate AI models, particularly in endodontics, where limited datasets and inconsistent labeling make implementation difficult [3]. Additionally, AI should complement, rather than replace, clinical expertise, ensuring that clinicians are always involved in decision-making processes. Studies by Kim CS et al. and Manila N. emphasized the ethical and educational challenges of integrating AI into dental curricula. The authors highlighted the need for standardized training programs to equip dental professionals with the skills to effectively utilize AI tools. Addressing these gaps is crucial for ensuring widespread adoption and maximizing AI's potential in clinical practice [49, 59, 63]. For example, AI sensitivity in caries detection has varied significantly depending on tooth position and caries type, with lower accuracy observed in interproximal and buccal caries [20,41]. This underscores the need for algorithm refinement and further research into removing dataset biases and preventing overfitting [4, 21].

Finally, the integration of AI into dental education remains a challenge. A recent study highlighted the gap in training programs for dental professionals, emphasizing the need for standardized curricula that incorporate AI tools and technologies [48, 59]. Without adequate training, the adoption of AI in clinical practice may face resistance, limiting its potential impact. Addressing these educational gaps will be crucial for ensuring that dental professionals are equipped to leverage AI effectively.

The seamless integration of collaborative solutions provides a nuanced understanding of both the promises and challenges in the application of AI to restorative dentistry. By addressing these limitations, the field can harness the full potential of AI to revolutionize patient care and clinical workflows.

Discussion

Despite these challenges, the following discussion explores key trends in AI applications in dentistry, examining the impact of dataset size, effectiveness of AI techniques, influence of modalities on accuracy, model-specific observations, and considerations for future research.

1) Impact of Dataset Size on Model Performance

One notable trend across the studies is the influence of dataset size on the performance of AI models. Studies with larger datasets generally exhibit higher accuracy rates, suggesting a positive correlation between dataset size and model proficiency. For instance, One study achieved an accuracy of 92.50% using CNN on a substantial dataset of 2,417 OCT and radiographic images, showcasing the potential benefits of ample data for training robust models [21]. However, the dependency on high-quality datasets poses a significant challenge. Poorly annotated or biased datasets can lead to suboptimal model performance and potential inaccuracies in clinical decision-making.

2) Effectiveness of AI Techniques

Diverse AI techniques were employed in the analyzed studies, including Convolutional Neural Networks (CNNs), Support Vector Machines (SVMs), Ensemble of Classifier Chains (ECC), and others. CNNs, known for their ability to learn hierarchical features, demonstrated high accuracy in various applications such as caries detection [22, 28] and dental restorations detection [32]. Support Vector Machines, as seen in studies, exhibited remarkable accuracy in recognizing carious lesions from smartphone images, emphasizing the versatility of different AI techniques in dental applications [23].

3) Influence of Modalities on Accuracy

The choice of imaging modalities played a crucial role in determining the success of the models. Studies using diverse modalities, such as OCT images [21] and periapical images [27], showcased the adaptability of AI models to various dental imaging technologies. Nonetheless, ensuring consistent quality and standardization of imaging data remains critical to achieving reliable results.

4) Emerging Trends in AI for Restorative Dentistry (2024–2025)

Recent studies in 2024 and 2025 have highlighted the growing role of AI in automating complex dental procedures. For example, researchers have developed AI-driven robotic systems capable of performing tooth preparation and cavity restoration with minimal human intervention [60]. These systems leverage real-time imaging and haptic feedback to ensure precision and safety during clinical procedures, significantly reducing chair time and improving patient comfort.

Additionally, AI-powered virtual assistants are being integrated into dental practices to enhance patient education and streamline administrative workflows. A recent study demonstrated that chatbots equipped with natural language processing (NLP) capabilities could effectively guide patients through oral hygiene routines and answer common dental queries [61]. Such innovations not only improve patient engagement but also reduce the burden on dental professionals.

A 2025 study explored the use of AI in predicting patient-specific risks for periodontal disease progression, enabling early interventions and personalized treatment plans [62]. This highlights the potential of AI to move beyond diagnostics and into preventive care, offering a holistic approach to patient management.

5) Considerations for Future Research

While the manuscript discusses data scarcity and ethical concerns, further limitations warrant attention. Variability in AI performance across different populations and dental settings highlights the need for standardized benchmarks to evaluate and compare AI tools effectively. Establishing such benchmarks would enable the development of universally applicable AI systems, reducing disparities in performance.

