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# Artificial Intelligence in Endodontics: Present Uses and Prospective Paths

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**Abstract: Artificial intelligence (AI) is a technology that mimics intelligent human behavior by using machines. In recent years, its popularity has grown all over the world. This is primarily due to its capacity to accelerate treatment planning processes, enhance patient outcomes, and improve the accuracy of the diagnosis. To enhance personalized learning, predictive analytics, and patient care plans, endodontic AI-based techniques have been essential in utilizing many models using Deep Learning (DL) and Machine Learning (ML). The purpose of the review was to discuss the current endodontic uses of AI as well as possible future paths.**

**In endodontics, AI models such as (e.g., convolutional neural networks and/or artificial neural networks) are used to study the anatomy of the root canal system, detect periapical lesions and root fractures, determine working length measurements, predict the viability of dental pulp stem cells, and determine the success of retreatment procedures. The future of this technology was discussed in terms of prognostic value diagnostics, drug interactions, scheduling, patient treatment, and robotically assisted endodontic surgery.**

**AI has the potential to be transparent, reproducible, unbiased, and easy to use with careful design and long-term clinical validation. More research is required to verify the cost-effectiveness, applicability, and reliability of AI models before they are routinely used in clinical practice.**

***Keywords**: Artificial Intelligence; Artificial Neural Networks; Convolutional Neural Networks; Endodontics*

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## I. INTRODUCTION

Artificial intelligence (AI) refers to the capacity of a comprehensive platform to gather, analyze, and utilize knowledge and abilities learned via training or expertise that are typically associated with human intelligence. AI is a general term that describes the use of computers and technology to perform tasks that are similar to those performed by humans. Many consider John McCarthy, a mathematician, to be the father of artificial intelligence because he coined the term in 1955. He used the phrase to describe the capability of machines to perform "intelligent" tasks.[1]

Over the years, computer technology has improved, as well as developments in specialized algorithms, machine learning (ML) and deep learning (DL), both subfields of artificial intelligence have become increasingly prevalent in recent years.

Machine learning is the branch of artificial intelligence that deals with developing algorithms that has the ability to learn from data and apply it to predictions or decisions. It employs a range of techniques, such as deep learning, and is used in several domains, including dental treatment planning, and analysis of patient data.

A subfield of machine learning called "deep learning" builds neural network models to learn from data in a way that is comparable to how the human brain does it. These networks are beneficial in fields like dental imaging analysis because they can interpret complicated data like sound as well as pictures. DL algorithms are superior to ML algorithms because they can learn from examples independently, without requiring human input from subject-matter specialists.[2]

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Artificial Intelligence has brought about a significant change in dentistry. Artificial intelligence (AI) applications use models like convolutional neural networks (CNN) and artificial neural networks (ANN) to carry out a variety of tasks in the dental field.[3]

The goal of endodontic therapy is to deliver exceptional care to preserve the tooth's functionality and avoid further problems. To deliver efficient endodontic treatment, the identification of root canal pathology, features, components, and treatment options of equipment have greatly enhanced in the last few years. In the field of endodontics, artificial intelligence has the potential to enhance a number of areas of treatment and diagnostic planning.[4]

➢ *Convolutional Neural Networks (CNN) and Artificial Neural Networks (ANN) are Two Examples*

In endodontics, artificial neural networks (ANN) and convolutional neural networks (CNN) are two types of AI models that are used to analyze the root canal system's anatomy, measure working length, identify periapical diseases and root fractures, predict the effectiveness of retreatment techniques, and determine how long the stem cells will remain in the dental pulp. (Fig. 1)

