

AI-Driven Approaches in Dental Caries Management from Detection to Treatment Planning: A narrative review¹Dr. Zoya Rouf Khan, BDS, Goregaon Dental Centre, Goregaon.²Dr Anoli Agrawal, BDS, MDS, Public Health Dentistry, ACPM Dental College and Hospital, Dhule.**Corresponding Author:** Dr. Zoya Rouf Khan, BDS, Goregaon Dental Centre, Goregaon.**Citation of this Article:** Dr. Zoya Rouf Khan, Dr Anoli Agrawal, “AI-Driven Approaches in Dental Caries Management from Detection to Treatment Planning: A narrative review”, IJDSIR – September – 2026, Volume – 9, Issue – 4, P. No. 31 – 40.**Copyright:** ©2026, Dr. Zoya Rouf Khan, et al. This is an open access journal and article distributed under the terms of the creative common's attribution non-commercial License. Which allows others to remix, tweak, and build upon the work non-commercially, as long as appropriate credit is given, and the new creations are licensed under the identical terms.**Type of Publication:** Review Article**Conflicts of Interest:** Nil**Abstract**

Artificial intelligence models can learn, infer and reason the data provided, mimicking the human brain, they recognise patterns and predict outcomes. Caries prevalence has been a major concern in different areas globally, beginning as early as childhood and it can be an issue in adulthood. The conventional way of diagnosing has taken us so far; after combining the traditional diagnostic measures with our knowledge about artificial intelligence, we can improve conservative and restorative dentistry in every aspect. Enhancement in the field of dentistry due to its integration in clinical computing, analysing old patients' records improves both decision-making and record-keeping processes. AI has been shown to improve the detection and diagnosis of dental caries, periapical lesions, morphology of roots etc. Recently, efforts have been made to develop a computerised dental X-ray image analysis system for clinical usage. AI offers significant potential when it comes to diagnosing the longevity of restorations

assessing prognosis and estimating its failure, it can also be used to predict caries risk in children based on their brushing habits, age, diet, weight etc. AI has shown promising results in generating templates for personalised teeth defect restorations and, in a dental laboratory setting for the fabrication of casting metal substructures using a CAD-CAM system and to estimate the ideal shade post bleaching. Furthermore, AI has proven its effectiveness in determining consecutive tooth wear using pairs of intraoral scans. The integration of AI systems in dental practice has helped clinicians to analyse complex data, identify subtle patterns in diagnostic imaging and help them in making evidence-based decisions. Eventually, with responsible decision-making and continuous innovation, AI will be able to raise the standards of dental practice, enhance patient outcomes, and contribute to the overall advancement of the dental profession.

Keywords: Artificial Intelligence, Caries, Diagnosis, Treatment, Machine Learning.

Introduction

Artificial intelligence (AI) term was introduced by John McCarthy in the year 1956. In simpler words, it means creation of a model that has an ability to learn, infer and reason the data provided, mimicking human brain. Machine learning is a subset of artificial intelligence, on providing required data, it recognises patterns and predicts outcomes. It can also be used to spot outliers. Deep learning, which comes under machine learning, is a type of machine algorithm. It includes training of model from given data for analytical learning.¹ The main constituent of any NN is the artificial neuron, which is a mathematical non-linear model that was inspired by the human neuron. By stacking and concatenating artificial neurons and connecting those layers using mathematical operations, a network is engineered that aims to solve a specific task like image classification (e.g., radiographic image showing a decayed tooth: yes or no).²

Neural networks consist of three parts- 1) Input layer (enter information here), 2) hidden layer (data processing), 3) output layer (system makes a decision). Most common types of neural networks are Artificial neural network (ANN), Convolutional Neural network (CNN) and recurrent neural networks. CNN is a deep learning architecture which is responsible for recognising visual patterns, on providing representation of original images, it recognises patterns of raw pixels and identifies the image.¹