Future research should explore integrating AI with emerging technologies, such as 3D printing, to revolutionize restorative procedures. Additionally, investigating the long-term clinical outcomes of AI-assisted interventions will provide insights into their efficacy and safety overtime.

Collaboration among researchers, clinicians, and policy makers is critical to overcome these challenges and ensuring the responsible development of AI in dentistry.

Conclusion

In conclusion the reliability of AI in restorative dentistry is substantiated by commendable diagnostic accuracy, precision in treatment planning, and predictive analytics capabilities. However, challenges such as the need for extensive and diverse datasets, ethical considerations, and ongoing validation remain. Collaborative efforts to address these challenges, along with continued research into emerging AI techniques and their applicability across different dental applications, are crucial for maximizing the positive impacts of AI in restorative dentistry. overall, the integration of AI into restorative dentistry represents a significant step forward in enhancing diagnostic capabilities, treatment planning, and patient care. As technology continues to evolve, the future of restorative dentistry holds promise for groundbreaking developments, with AI-powered solutions paving the way for precision-driven, patient-centric dental care.

Abbreviations

AI	Artificial Intelligence
LLM	Large Language Model
CNN	Convolutional Neural Networks
SVM	Support Vector Machines
ECC	Ensemble of Classifier Chains
TSL	Tooth Surface Loss
ANN	Artificial Neural Networks
OPG	Orthopantomography
DL	Deep Learning
NN	Neural Network
PRISMA	Preferred Reporting Items for Systematic reviews and Meta-Analyses
ML	Machine Learning

Acknowledgements
Not applicable.

Author contributions
Dr. Shahid Islam and Dr Mariya Najeeb are the main authors of this manuscript. They both conceptualized, designed, and conducted the study, analyzed the data, and drafted the manuscript.

Funding
This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Data availability
The datasets generated and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate
Not applicable.

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interests.

Author details
[1]Department of Operative Dentistry and Endodontics, Fatima Jinnah Dental College Hospital, 100 Feet Road, Azam Town Near DHA Phase 1, Karachi, Pakistan

Received: 7 December 2024 / Accepted: 11 April 2025
Published online: 18 April 2025

References

1. Arjumand B. The application of artificial intelligence in restorative dentistry: A narrative review of current research. Saudi Dent J. 2024;36(6):835–40.
2. Fan FY, Lin WC, Huang HY, Shen YK, Chang YC, Li HY, et al. Applying machine learning to assess the morphology of sculpted teeth. J Dent Sci. 2024;19(1):542–9.
3. Binhuraib H, Aloqayli S, Alkhalifah S, Aljohani A, Alotaibi R, Almalki R, et al. Digital shade matching techniques in fixed prosthodontics. J Healthc Sci. 2024;04(01):34–40.
4. Turosz N, Chęcińska K, Chęciński M, Lubecka K, Bliźniak F, Sikora M. Artificial intelligence (AI) assessment of pediatric dental panoramic radiographs (DPRs): A clinical study. Pediatr Rep. 2024;16(3):794–805.
5. Babu A, Andrew Onesimu J, Martin Sagayam K. Artificial Intelligence in dentistry: Concepts, Applications and Research Challenges. Krit S, editor. E3S Web Conf. 2021;297:01074.

