Application of Deep Convolutional Neural Network in Dentistry and Endodontics

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Abstract

The advancement of artificial intelligence (AI) has significantly influenced various aspects of everyday life, particularly through enhanced capabilities to analyze data that support informed decision-making. In the health care sector, AI is rapidly evolving and holds immense potential, with dentistry being one of its most promising areas of application. Key areas where AI is being integrated into dental practice include patient management, diagnosis, treatment planning, and administrative operations. As this technology becomes increasingly prevalent, it is essential for dental professionals to develop a foundational understanding of its capabilities and future implications. In the field of endodontics, AI technologies—particularly convolutional neural networks and artificial neural networks—have shown effectiveness in tasks such as analyzing root canal anatomy, predicting the viability of dental pulp stem cells, estimating working lengths, detecting root fractures and periapical lesions, and forecasting outcomes of retreatment procedures. Furthermore, AI holds significant potential in streamlining patient scheduling, identifying drug interactions, providing prognostic evaluations, and facilitating robotic-assisted endodontic procedures. Owing to its high level of accuracy and reliability in diagnosis, assessment, and prediction, AI is poised to transform endodontic practice by enhancing diagnostic accuracy and optimizing treatment outcomes.

Keywords
- artificial intelligence
- deep learning
- dentistry
- endodontics
- machine learning

Introduction

John McCarthy was the pioneer who introduced the term “artificial intelligence” (AI), referring to machines capable of replicating human cognition and behavior.[1] This intelligent behavior can be achieved through a series of interconnected algorithms. With advancements in computing technology, AI systems are now able to handle vast datasets, interpret human behavior computationally, and facilitate interactions between individuals.[2–4]

In recent times, AI has attracted widespread attention and has begun transforming industries across the globe.[5] Its impact is particularly notable in health care, where it can automate time-consuming tasks, enhance the quality and safety of patient care, and reduce the burden on medical professionals and institutions.[4,5] AI, a specialized area within computer science, is focused on the development and understanding of intelligent systems, often implemented as software. These systems operate through a sequence of processes aimed at completing defined objectives.[6] Traditionally, AI

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applications relied on rule-based approaches, where systems were manually engineered and tailored by experts to solve specific problems using domain knowledge.[7] For example, a diagnostic tool designed to detect abnormalities in medical images might be programmed to identify masses based on irregular shapes and color variations, with adjustable parameters such as tissue color ranges or lesion dimensions.

Currently, the most prevalent branches of AI in the medical field are machine learning (ML) and deep learning (DL), which enable systems to learn from data and improve over time (►**Fig. 1**).[8]

Artificial Intelligence

British mathematician and visionary Alan Turing introduced the Turing Test to evaluate whether a machine could imitate human problem-solving and reasoning capabilities.[1] The term "artificial intelligence" was later coined by John McCarthy in 1956. AI is broadly defined as a scientific and engineering discipline aimed at designing systems or tools that exhibit behavior considered intelligent, achieved through computational models.[7]

AI refers to the design and development of computer systems capable of performing functions typically associated with human intelligence—such as perception, language comprehension, learning, reasoning, planning, and problem-solving.[9] In the context of health care, the current focus is primarily on "narrow AI," which refers to systems built to execute specific tasks that still require a degree of human-like intelligence.[4,10] However, these narrow AI systems do not encompass the complex cognitive abilities required for comprehensive decision-making, such as integrating patient values, clinician expertise, and diverse data sources. They lack true consciousness, self-awareness, or the broader cognitive scope necessary to rival human intellect.[11]

A principle in informatics suggests that collaboration between a human and a computer can outperform the human alone—an idea that also holds true for AI, which is increasingly viewed as a tool to enhance, rather than replace, human intelligence (►**Figs. 2** and **3**).[12,13]

ML, a key subset of AI, enables computers to identify patterns within data without those patterns being explicitly programmed by humans.[14] This field encompasses a variety of methods to extract statistical trends and structures from datasets. The major learning approaches are outlined below.

Supervised Learning

This is the most widely used approach in ML. In supervised learning, algorithms are trained using labeled datasets where the desired output is known. For example, a system trained on images tagged as "dog" learns to detect dogs in new, unlabeled images by recognizing similar features. This process requires substantial effort in labeling, especially in fields like medicine, where expert supervision and resources are necessary to create accurate labels.[13]

Unsupervised Learning

Unlike supervised learning, unsupervised learning does not rely on labeled outputs. Instead, it aims to identify patterns, groupings, or relationships within the data itself. The algorithm processes unlabeled data to discover underlying structures. Common applications include e-commerce recommendation systems that suggest products often purchased together and the classification of genetic sequences to explore evolutionary relationships.[13]