Caries prevalence has been a major concern in different areas globally. It begins as early as childhood and can be an issue in adulthood. A study was conducted for students of 21st century, a total of 2642 records were screened, and 43 observational studies were finally included. Carious lesions were commonly found in the maxillary incisors and molars in both upper and lower arches among preschool children. The highest caries

prevalence was found in the maxillary central incisors (29.1%, 95%CI: 25.5%-32.7%) and the mandibular second molars (28.5%, 95% CI: 24.7%-32.3%), while the mandibular lateral incisors had the lowest prevalence (1.7%, 95%CI: 1.5%-2.0%)³. Occlusal surfaces of the mandibular molars were the most frequently affected by caries, whereas caries hardly affected the lingual surfaces of lower anterior teeth.³

The conventional way of diagnosing using mouth mirrors and probes have taken us so far, thanks to digitalisation in dentistry, introduction of radiography, CBCT, use of diagnostic tools like electric pulp testers have made our job easier. After combining the traditional diagnostic measures with our knowledge about artificial intelligence, we can improve conservative and restorative dentistry in every aspect. In the work by Geetha et al., an artificial neural network was used to determine whether caries was present or not in the 105 radiograph images. They extracted sixteen feature vectors from the segmented image, and these were the input nodes. There were two output nodes that consisted of caries or sound tooth. The accuracy of caries detection was 97.1%, and the false positive rate was 2.8%¹. This study revealed that neural networks may be much more precise in tooth decay detection than traditional dental examinations. In Saghiri et al.'s research, endodontic files were used to determine the length of the canals on the radiology images with the use of artificial neural networks. The measurements were taken before the extraction of the teeth and after the extraction with the use of stereomicroscopy. The correct assessment made by the endodontics only was in 76% and by the artificial neural network in 96%. This shows that artificial intelligence not only has a future in accuracy of diagnosis and treatment planning but also fastens the process.¹

Caries prevention is necessary not only on individual level but also on community level. Water fluoridation as a population strategy has been used to prevent dental caries. With the help machine learning, we can assess the effectiveness of this prevention technique in different areas of society⁴. In a study, Data from the National Child Oral Health Study-a national representative study conducted in 2012-14, linked to the information on lifetime exposure to fluoridated water-were analysed (n = 17 517 children aged 5-14 years). In total, 58.1% were fully exposed to water fluoridation throughout their lifetime. Water fluoridation was associated with having - 0.9 (95% confidence interval: -1.1, -0.8) fewer dental caries incidents.⁴

Currently, Artificial Intelligence is being used majorly for the purpose of diagnosis through dental radiology and treatment planning. Other applications could be diagnosis of soft tissue lesions, periapical diseases, detection of root fractures, prediction of post-operative complications etc. Artificial intelligence is developing at a rapid pace and soon will be a commonly used tool in modern dentistry¹. This review has an aim to examine Artificial intelligence in diagnosis and treatment planning of caries, primordial prevention in patients with high-risk caries and customised maintenance plan for individual patients.

Methodology

To review the literature, Studies were selected from PubMed, Web of Science, and Google Scholar without restrictions on publication year, to provide a comprehensive overview of current knowledge on application of artificial intelligence in diagnosis and treatment planning of caries. The review focused on evaluating the use of artificial intelligence in caries diagnosis and treatment planning. The search terms included: “Caries,” “Artificial Intelligence,” “diagnosis,” “restorative dentistry,” “conservative dentistry,” “dental

radiology,” “caries prevalence,” “Neural networks,” and “Deep learning.”. The research encompassed, Case reports, laboratory studies, clinical studies, and systematic reviews.

Assessment of patient data and previous records.