6. Carrillo-Perez F, Pecho OE, Morales JC, Paravina RD, Della Bona A, Ghinea R, et al. Applications of artificial intelligence in dentistry: A comprehensive review. J Esthet Restor Dent. 2022;34(1):259–80.
7. Kazimierczak N, Kazimierczak W, Serafin Z, Nowicki P, Nożewski J, Janiszewska-Olszowska J. AI in orthodontics: revolutionizing diagnostics and treatment planning—A comprehensive review. J Clin Med. 2024;13(2):344.
8. Al Hendi KD, Alyami MH, Alkahtany M, Dwivedi A, Alsaqour HG. Artificial intelligence in prosthodontics. Bioinformation. 2024;20(3):238.
9. Rokaya D, Jaghsi AA, Jagtap R, Srinameepong V. Artificial intelligence dentistry and dental biomaterials. Front Dent Med. 2024;5:1525505.
10. Armoogum S, Li X. Chapter 2 - Big Data Analytics and Deep Learning in Bioinformatics With Hadoop. In: Sangaiah AK, editor. Deep Learning and Parallel Computing Environment for Bioengineering Systems [Internet]. Academic Press; 2019. pp. 17–36. Available from: https://www.sciencedirect.com/science/article/pii/B9780128167182000099
11. Shamaun M, Field J. A Scoping Review of Machine Learning in Dental Radiography: Its Current Applications and Relevance in Dentistry [Internet]. In Review; 2023 May [cited 2023 Nov 29]. Available from: https://www.researchsquare.com/article/rs-2865258/v1
12. Tabatabaian F, Vora SR, Mirabbasi S. Applications, functions, and accuracy of artificial intelligence in restorative dentistry: A literature review. J Esthet Restor Dent. 2023;35(6):842–59.
13. Elahi M, Afolaranmi SO, Martinez Lastra JL, Perez Garcia JA. A comprehensive literature review of the applications of AI techniques through the lifecycle of industrial equipment. Discov Artif Intell. 2023;3(1):43.
14. Schwendicke F, Samek W, Krois J. Artificial intelligence in dentistry: chances and challenges. J Dent Res. 2020;99(7):769–74.
15. Thurzo A, Urbanová W, Novák B, Czako L, Siebert T, Stano P, et al. Where is the artificial intelligence applied in dentistry?? Systematic review and literature analysis. Healthcare. 2022;10(7):1269.
16. Görürgöz C, Orhan K, Bayrakdar IS, Çelik Ö, Bilgir E, Odabaş A, et al. Performance of a convolutional neural network algorithm for tooth detection and numbering on periapical radiographs. Dentomaxillofacial Radiol. 2022;51(3):20210246.
17. Lee SJ, Chung D, Asano A, Sasaki D, Maeno M, Ishida Y, et al. Diagnosis of tooth prognosis using artificial intelligence. Diagnostics. 2022;12(6):1422.
18. Gardiyanoğlu E, Ünsal G, Akkaya N, Aksoy S, Orhan K. Automatic segmentation of teeth, Crown–Bridge restorations, dental implants, restorative fillings, dental caries, residual roots, and root Canal fillings on orthopantomographs: convenience and pitfalls. Diagnostics. 2023;13(8):1487.
19. Ahmed N, Abbasi MS, Zuberi F, Qamar W, Halim MSB, Maqsood A et al. Artificial Intelligence Techniques: Analysis, Application, and Outcome in Dentistry—A Systematic Review. Grassia V, editor. BioMed Res Int. 2021;2021:1–15.
20. Zhang JW, Fan J, Zhao FB, Ma B, Shen XQ, Geng YM. Diagnostic accuracy of artificial intelligence-assisted caries detection: a clinical evaluation. BMC Oral Health. 2024;24(1):1095.
21. Kühnisch J, Meyer O, Hesenius M, Hickel R, Gruhn V. Caries detection on intraoral images using artificial intelligence. J Dent Res. 2022;101(2):158–65.
22. Lian L, Zhu T, Zhu F, Zhu H. Deep learning for caries detection and classification. Diagnostics. 2021;11(9):1672.
23. Duong DL, Kabir MH, Kuo RF. Automated caries detection with smartphone color photography using machine learning. Health Inf J. 2021;27(2):14604582211007530.
24. Duong DL, Nguyen QDN, Tong MS, Vu MT, Lim JD, Kuo RF. Proof-of-Concept study on an automatic computational system in detecting and classifying occlusal caries lesions from smartphone color images of unrestored extracted teeth. Diagnostics. 2021;11(7):1136.
25. Cantu AG, Gehrung S, Krois J, Chaurasia A, Rossi JG, Gaudin R, et al. Detecting caries lesions of different radiographic extension on bitewings using deep learning. J Dent. 2020;100:103425.
26. ping Huang Y, Lee SY. Deep Learning for Caries Detection using Optical Coherence Tomography. In. 2021. Available from: https://api.semanticscholar.org/CorpusID:236528294
27. Zheng L, Wang H, Mei L, Chen Q, Zhang Y, Zhang H. Artificial intelligence in digital cariology: a new tool for the diagnosis of deep caries and pulpitis using convolutional neural networks. Ann Transl Med. 2021;9(9):763–763.
28. Bayraktar Y, Ayan E. Diagnosis of interproximal caries lesions with deep convolutional neural network in digital bitewing radiographs. Clin Oral Investig. 2022;26(1):623–32.