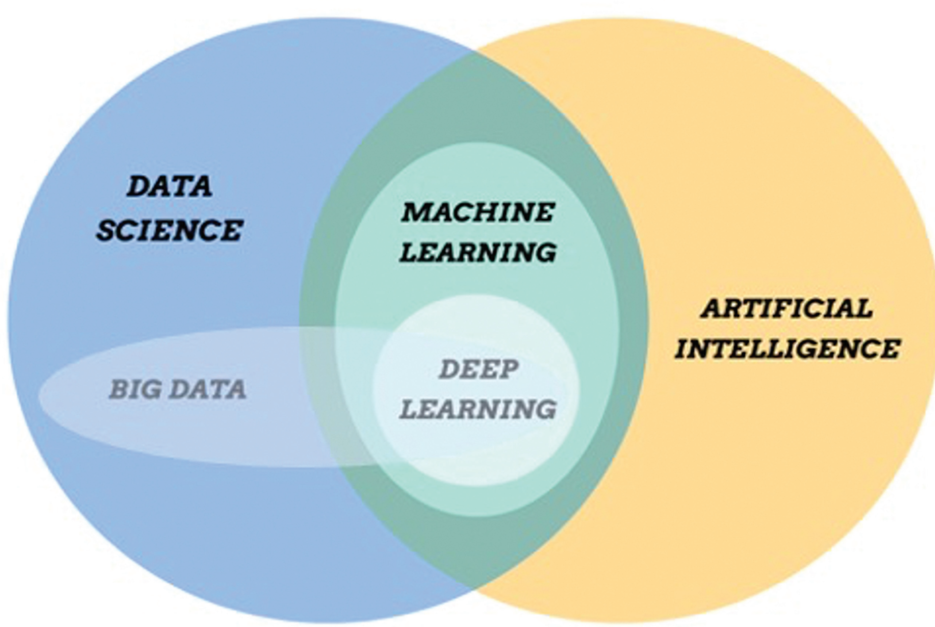

Fig. 1 The fundamental components of AI systems. AI, artificial intelligence.

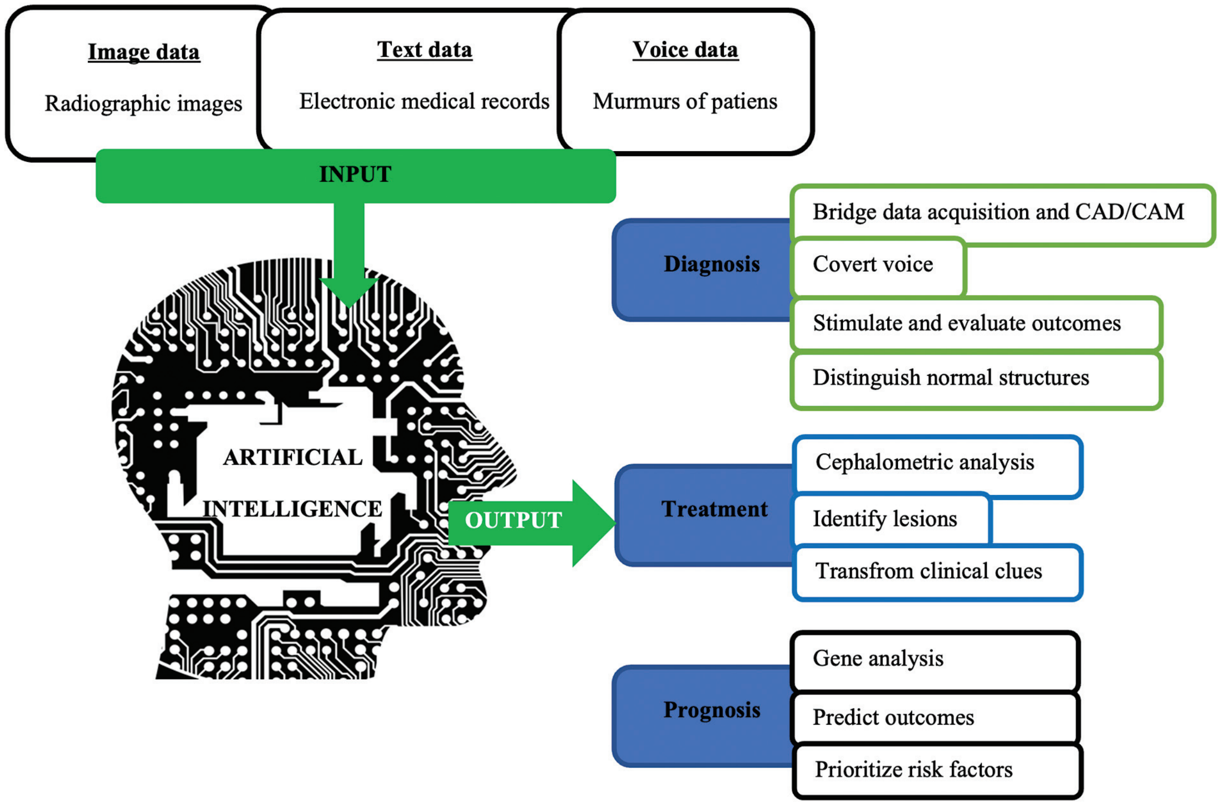

Fig. 2 Artificial intelligence system application.

Common Terminology in Artificial Intelligence

Machine Learning

ML is a subset of AI that enables algorithms to perform specific tasks by detecting patterns within data, rather than being explicitly programmed to do so.[8] The implementation of ML techniques often requires fine-tuning of key parameters, which vary depending on the method. For example, neural networks may require adjustments to the number of layers, neurons, or training iterations (epochs), while fuzzy logic systems need selection of membership functions. Genetic algorithms involve choices like population size, mutation and crossover rates, and selection strategies. Hybrid models combining elements like fuzzy logic and neural networks also follow similar optimization principles.