Digitalisation has significantly changed and enhanced the field of dentistry due to integration of clinical computing. Many healthcare providers are shifting from traditional paper-based record keeping to using digital platforms. Artificial intelligence has further enhanced the process by improving diagnostic accuracy and clinical outcomes by analysing old patient's records, diet habits, medical and dental histories, along with their current clinical and radiographic findings, improving both decision making and record keeping processes. AI systems are capable of sensing, engaging, and learning and interacting – such as image recognition, speech interpretation, motion analysis and data organization. ML methods can be applied to datasets of any size, more the data, better the results. ML assumes feeding these features into computational models that can offer insights into the observations, such as clustering similar observations into groups or predicting certain outcomes.⁵

Deep learning (DL), an advanced form of ML, here algorithms can train themselves due to the “self-learning” ability achieved through a sequential chain of pivotal features from input data. Deep neural networks (DNNs) can learn complex nonlinear mathematical functions. For instance, a patient with a history of smoking has increased risk for gingival and periodontal diseases. By documenting the frequency and duration of smoking habit, and other factors, it can assist in classifying the patient's condition as mild, moderate, or severe periodontitis, enabling more precise and individualised treatment planning.⁶

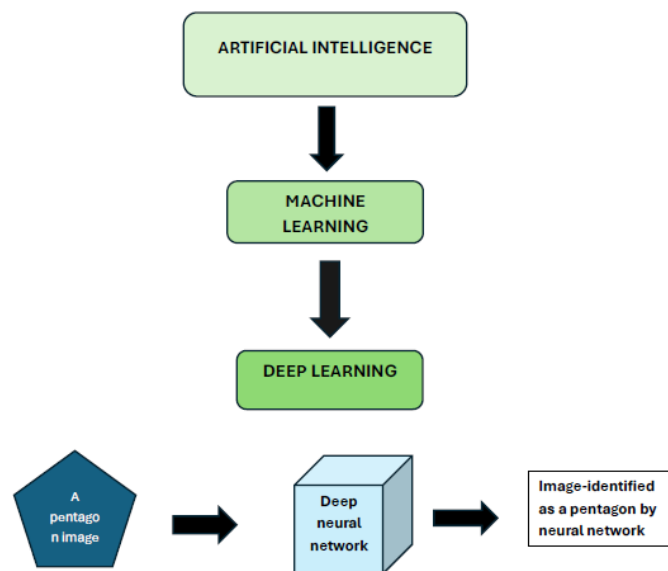


Figure (a): Flowchart representing working of Neural Networks to identify patterns.

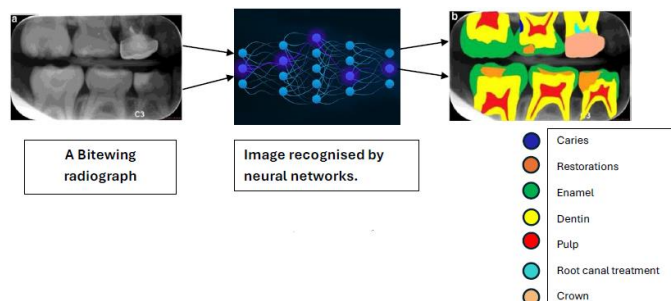


Figure (b): Flowchart representing radiograph recognition by Neural networks⁷

In a study by Kim et al. used Artificial neural network to build a model that predicts toothache on the basis of association between toothache and daily tooth brushing frequency, use of dental floss, toothbrush replacement pattern, and other factors. It helped in development of a toothache predictive model with great accuracy.⁸

For increased patient data, clinical decision support systems are becoming important tools for healthcare providers. CDSS (clinical decision support systems) are computer programs that provide expert support to health professionals making clinical decisions. They use inbuilt clinical knowledge to analyse the data of patients and assist dental health professionals in taking decisions regarding diagnosis, prognosis, treatment and prevention

of disease. It has been used for screening of patients with diabetes, hypertension, tobacco, use, and nutrition counselling at chair side. This system is designed to provide extra support and to improve the clinical decision-making.⁹