29. Zhu H, Cao Z, Lian L, Ye G, Gao H, Wu J. CariesNet: a deep learning approach for segmentation of multi-stage caries lesion from oral panoramic X-ray image. Neural Comput Appl. 2023;35(22):16051–9.
30. Vinayahalingam S, Kempers S, Limon L, Deibel D, Maal T, Hanisch M, et al. Classification of caries in third molars on panoramic radiographs using deep learning. Sci Rep. 2021;11(1):12609.
31. Hur SH, Lee EY, Kim MK, Kim S, Kang JY, Lim JS. Machine learning to predict distal caries in mandibular second molars associated with impacted third molars. Sci Rep. 2021;11(1):15447.
32. Mao YC, Chen TY, Chou HS, Lin SY, Liu SY, Chen YA, et al. Caries and restoration detection using bitewing film based on transfer learning with CNNs. Sensors. 2021;21(13):4613.
33. Gokul GL. Artificial Intelligence in Dentistry - A Review.
34. Karhade DS, Roach J, Shrestha P, Simancas-Pallares MA, Ginnis J, Burk ZJ et al. An Automated Machine Learning Classifier for Early Childhood Caries. 2021.
35. Park YH, Kim SH, Choi YY. Prediction models of early childhood caries based on machine learning algorithms. Int J Environ Res Public Health. 2021;18(16):8613.
36. Fontenele RC, Gerhardt MDN, Pinto JC, Van Gerven A, Willems H, Jacobs R, et al. Influence of dental fillings and tooth type on the performance of a novel artificial intelligence-driven tool for automatic tooth segmentation on CBCT images– A validation study. J Dent. 2022;119:104069.
37. Chen SL, Chen TY, Mao YC, Lin SY, Huang YY, Chen CA, et al. Detection of various dental conditions on dental panoramic radiography using faster R-CNN. IEEE Access. 2023;11:127388–401.
38. Farook TH, Ahmed S, Jamayet NB, Rashid F, Barman A, Sidhu P, et al. Computer-aided design and 3-dimensional artificial/convolutional neural network for digital partial dental crown synthesis and validation. Sci Rep. 2023;13(1):1561.
39. Al-Sarem M, Al-Asali M, Alqutaibi AY, Saeed F. Enhanced tooth region detection using pretrained deep learning models. Int J Environ Res Public Health. 2022;19(22):15414.
40. Takahashi T, Nozaki K, Gonda T, Mameno T, Ikebe K. Deep learning-based detection of dental prostheses and restorations. Sci Rep. 2021;11(1):1960.
41. Ourang SA, Sohrabniya F, Mohammad-Rahimi H, Dianat O, Aminoshariae A, Nagendrababu V, et al. Artificial intelligence in endodontics: fundamental principles, workflow, and tasks. Int Endod J. 2024;57(11):1546–65.
42. Gao X, Xin X, Li Z, Zhang W. Predicting postoperative pain following root Canal treatment by using artificial neural network evaluation. Sci Rep. 2021;11(1):17243.
43. Li CW, Lin SY, Chou HS, Chen TY, Chen YA, Liu SY, et al. Detection of dental apical lesions using CNNs on periapical radiograph. Sensors. 2021;21(21):7049.
44. Moidu NP, Sharma S, Chawla A, Kumar V, Logani A. Deep learning for categorization of endodontic lesion based on radiographic periapical index scoring system. Clin Oral Investig. 2022;26(1):651–8.
45. Qu Y, Lin Z, Yang Z, Lin H, Huang X, Gu L. Machine learning models for prognosis prediction in endodontic microsurgery. J Dent. 2022;118:103947.
46. Calazans MAA, Ferreira FABS, Alcoforado MDLMG, Santos AD, Pontual ADA, Madeiro F. Automatic classification system for periapical lesions in Cone-Beam computed tomography. Sensors. 2022;22(17):6481.
47. Albitar L, Zhao T, Huang C, Mahdian M. Artificial intelligence (AI) for detection and localization of unobturated second mesial buccal (MB2) canals in Cone-Beam computed tomography (CBCT). Diagnostics. 2022;12(12):3214.
48. Puleio F, Lo Giudice G, Bellocchio AM, Boschetti CE, Lo Giudice R, Clinical. Research, and educational applications of ChatGPT in dentistry: A narrative review. Appl Sci. 2024;14(23):10802.
49. Kim CS, Samaniego CS, Sousa Melo SL, Brachvogel WA, Baskaran K, Rulli D. Artificial intelligence (A.I.) in dental curricula: ethics and responsible integration. J Dent Educ. 2023;87(11):1570–3.
50. Pethani F. Promises and perils of artificial intelligence in dentistry. Aust Dent J. 2021;66(2):124–35.
51. Hung CL. Chapter 11 - Deep learning in biomedical informatics. In: Zheng Y, Wu Z, editors. Intelligent Nanotechnology [Internet]. Elsevier; 2023. pp. 307–29. (Materials Today). Available from: https://www.sciencedirect.com/science/article/pii/B9780323857963000111
52. Huang C, Wang J, Wang S, Zhang Y. A review of deep learning in dentistry. Neurocomputing. 2023;554:126629.
53. Mittal P, Singh R, Sharma A. Deep learning-based object detection in low-altitude UAV datasets: A survey. Image Vis Comput. 2020;104:104046.
54. Mujtaba IM, Sowgath MT. Chapter 13 - Application of artificial intelligence in desalination processes. In: Mujtaba IM, Sowgath MT, editors. Desalination