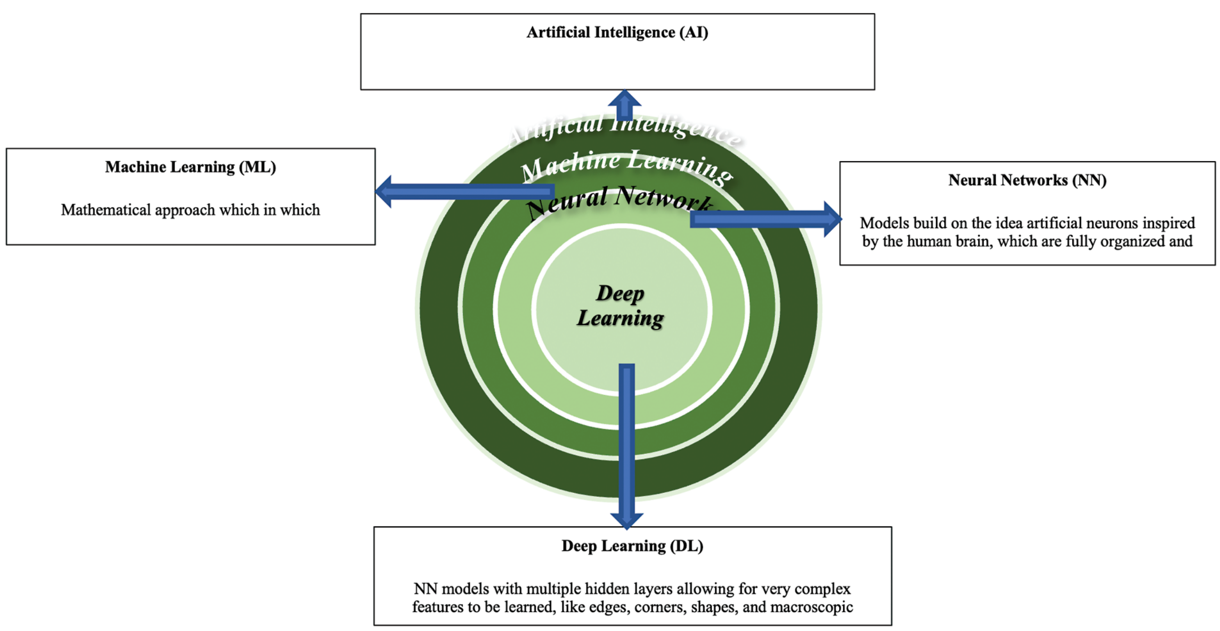

Fig. 3 Hierarchy of AI. AI, artificial intelligence.

Several ML models, including support vector machines, genetic algorithms, and artificial neural networks (ANN), are capable of learning from existing data to perform a variety of tasks.[15]

Rather than relying on hand-coded instructions, ML systems learn by identifying trends and structures in large datasets. A specific objective is set, and the algorithm refines its internal settings over time to achieve this goal more effectively. This process—called training—relies on feeding the system numerous data examples and gradually adjusting its internal parameters toward the correct outcome. It is similar to how a child learns to recognize a cat by viewing many images; over time, the child internalizes the features that define a cat and can identify it in new pictures.[16]

Deep Learning

DL, a specialized form of ML, utilizes ANNs with multiple layers to process data in a hierarchical manner.[1,4,17–19] The primary distinction between traditional neural networks and DL lies in their structural complexity—DL systems incorporate more layers and neurons, employ automatic feature extraction, and demand greater computational resources during training. These models can recognize basic image components such as lines and textures, as well as more advanced features like lesions or anatomical structures.[20]

Unlike shallow models that detect simple patterns, DL builds multiple layers of representation, allowing for the recognition of increasingly complex structures. For instance, a child learning to identify a cat might first observe edges, then group those into features like eyes or ears, and finally understand the complete form of the animal by integrating all observed elements.[18]

ANNs, a core component of DL, consist of interconnected processing units called neurons, organized into an input layer, multiple hidden layers, and an output layer. Networks with only a few hidden layers are referred to as shallow, while those with many are called deep neural networks.[8,21–23] These hidden layers extract and transform input data to produce accurate outputs. The structure of a neural network is defined by how neurons are connected, and the strength of these connections—known as weights—can be adjusted during training to optimize performance.[24]

A particularly prominent ANN architecture in health care is the convolutional neural network (CNN), which is designed to process structured grid data such as images. CNNs use a sliding filter to scan across the input, analyzing one region at a time, making them ideal for tasks like image classification and medical imaging.[16]

Artificial Neural Networks

ANNs are computational models inspired by the human brain's network of neurons. The concept dates back to 1943, when McCulloch and Pitts developed the first artificial neuron using binary threshold functions. A major milestone followed in 1958 with Frank Rosenblatt's development of the Perceptron, a multilayer feed-forward neural model.[4,10,18] Another breakthrough occurred in 1974, when Paul Werbos introduced the backpropagation algorithm, enabling networks to learn by adjusting their weights based on errors.[3]

ANNs are made up of numerous interconnected units—neurons—arranged in layered structures comprising an input layer, one or more hidden layers, and an output layer. Except for the input nodes, each neuron processes multiple inputs weighted differently and produces a nonlinear output. Through repeated adjustments of these weights during training, the network learns how to map inputs to outputs. ANNs are particularly suited for health care applications due to their ability to handle imprecise data, model complex nonlinear relationships, generalize from past examples, and manage ambiguous information. As such, they are widely applied in clinical diagnostics, image interpretation in radiology and pathology, intensive care unit data analysis, and waveform monitoring.[22,25,26]

Recent Advances in Neural Networks

Two notable advancements in ANNs—CNNs for tackling image recognition tasks and dilated CNNs (DCNNs) for semantic scene segmentation—have garnered considerable attention in recent years. In volumetric prediction, DCNNs and Tiramisu-based models represent two leading CNN architectures. Tiramisu-derived networks, such as U-net, demonstrate strong capabilities in predicting dose distributions that closely align with anatomical structures—for instance, estimating radiation doses to the prostate. In contrast, DCNNs utilize a type of convolution that omits certain data during the encoding process, enabling a broader receptive field. This makes them particularly effective for scenarios where the dose distribution may shift relative to anatomy, such as in head and neck cancer cases. These evolving approaches are expected to be increasingly applied in volumetric dose prediction for intensity-modulated radiation therapy in the head and neck region.[27]

Clinical Decision Support Systems

A clinical decision support system (CDSS) is a computerized tool designed to aid health care professionals by processing clinical data and medical knowledge to enhance decision-making.[1,9,12,25] Most CDSSs are built around four essential components: the inference engine (IE), knowledge base (KB), explanation module (EM), and working memory (WM). The IE plays a central role by analyzing patient-specific data to draw medical conclusions. The KB comprises the information and resources required for the IE to function effectively. WM holds the patient data, either as stored records or real-time input. When the IE uses the KB to interpret the WM data, the EM—if present—provides reasoning for the conclusions made.[26] However, some CDSS implementations may lack an explanation module.