Assistance in radiographic examination

Radiographic examination is an important component of diagnosis and treatment planning. In the clinical practice, caries lesions have traditionally been diagnosed by visual inspection along with radiography. AI has shown to improve the detection and diagnosis of the dental caries, type of dental caries, periapical lesions, morphology of roots etc. Recently, efforts have been made to develop computerised dental X-ray image analysis system for clinical usage. In a study, Ronneberger et al. presented a pure machine learning approach using u-shaped deep convolutional neural network (“u-net”) for the fully automated segmentation of dental x-ray images. It consisted of a contracting path to capture context and a symmetric expanding path for precise localization. It could be trained end-to-end from very few images, learn the robustness to deformations by augmenting the training data with randomly deformed images and automatically learn the hierarchical structure within the images. Ronneberger’s study performed well and achieved F-scores greater than 0.7 for the three fundamental dental structures (enamel, dentin and pulp). In another cross-sectional study, a dataset comprising 1000 panoramic radiographs from 500 adult patients were analysed by an AI system and compared. A strong correlation ($R > 0.5$) was observed between AI perception and observers 1 and 2 in carious teeth (0.691-0.878) and restored teeth (0.773-0.834).^{10,11}

Similarly, thirty dentists with varying levels of experience evaluated 50 panoramic radiographs for the presence or absence of periapical radiolucency, with and

without the aid of AI, using a cross-over design. AI assistance significantly improved overall diagnostic accuracy (91.6 % unaided vs. 93.3 % AI-aided; $p < 0.001$), mainly by reducing false positive diagnoses (false positive rate: 4.3 % unaided vs. 2.0 % AI-aided).¹²

According to Hiraiwa et al. the distal roots of the mandibular first molars (radix entomolaris) could be differentiated with deep learning algorithm and panoramic radiographs. Lahoud et al, in a rapid, accurate, and effective clinical reference evaluated 433 cone-beam computed tomographic segmentations of teeth and found that artificial intelligence performed exactly as well as a human operator while working much faster. Saghiri et al. discovered no change in the root length of cadaver teeth, between artificial neural network and the clinician's measurement. They also noted that the ANN (96%) outperformed an endodontist (76%) by a wide margin when using periapical radiographs to determine minor anatomic constriction.⁷

One of the drawbacks of poor restoration is overhangs, which can go undetected by the clinicians. With the help of AI detection of the overhangs in restoration can be improved. A model was created where it helped detecting and segmentation of overhanging dental restorations in bitewing radiographs. It demonstrated a precision of 90.9%, a sensitivity of 85.3%.¹³

Efficient diagnosis of prevalent caries and prediction of future caries: Artificial intelligence offers significant potential when it comes to diagnosing the longevity of restorations assessing prognosis and estimating its failure. By integrating treatment related data, we can predict meaningful outcomes. For example, one study reported that a two-surface resin composite restoration weakened the tooth by 23.25%. The combined influence of both cavity preparation and root canal enlargement led to a weakening of 62.6% under a load of 710N,

ultimately causing tooth fracture¹⁴. In another study, it was seen that teeth with four walls of remaining coronal dentine had significantly higher fracture resistance than teeth with only three walls¹⁵. These findings combined with patient specific information like oral habits; dental and medical history can help us design optimal treatment plans. In fact, a model was created to predict caries risk in children based on their brushing habits, age, diet, weight etc where a total of 481 out of 745 children without a history of caries experience at baseline remained for analysis. During the follow-up exams, 66 (13.6%) children had new-onset caries. In three months, among children aged < 60 months, caries could be predicted by answering twelve nonbiological questions¹⁶. In another study, an AI-based model for the detection, classification, localisation and segmentation of enamel/molar incisor hypomineralisation has been created, which would help us predict and plan future dental appointments for children promptly¹⁷. In another application, AI model is used to predict primary and secondary caries. An accurate CNN-based automated system was developed to detect primary and secondary caries lesions on bitewings, highlighting a significant advancement in automated caries diagnostics¹⁸. Another application includes identifying distal caries in mandibular second molars associated with third molars. It was revealed that men, older patients, and patients having mesioangular, horizontal, and Pell and Gregory class A impactions are more likely to develop distal caries in mandibular second molars.¹⁹