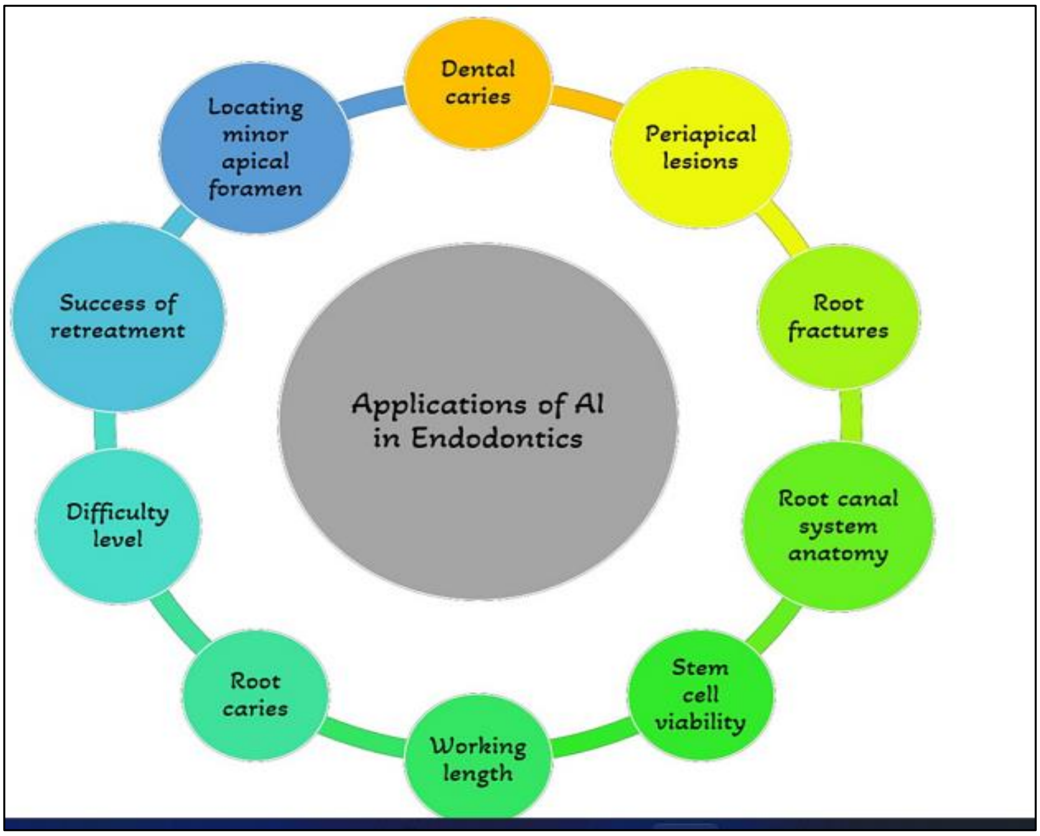


Fig 1. Application of AI in Endodontics

Therefore, identifying current gaps in the usage of AI is the goal of this review articleas well as to go over the literature on its uses in endodontics, including effective treatment prediction, clinical decision-making, and diagnostics.

## II. OVERVIEW OF NEURAL NETWORK ARCHITECTURES

### *A. Artificial Neural Networks (ANN)*

ANNs, also known as multi-layer perceptrons (MLPs), are computer models that are inspired by the structure and functions of the human brain. [5]

An ANN is composed of three primary layers: the input layer, hidden layers, and output layer. In the input layer, each neuron represents a different property of the input data. For example, each neuron may represent the intensity of a particular pixel in a grayscale dental radiography image. The hidden layers, situated between the input and output layers, process the data further. The width (number of neurons in a layer) and height (number of layers) of these hidden layers define the network's complexity and capabilities.[6]

The output layer completes the predictions made by the network. The task determines how many neurons are present. One neuron may be enough for binary classifications, such as identifying whether or not the tooth contains periapical lesions (Fig 2). But for increasingly complicated tasks, more layers are needed. For example, the authors of a study that predicted post-operative discomfort after root canal therapy used 13 input layers, 10 hidden levels, and 6 output layers. This allowed the model to comprehend the connection between various characteristics and the results.[7]

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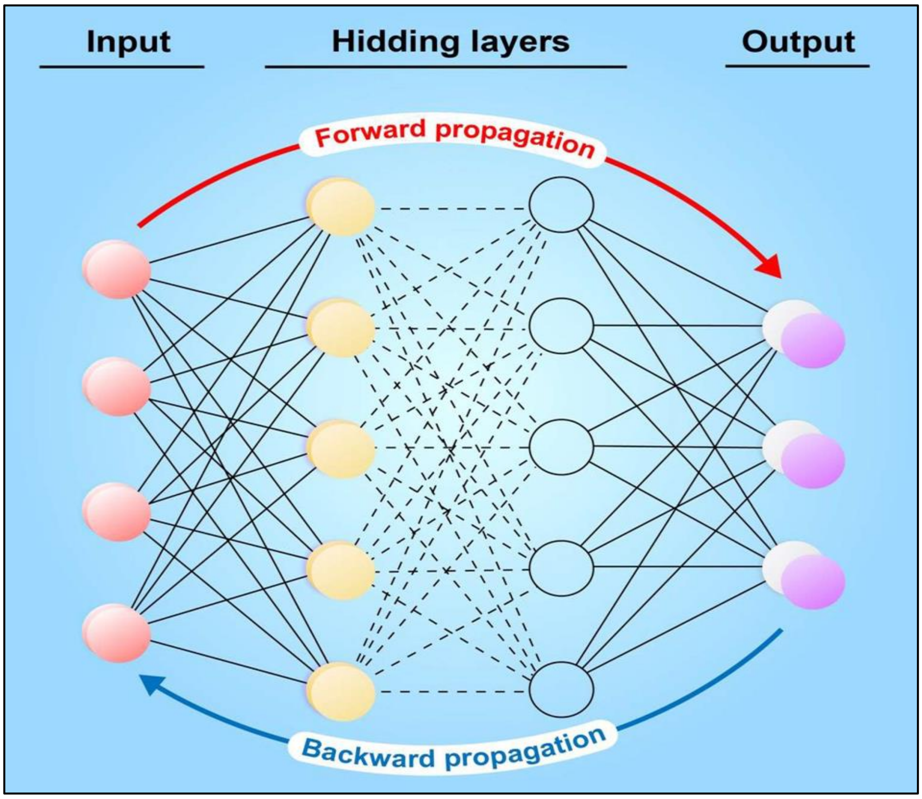