Clinical Applications of AI in Dentistry

Rapid advancements in technology are transforming the dental field, especially in diagnostic and therapeutic areas. In modern dental radiology, AI and neural network-based systems are increasingly used to enhance diagnosis speed, facilitate treatment planning, and improve prognostic evaluations. Beyond radiology, neural networks are also finding

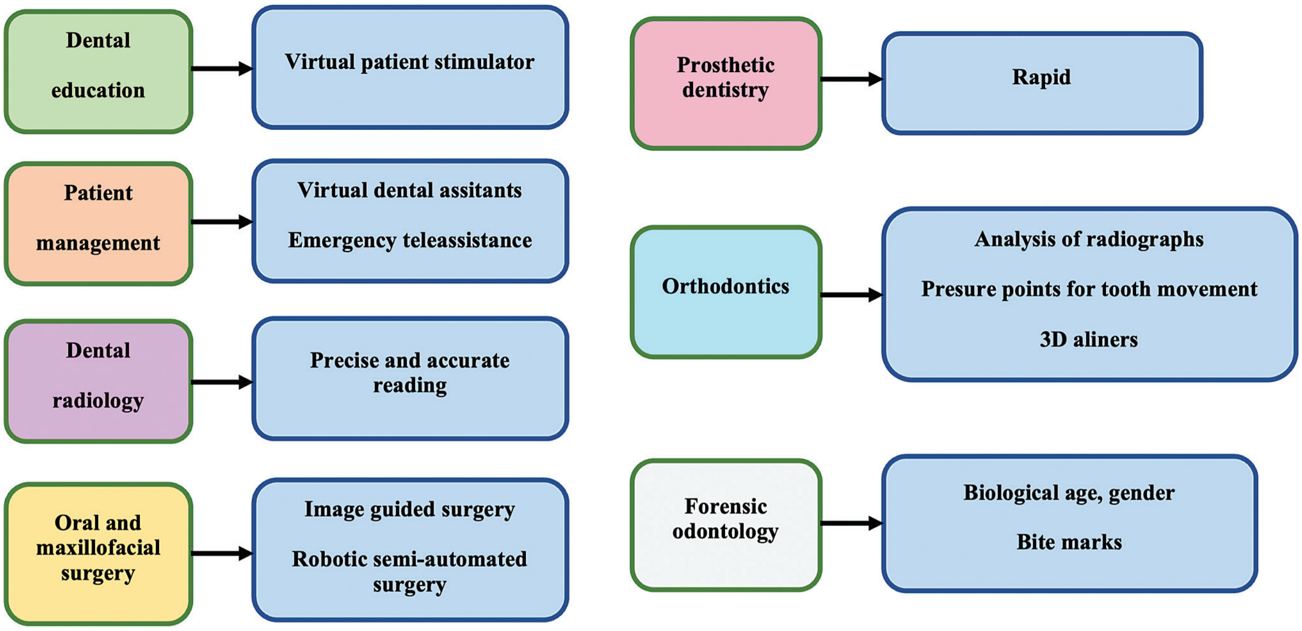

Fig. 4 Artificial intelligence applications in dentistry.

applications in diverse dental disciplines such as genetics, psychology, and microbiology. Among these, ANNs and CNNs are the most commonly adopted models (►**Fig. 4**).[18]

Radiology

CNNs have demonstrated notable capabilities in recognizing and analyzing anatomical features. For instance, some CNN models have been specifically trained to identify and classify teeth using periapical radiographs. These models have achieved precision rates between 95.8 and 99.45%, which is nearly equivalent to that of experienced clinicians, who exhibit a precision of 99.98%.[28–34]

CNNs have also proven effective in the detection and diagnosis of dental caries. One deep CNN model evaluated 3,000 periapical radiographs of posterior teeth and demonstrated an accuracy of 75.5 to 93.3%, with sensitivity ranging from 74.5 to 97.1%. These figures mark a significant improvement over traditional diagnostic methods, where sensitivity based solely on radiographic interpretation by clinicians can range from 19 to 94%. Given their speed and enhanced diagnostic sensitivity, deep CNNs are currently among the most powerful tools available for detecting carious lesions.[21]

AI is increasingly being integrated into dental image analysis, particularly in enhancing interpretations of two-dimensional (2D) radiographic images. Digital radiographs are made up of numerous pixels, each representing varying levels of brightness.[4,5] Pixels that show radiopacity often correspond to metallic objects or other high-density structures. AI systems can be trained to interpret these pixel patterns by learning from such features.[1,4–8,13,19] For