Artificial intelligence in dental clinical procedures: Besides the diagnosis of dental caries, the most critical part of successful treatment lies in utilising appropriate clinical technique. Traditionally, dentists have relied on combination of their expertise, diagnostic tools, and machinery to address challenging cases. However, With

the integration of artificial intelligence (AI), significant advancements have been made in treatment accuracy, efficiency, and aesthetic results. A recent study developed a deep learning (DL)-based model to generate templates for personalised teeth defect restorations. It included corner, incisive and medium defects. The given DL model successfully reconstructed the morphology of anterior teeth with various degrees of defects and achieved satisfactory accuracy²⁰. An accurately designed access cavity plays an important role in determining the success of root canal treatment, by preventing procedural errors like inadequate biomechanical preparation or ledge formation. AI technology can assist in evaluating root morphology and locating root canal orifices with precision. In a study, the diagnostic performance of artificial intelligence (AI) in detecting root canal orifices was evaluated. Images were captured with a dental operating microscope. A total of 80 human maxillary first and second molars were included in the study. The system had correctly identified 502 out of 526 root canal orifices, yielding an accuracy of 91%²¹. Root Canal treatment of maxillary first molar poses additional challenge, particularly in identification and management of second mesiobuccal (MB2) Canal. Using cone beam, computed, tomography (CBCT) imaging, AI algorithm has demonstrated a notable performance in this area. In a study, segmentation of the second mesiobuccal canal (MB2) of maxillary first molar teeth on cone beam computed tomography (CBCT) scans was done. CBCT scans of 37 patients were imported into 3D slicer software to crop and segment the canals of the mesiobuccal (MB) root of the maxillary first molar. F1 score, testing accuracy, recall and precision values were 0.93, 0.87, 1.0 and 0.87 respectively, it was seen that MB2 in the maxillary first molar could be precisely

detected and segmented via the developed AI algorithm in CBCT images.²²

Choice of ideal restoration and prosthesis

A wide range of restorative materials are available for treatment ranging from glass ionomer cement to ceramic composites. The choice of material, the brand and other factors like bulk fill and composition, play an important role in determining the success of restoration. Integrating artificial intelligence into dental material selection can enhance treatment outcomes and clinical precision. In a study, three distinct types of composite fillings were compared where, each tooth was scanned at cavity preparation, after cavity filling, and after light-curing. Both low-shrinkage composites showed less volumetric polymerisation contraction than the regular composite. AI shown promising results in dental laboratory setting²², In a study on fabrication of casting metal substructures, a CAD-CAM system was used for the design of simulation models for casting metal substructures of metal-ceramic restorations using software tools²³. Another area of advancement is shade matching in teeth bleaching. Using artificial intelligence models, it is possible to estimate the ideal shade post bleaching. In one study AI model received the tooth shade based on the Vita classical shade guide as an input. The model converted the tooth Vita shade to CIELab (L*: lightness, a*: redness-greenness, and b*: yellowness-blueness) values to the accurate Vita shade as an output. Additionally, in the field of CAD/CAM fabricated prosthesis and veneers, a study used machine learning regression models in predicting the final colour of leucite-reinforced glass CAD/CAM ceramic veneer restorations. Different substrates, ceramic shades, and thicknesses influenced the L, a, and b of the final restoration, of all variables, the substrate influenced the final ceramic shade most, followed by the thickness of ceramic and the dimensions L, a, and b of the ceramic.