Fig 2. Artificial Neural Network

This diagram illustrates a neural network that goes through the “learning” process in two phases: The ‘Forward propagation ’shows data moving from the input, through hidden layers where processing occurs, to the output where the result is produced. After the output, the ‘Backward propagation’ occurs, where the network adjusts its settings to improve, based on the difference between the predicted and actual results. This cycle repeats, helping the network to improve its performance over time.

*B. Convolutional Neural Networks (CNN)*

CNN is a network created especially to analyze visual data, including images. CNNs and conventional ANNs differ primarily in their network architecture, which attempts to learn spatial hierarchies. from pictures in an automatic and flexible manner. Because it can understand visual data, including radiographic images, this design is quite popular in endodontic investigations.[8]

CNNs use specialized layers like pooling and convolutional layers to do this. Convolutional layers create feature maps by having small, learnable filters "convolve" or glide around the input image (Fig 3). These filters are made to recognize and extract particular characteristics, such colors, textures, or edges. These filters are able to identify more intricate patterns as the network gets deeper .[9]

High-level reasoning in the neural network takes place in the fully connected layers following a number of convolutional, pooling, and downsampling layers. By combining data from nearby pixels, downsampling layers shrink the spatial dimensions of feature maps. While lowering computational complexity and concentrating on high-level patterns in later layers, this procedure aids in the extraction of the most pertinent features. Every neuron in a completely linked layer communicates with every other neuron in the layer above, identifying patterns and drawing conclusions from the characteristics the earlier layers have found.[10]

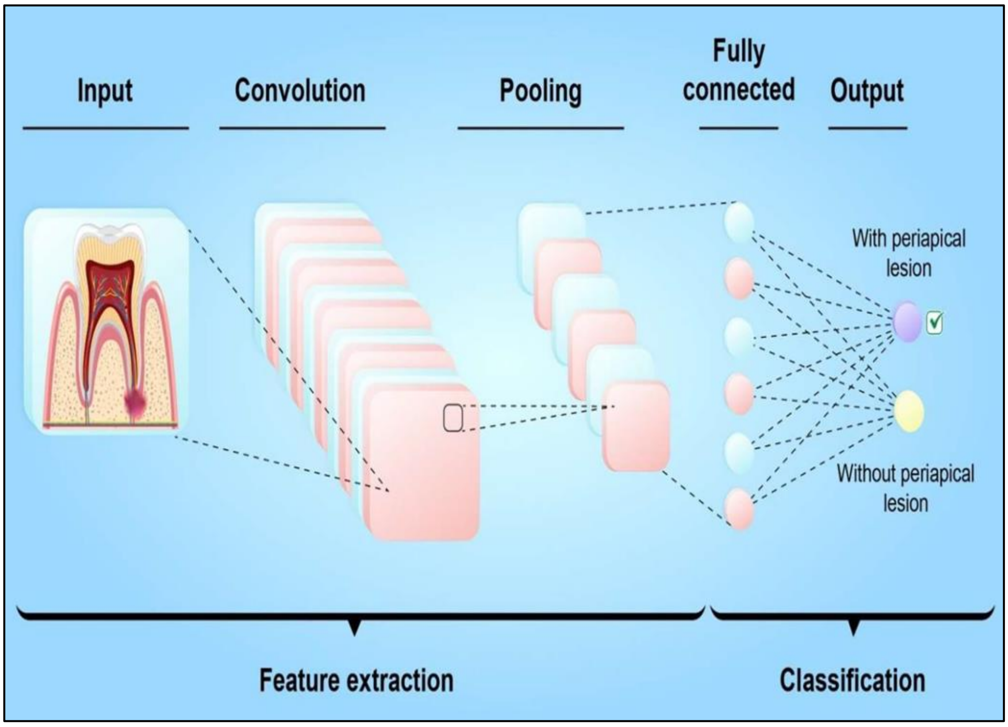

Fig 3. Convolutional Neural Network

This illustration demonstrates how a convolutional neural network (CNN) processes a dental image to classify it. The ‘Input’ stage shows an annotated tooth image, which is then passed through several ‘Convolution’ layers to extract features. These features are downsampled in ‘Pooling’ layers to reduce dimensionality. Afterward, the ‘Fully connected’ layers analyse the pooled features to make a final decision in the ‘Output’ stage, classifying the image as either ‘With periapical lesion’ or ‘Without periapical lesion’. The bottom labels ‘Feature extraction’ and ‘Classification’ summarize the two main phases of the CNN's processing.