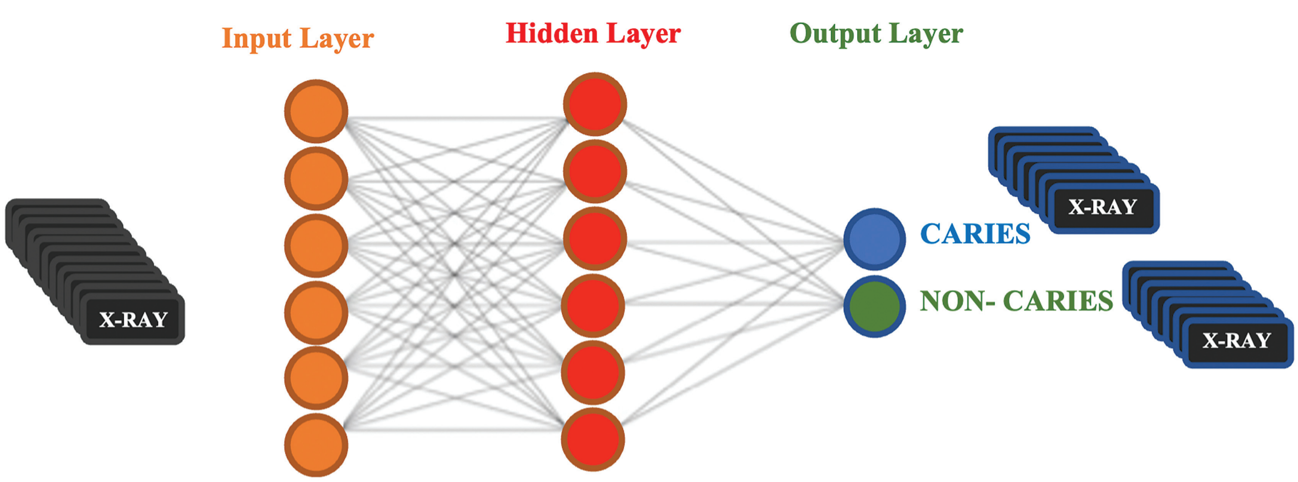

Fig. 5 An example of deep learning with the application of detecting caries using radiographs. The radiographs will be imported to the software as the input layer. Through multiple "hidden layers," the algorithms will classify imported radiographs as "caries" or "noncaries" based on the AI training. AI, artificial intelligence.

example, algorithms use input, hidden, and output layers to process digital radiographs, enabling the detection of caries as illustrated in ►**Fig. 5**.[5]

Orthodontics

ANNs present considerable promise in enhancing clinical decision-making. Careful planning is essential in orthodontic treatments to ensure consistent outcomes, particularly when the treatment plan includes potential tooth extractions. Making informed decisions before initiating irreversible procedures is critical. In cases of malocclusion, ANNs can assist in determining whether extractions are needed prior to orthodontic intervention. Four ANNs developed for this purpose achieved an accuracy rate of 80 to 93% in predicting extraction needs, utilizing various clinical parameters.[23,33–36]

Periodontics

According to the 1999 classification by the American Academy of Periodontology, periodontitis can be categorized into aggressive (AgP) and chronic (CP) forms. However, distinguishing between them remains challenging, as no single diagnostic method—whether clinical, microbial, histologic, or genetic—can conclusively differentiate them.[1,12,14,21,27,30] Papantonopoulos and colleagues employed ANNs using immunological markers such as leukocyte counts, interleukin levels, and immunoglobulin G titers to successfully differentiate AgP from CP.[37] One model achieved 90 to 98% accuracy, with another model using inputs like monocytes, eosinophils, neutrophils, and the CD4+/CD8+ T cell ratio offering the most reliable predictions. These findings suggest that ANNs can accurately diagnose AgP or CP using accessible data like peripheral blood leukocyte levels.[4,5]

Various surgical and nonsurgical interventions have been developed to manage periodontally compromised teeth (PCT).[27,38,39] Despite these advancements, methods for assessing prognosis and diagnosis have seen limited progress, often relying on clinician experience. A study by Lee et al evaluated the application of deep CNNs in diagnosing and predicting the prognosis of PCT.[27] The CNN model demonstrated a diagnostic accuracy between 76.7 and 81.0% and predicted extraction requirements with an accuracy of 73.4 to 82.8%. Premolars, being anatomically simpler with single roots, had higher diagnostic accuracy compared with molars.[11,21,22]

Oral Pathology

Early and accurate diagnosis of oral lesions is essential, particularly when lesions are potentially malignant or cancerous. CNNs have proven beneficial in identifying such lesions in clinical and radiographic images, with reported specificity and accuracy between 78 to 81.8% and 80 to 83.3%, respectively—values close to those achieved by specialists.[34,36–41]

In another study, a CNN was trained to distinguish between ameloblastomas and odontogenic keratocystic tumors—two maxillary tumors with similar radiographic features but different clinical behavior. The CNN achieved a diagnostic accuracy of 83.3% and a specificity of 81.8%, comparable to specialists' results of 83.2 and 81.1%. The diagnostic time was significantly shorter, with the CNN taking only 38 seconds compared with 23.1 minutes by human experts.[29]

Oral and Maxillofacial Surgery

AI has made significant strides in oral surgery, especially with the development of robotic-assisted procedures that emulate human movement and decision-making.[4] Techniques involving image-guided surgery are being applied in temporomandibular joint operations, implant placement, tumor resections, and biopsies. These AI-enhanced methods have shown improved precision over traditional approaches, with no major performance differences between experienced and novice surgeons. Benefits include reduced surgical time, enhanced accuracy, and safer manipulation around delicate anatomical areas. Surgical planning is now more comprehensive, decreasing the likelihood of repeat interventions. Robotic systems currently enable semi-autonomous procedures under expert supervision.[8,10,13,14,24,42,43]