The regression model had the lowest mean absolute error and the highest accuracy. In another study, a computer aided colour matching (CCM) system showed acceptable colour differences when matching the colours of natural teeth and zirconia-based restorations. Also, back propagation neural network-based CCM model demonstrated superior shade reproduction outcomes compared with visual shade selection methods while providing a desirable accuracy with colour differences less than the thresholds.²⁴

Determination of required maintenance and recalls

Dental treatments require continuous care and regulated follow ups to ensure long term success. For instance, patients with high caries risk would require frequent recall visits. AI based models can effectively identify the needs of patients and estimate probable outcomes. A study was conducted involving Impedance spectroscopy, a measurement technique based on the measurement of electrical impedance over a range of frequencies, which can be employed to measure changes in the electrical conductivity of dental tissues associated with the demineralisation process. This study highlighted the feasibility of using impedance spectroscopy to distinguish between healthy and demineralised teeth. The particular integration of AI with tooth impedance spectra could be the future of predicting caries²⁵. Another study was conducted utilising raw metagenomics and full-length 16 S rRNA gene sequencing data from previous studies on saliva and plaque to construct a caries AI training dataset. The caries diagnostic model achieved a maximum accuracy of 100% for children under 6 years old in both saliva and plaque groups. Remarkably the model provided reliable diagnostic models for early childhood caries and set up a robust computational framework for AI-driven microbiome analysis.²⁶

Machine learning can particularly be useful for tele consultations and identifying primordial and prevalent caries. In a study published in 2026, A dataset consisting of 3,221 photographs was created and labeled based on the International Caries Detection and Assessment System with the help of Roboflow software. model in the HI Bogi app precision was 72.6%, and recall was 41.1% Detection of caries (D1-D6) was observed to have a sensitivity ranged from 82.31% to 96.45% and specificity ranged from 77.10% to 99.33%, showed diagnostic performance equal to dentists and a drastically shortened examination time, validating its use in school-based dental health programs.²⁷

Similarly, for a study, identification of the high-risk group for root caries was conducted using unsupervised machine learning and to explore the associated factors. The model was successful in predicting root caries, with an accuracy of 0.81, sensitivity of 0.79, and specificity of 0.83. It was revealed that Individuals who are older, female, with poorer oral and systemic health status, suboptimal oral hygiene behaviours, and lower oral health knowledge levels are more likely to be identified as high-risk group.²⁸

Furthermore, AI has proven its effectiveness in determination of consecutive tooth wearing. For instance, a study was developed to evaluate a fully automated method for visualizing and measuring tooth wear progression using pairs of intraoral scans at a duration of 1 year, 3 and 5 years respectively. The study showed quicker diagnosis and measurement of tooth wear and decreased the time required to less than two minutes compared with the manual approach, which took at least two hours.²⁹

Conclusion

Artificial intelligence (AI) is continuously transforming the landscape of modern dentistry, introducing new

possibilities for enhancing diagnostic accuracy, treatment planning and overall patient care. The integration of AI systems in dental practice has helped clinicians to analyse complex data, identify subtle patterns in diagnostic imaging and help them in making evidence-based decisions with improved efficiency and consistency. From restorative and endodontics to prosthetic procedures, AI applications are being used to support a wide range of clinical procedures, including radiographic, interpretation, caries detection, treatment planning, and digital smile design. These tools not only complement the expertise of dental professionals but also reduce workload, minimise human error and improve the outcomes. However, despite these advancements, AI currently functions as an adjunctive technology rather than a replacement for human expertise. The human element of ethical decision-making and experiential understanding cannot be replaced. The widespread inclusion of AI in dentistry should be done carefully considering the legal, ethical and methodological challenges. Issues related to data privacy and transparency with clinical accountability must be addressed to ensure that AI integration is safe and beneficial to patients and dental practitioners. Constant research has continued to refine the algorithms, making them more explainable and adaptive. As these technologies evolve, they will unlock the potential to revolutionise preventive dentistry and personalise treatment planning and patient monitoring. The collaboration between dental professionals, data scientists, and policymakers will be a key component in implementing this transformation. Eventually, with responsible decision-making and continuous innovation, AI will be able to raise the standards of dental practice, enhance patient outcomes, and contribute to the overall advancement of the dental profession.

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