Technologies [Internet]. Elsevier; 2022. pp. 541–93. Available from: https://www.sciencedirect.com/science/article/pii/B9780128137901000116
55. POPOVIC D. CHAPTER 18 - Intelligent Control with Neural Networks. In: SINHA NK, GUPTA MM, editors. Soft Computing and Intelligent Systems [Internet]. San Diego: Academic Press. 2000. pp. 419–67. (Academic Press Series in Engineering). Available from: https://www.sciencedirect.com/science/article/pii/B9780126464900500214
56. Subasi A, Panigrahi SS, Patil BS, Canbaz MA, Klén R. Chapter 8 - Advanced pattern recognition tools for disease diagnosis. In: Bhoi AK, Albuquerque VHC de, Sur SN, Barsocchi P, editors. 5G IoT and Edge Computing for Smart Healthcare [Internet]. Academic Press; 2022. pp. 195–229. (Intelligent Data-Centric Systems). Available from: https://www.sciencedirect.com/science/article/pii/B9780323905480000115
57. Subasi A. Chapter 3 - Machine learning techniques. In: Subasi A, editor. Practical Machine Learning for Data Analysis Using Python [Internet]. Academic Press; 2020. pp. 91–202. Available from: https://www.sciencedirect.com/science/article/pii/B9780128213797000035
58. Wang Z, Wang T, Wan B, Han M. Partial classifier chains with feature selection by exploiting label correlation in Multi-Label classification. Entropy. 2020;22(10):1143.
59. Manila N, Glick A, Xenoudi P. AI reshaping the dental landscape: integrating the future into curriculum. J Calif Dent Assoc. 2024;52(1):2365953.
60. Veseli E. Revolutionizing dentistry: the integration of artificial intelligence and robotics. KHYBER Med Univ J. 2024;16(4).
61. Chang WJ, Chang PC, Chang YH. The gamification and development of a chatbot to promote oral self-care by adopting behavior change wheel for Taiwanese children. Digit Health. 2024;10:20552076241256750.
62. Khan SF, Siddique A, Khan AM, Shetty B, Fazal I. Artificial intelligence in periodontology and implantology—a narrative review. J Med Artif Intell. 2024;7.
63. Uribe SE, Maldupa I, Schwendicke F. Integrating Generative AI in Dental Education: A Scoping Review of Current Practices and Recommendations. Eur J Dent Educ. 2025 Jan 31. https://doi.org/10.1111/eje.13074. Epub ahead of print. PMID: 39891376.
64. Ketenci Çay F, Yeşil Ç, Çay O, Yılmaz BG, Özçini FH, İlgüy D. DeepLabv3 + method for detecting and segmenting apical lesions on panoramic radiography. Clin Oral Investig. 2025;29(2):101. https://doi.org/10.1007/s00784-025-06156-0. PMID: 39888441.
65. Nagareddy B, Vadlamani R, Venkannagari NR, Jain S, Basheer SN, Murugesan S. Comparison of the artificial intelligence versus traditional radiographic interpretation in detecting periapical periodontitis: A diagnostic accuracy study. J Pharm Bioallied Sci. 2024;16(Suppl 4):S3676–8.
66. Santos-Junior AO, Fontenele RC, Neves FS, Tanomaru-Filho M, Jacobs R. A novel artificial intelligence-powered tool for automated root Canal segmentation in single-rooted teeth on cone-beam computed tomography. Int Endod J. 2025 Jan 28.
67. Alsolamy M, Nadeem F, Azhari AA, Alsolami W, Ahmed WM. Automated detection and labeling of posterior teeth in dental bitewing X-rays using deep learning. Comput Biol Med. 2024;183:109262.
68. Slim ML, Jacobs R, de Souza Leal RM, Fontenele RC. AI-driven segmentation of the pulp cavity system in mandibular molars on CBCT images using convolutional neural networks. Clin Oral Invest. 2024;28(12):1–1.

Publisher's note