Prosthetic Dentistry

RaPid, an intelligent design assistant for prosthodontics, integrates various factors—including anthropometric data, facial ratios, ethnicity, and personal preferences—to optimize aesthetic outcomes. This system uses logic-based modeling to link knowledge bases, databases, and computer-aided design platforms. Neural networks have enabled dental laboratories to automate the creation of prosthetics that meet high standards for aesthetics, functionality, and fit. These technologies are also making waves in orofacial and craniofacial prosthetics.[4,6,8,10,14,42]

Forensic Odontology

AI technologies are increasingly used in forensic dentistry to estimate biological age and gender and analyze bite marks and mandibular contours.[2,4,5,10,44] Notably, dental chairs—essential equipment in every dental office—have evolved significantly. From manually operated hydraulic models, the latest versions now include sensor-equipped, voice-activated systems. These intelligent chairs can monitor vital signs, track procedure duration, assess patient anxiety levels, and provide alerts in response to abnormalities—all managed via voice commands.[1,12,44] Furthermore, "bioprinting" is emerging as a revolutionary AI application. It allows for the layer-by-layer fabrication of living tissues and may one day be used to reconstruct damaged oral structures.[4,5]

Endodontics

Mandibular molars typically share similar root canal anatomies, though exceptions exist.[38] While cone-beam computed tomography (CBCT) has become a key tool in diagnosing these anatomical variations, its use is limited due to higher radiation exposure compared with conventional imaging. To mitigate this, AI—particularly CNNs—has been applied to assess whether additional canals are present in the distal roots of mandibular first molars. A study analyzed CBCT images from 760 molars.[30] After detecting atypical features,

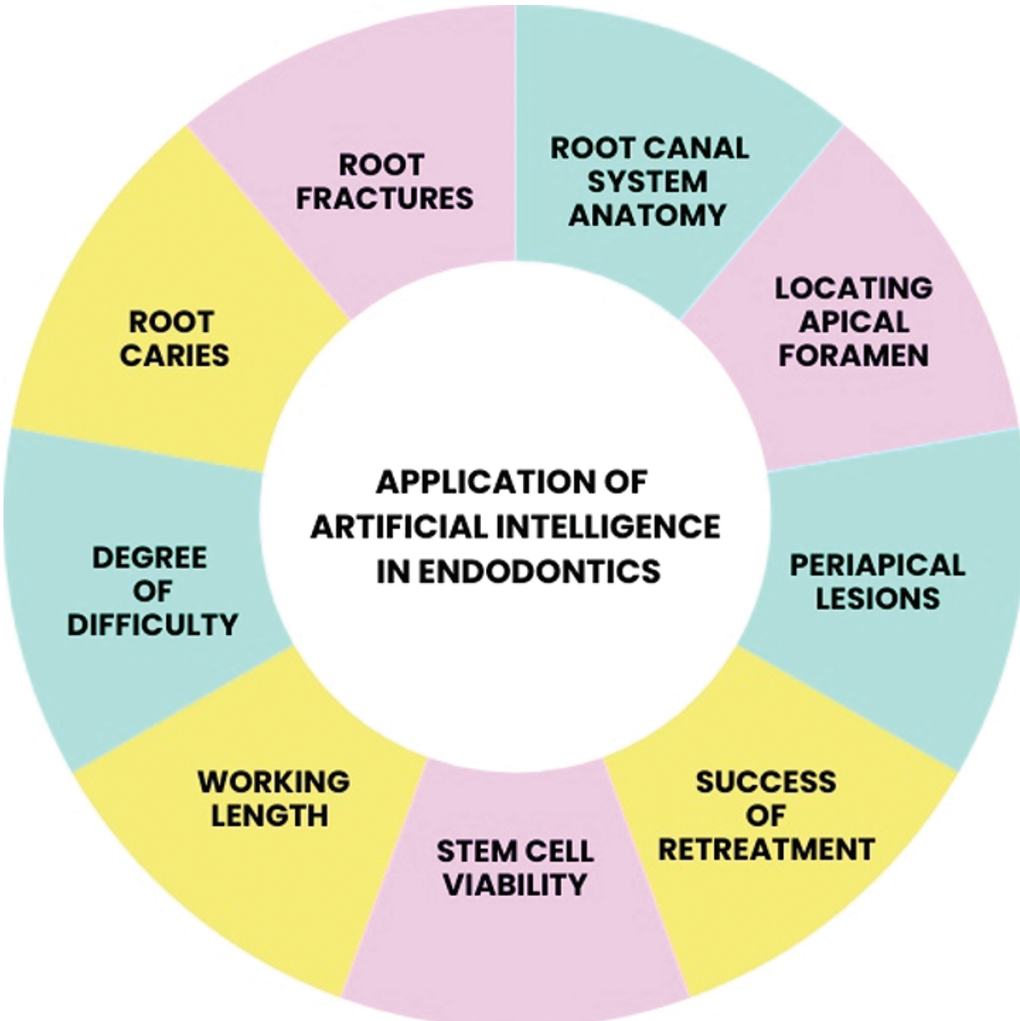

Fig. 6 Artificial intelligence applications in endodontics.

image patches were processed by a DL system that classified canal morphologies.[3,17,45,46]

Although CNNs achieved an accuracy of 86.9%, several limitations remain. Image segmentation must be done manually, and the input data must be optimized for size, focus, and coverage to ensure effective learning.[2,4,10] AI's relevance in endodontics continues to grow, particularly in diagnosis and treatment planning. These systems can detect extremely subtle image variations—down to a single pixel—that human observers might miss.[34] ►**Fig. 6** illustrates a range of endodontic applications where AI is making a significant impact.[2,4,10]

Detection of Periapical Lesions

Diagnosing and planning treatment for teeth affected by periapical lesions or related symptoms can be difficult for dental practitioners.[47–50] Apical periodontitis is one of the most common conditions, accounting for approximately 75% of radiolucent jaw lesions.[4] Timely identification of this condition can enhance treatment success, limit its spread to adjacent structures, and reduce long-term complications. Among the most commonly used diagnostic tools in everyday dental practice for detecting apical periodontitis are intraoral periapical (IOPA) and orthopantomogram radiographs. Periapical lesions typically appear as radiolucent areas in radiographs.[4] However, as 2D images flatten the complex three-dimensional (3D) anatomy of dental structures, this can result in diagnostic inaccuracies. CBCT was introduced to provide a more accurate 3D evaluation of periapical lesion location and extent. A meta-analysis revealed diagnostic accuracy rates of 0.96 for CBCT, 0.73 for conventional IOPA, and 0.72 for digital IOPA. Notably, CBCT demonstrated reduced accuracy in detecting apical periodontitis in endodontically treated teeth.[1,3,4,17,29,45]

AI algorithms can assist in identifying periapical pathologies by leveraging features such as radiolucent areas and alveolar bone loss. Lin et al developed two AI models—one to detect alveolar bone loss and another to quantify its severity.[51,52] Similarly, Lee et al designed a DL-based neural network to identify compromised molars and premolars, including those deemed nonrestorable due to bone loss.[53] Other studies by Mol and van der Stelt and Carmody et al focused on classifying the severity of periapical lesions.[25,54] Endres et al reported that a DL model could detect periapical radiolucencies with performance comparable to that of 24 oral and maxillofacial surgeons.[32] Another study found that AI systems correctly identified 142 out of 153 lesions, yielding a 92.8% detection accuracy.[55] ANNs have also been explored for differentiating cystic lesions. Okada et al proposed a method using CBCT images to distinguish between periapical granulomas and cysts—a critical clinical distinction since granulomas often heal nonsurgically following root canal therapy.[5,20,30,56–58]

Detection of Root Fractures

Vertical root fractures (VRFs), accounting for 2 to 5% of crown/root fractures, often necessitate root resection or extraction.[4] Accurate detection is challenging, usually relying on CBCT and conventional radiographs. A delayed diagnosis may lead to unnecessary interventions. The limitations of traditional radiographs—especially their low sensitivity—make it difficult for clinicians to confidently diagnose VRFs.[4,5,28–31,34]

Fukuda et al demonstrated that CNNs can effectively identify VRFs on panoramic radiographs.[59] Another approach combined CBCT and periapical radiographs with a neural network to detect fractures in both untreated and root-filled teeth. The findings revealed that CBCT provided better specificity, sensitivity, and accuracy than 2D imaging. Shah et al simulated second molar fractures and applied wavelet analysis to enhance fracture detection using artificial datasets.[60] Despite a limited sample size, steerable wavelets helped accurately detect fractures in high-resolution CBCT images.[24]

Determining Working Length

Accurate determination of working length is vital for successful root canal procedures. Among several techniques, radiography is most commonly employed.[1,4,5] Other approaches include CBCT, electronic apex locators, tactile feedback, and patient sensitivity to instrumentation. Of these, radiographs and apex locators are most frequently used in practice. However, radiographic accuracy can be affected by several variables, potentially leading to diagnostic errors. Thus, AI-based tools have been introduced to improve measurement reliability. Saghiri et al reported that ANNs used alongside radiographs could enhance the accuracy of locating the apical foramen.[61] In another investigation simulating clinical conditions using cadaver models, the same team found that ANNs matched actual post-extraction measurements with high accuracy.[62] Their study showed that ANN's performance (96%) exceeded that of experienced endodontists (76%) when using periapical radiographs to detect minor anatomical constrictions.[61,62] Hence, ANNs offer a dependable alternative for working length determination.[1,12,46]

Root and Root Canal Morphology

Successful nonsurgical root canal treatment depends on recognizing variations in root and canal anatomy.[63] This is typically achieved using periapical radiographs or CBCT, with CBCT providing more precise anatomical details. However, due to radiation concerns, CBCT is not routinely recommended.[40] Hiraiwa et al demonstrated that DL algorithms could identify radix entomolaris—an extra distal root of mandibular molars—on panoramic radiographs.[56] Lahoud et al employed CNNs to achieve automated 3D tooth segmentation.[64] Their evaluation of 433 CBCT segmentations confirmed that AI not only outperformed human evaluators but also operated much more efficiently.[21,22]

Retreatment Prognosis

Campo et al developed a case-based reasoning model to forecast the outcomes of nonsurgical root canal retreatments by weighing potential risks and benefits.[65] This system incorporated recall data, clinical outcomes, and probability statistics to advise on whether retreatment was warranted. One of the system's major strengths lies in its ability to make data-driven predictions. However, its accuracy depends entirely on the quality and completeness of its training data. As case-based reasoning relies on previous similar experiences, variability in clinical approaches can affect outcomes. To improve accuracy, future models should incorporate larger and more diverse datasets.[53]

Predicting Stem Cell Viability

Bindal et al evaluated the viability of dental pulp stem cells used in regenerative procedures by applying a neuro-fuzzy inference system.[65,66] This AI-based method predicted stem cell survival after bacterial lipopolysaccharide exposure, simulating a real-world inflammatory environment. The neuro-fuzzy inference model proved effective at forecasting outcomes during regenerative therapies potentially affected by microbial invasion. Following inflammatory stimulation, stem cells were analyzed for viability, and the AI system accurately predicted survival outcomes.[1,10,18,66]

The Role of AI in Dentistry: Human versus Machine

While AI is anticipated to revolutionize many aspects of dental practice, complete replacement of dentists remains unlikely.[67] Clinical dentistry relies not just on technical skill but also on human intuition, empathy, and professionalism—qualities that machines cannot replicate. Personalized care and patient interactions are integral to successful outcomes and cannot be translated into algorithms.[19,25,40,68]

Even though AI tools have shown promising results, it is essential to validate their performance and generalizability using independent data from new patients or other dental institutions. Advancements in AI research aim not only to match expert-level performance but also to detect early-stage lesions that remain invisible to the human eye (►**Fig. 7**).[4]

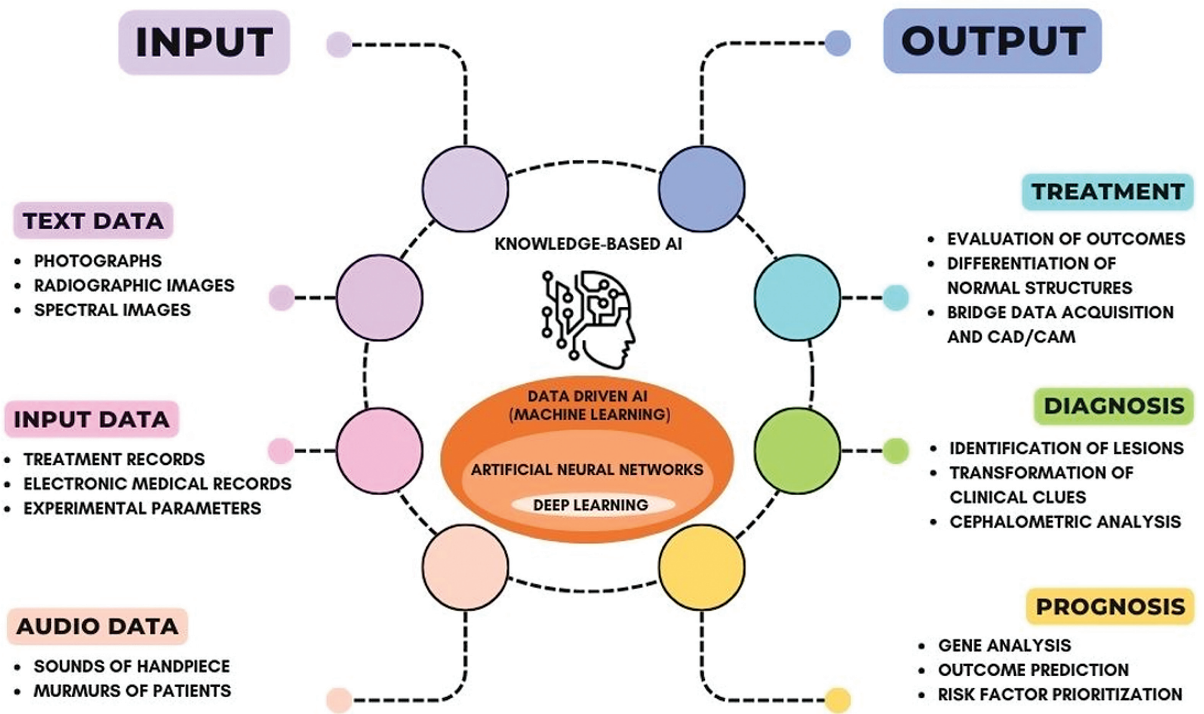

Fig. 7 Overview of the artificial intelligence (AI) hierarchy and its key dental applications. CAD/CAM, computer-aided design/computer-aided manufacturing.

Summary of Dental Applications of Artificial Intelligence

AI offers valuable support to dental professionals, enhancing their ability to provide optimal care. It serves as an adjunctive tool, improving the accuracy of diagnostics, treatment planning, and prognosis. DL systems, in particular, assist general practitioners by enhancing diagnostic efficiency. Furthermore, automated technologies can streamline routine clinical tasks, such as automatically recognizing teeth and numbering them to complete electronic dental records. The integration of such AI-based auxiliary views enhances diagnostic reliability and boosts clinical workflow efficiency.

Conclusion

The use of AI technologies in endodontics has grown significantly in recent years. Research indicates that neural networks can often surpass dental professionals in diagnostic accuracy and precision. In certain studies, AI models have even demonstrated superior performance compared with expert clinicians. These findings highlight the potential of AI systems to serve as a valuable resource for novice practitioners and nonspecialists, offering insights comparable to expert opinions.

AI should not be seen as a replacement but rather as a support mechanism that enhances a dentist's practical capabilities—helping to manage patient data, streamline tasks, and nurture professional relationships. While AI excels at processing structured data and extracting patterns from large datasets, it lacks the nuanced reasoning and complex decision-making abilities of the human brain. Especially in ambiguous clinical scenarios, the integration of medical history, aesthetic considerations, and hands-on examination relies heavily on the clinician's experience.

Moreover, strong patient–dentist communication—essential for successful treatment—relies on the dentist's ability to interpret nonverbal cues such as patients' expectations, concerns, and emotional states. Despite ongoing debates about the role of affective computing and whether empathy should be programmed into AI to mimic human emotions, it remains evident that certain elements of human interaction cannot be fully replicated by machines.

Authors' Contribution
D.D. and S.S. contributed to data acquisition, analysis, and interpretation and drafted the manuscript; D.D., S.S., contributed to conception and design and critically revised the manuscript. All authors gave final approval and agreed to be accountable for all aspects of the work.

Conflict of Interest
None declared.

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