## III. CURRENT APPLICATIONS OF AI IN ENDODONTICS

### A. *Identification of Periapical Lesions*

Diagnosing and treating teeth with periapical lesions and symptoms can be challenging for clinicians. A common condition that affects about 75% of radiolucent jaw lesions is apical periodontitis. Early detection could improve treatment efficacy, stop the disease from spreading to nearby tissues, and minimize further complications.[10]

In routine clinical practice, intraoral periapical radiography and panoramic images are the most commonly used 2-dimensional diagnostic tools for identifying apical periodontitis. Radiolucencies on radiographs are a common way to identify periapical lesions. However, because the initial 3-dimensional anatomy is transformed into a 2-dimensional image, data from periapical radiographs is imprecise.[11]

As a result, a three-dimensional imaging method called cone-beam computed tomographic (CBCT) imaging was developed and used to accurately detect periapical lesions as well as their location and dimensions. A meta-analysis found that the accuracy values for detecting periapical lesions were 0.96, 0.73, and 0.72 for CBCT imaging, traditional periapical radiography, and digital periapical radiography, respectively. However, CBCT imaging's capacity to precisely identify apical periodontitis in teeth with filled roots is limited due to its high expense and radiation exposure, which limits its use in specific clinical contexts.[12]

The diagnostic performance of 24 oral and maxillofacial surgeons in identifying periapical radiolucencies on panoramic radiographs can be matched by a deep learning algorithm model, according to Endres et al. [13]

In one study, three radiologists who specialize in oral and maxillofacial imaging assessed CNN models' ability to recognize simulated periapical lesions on intraoral images. They came to the conclusion that the group of CNN outperformed oral and maxillofacial radiologists in terms of sensitivity, specificity, and area under the receiver operating characteristic curve.[14]

As per Ekert et al. [15], when compared to dentists with over ten years of clinical experience, deep CNNs demonstrated an accurate discriminatory capacity to identify apical lesions on panoramic radiographs. Nevertheless, both studies had a small sample size and employed panoramic radiography, a diagnostic method that endodontists hardly ever employ. [14,15]

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Examiners can distinguish periapical lesions on radiographs in a variety of ways, and their level of experience has a big impact on their ability to discriminate. Bias and examiner differences can be lessened with the help of AI technologies.

Deep learning segmentation showed remarkable accuracy in detecting a periapical lesion on CBCT images.[16] Roughly 92.8% of CBCT images could be used to detect a periapical lesion using a CNN system. Furthermore, some researchers have pointed out that while the volume measurements of the humans and the deep CNN system were matching, the study's validity may have been jeopardized because the volume deviation of lesions was not taken into account.

AI systems have the potential to improve detection accuracy and assist doctors in reaching detection accuracy levels comparable to or superior to those of experienced specialists by identifying periapical lesions from radiographs and CBCT scans. [16,17,15]Also, it can lessen the dentist's diagnostic attempts by enabling semiautomated documenting and saving evaluation time. However, more research should be done and the AI system's sensitivity should be increased before they are used in therapeutic settings.

### *B. Detection of Root Fractures*

VRFs, or Vertical Root Fractures, account for 2% to 5% of crown/root fractures and are regarded as a serious complication that may lead to tooth extraction or root resection. [18, 19] It's difficult to diagnose VRF through radiographs and CBCT. In the absence of a conclusive diagnosis, an unnecessary dental extraction or surgical procedure may be necessary.

For a clinician, the clinical manifestation and sensitivity issues of standard radiography in identifying VRFs pose a diagnostic conundrum frequently. Radiographs were only slightly more effective at identifying VRFs in teeth with root fillings than CBCT imaging in unfilled teeth, according to Talwar et al.'s meta-analysis.[19] Since conventional methods are ineffective at detecting VRFs, the development of novel techniques to enhance VRF diagnostics has been proposed.

With recall 5 0.75 [sensitivity], precision 5 0.93 [positive predictive value], and the F measure 5 0.83[machine learning performance evaluation indicator], CNNs could be a helpful tool for identifying VRFs on panoramic radiographs, according to Fukuda et al. [20]. Another study sought to develop a probabilistic neural network for the diagnosis of VRFs in teeth that were both intact and root-filled using CBCT images and periapical radiographs.[21] They concluded that CBCT images are more accurate, sensitive, and specific in identifying root fractures than pictures from radiographs in two dimensions. Nevertheless, this conclusion was reached after examining premolar teeth with a single root. Future research should examine the possibility of using a probabilistic neural network for verifying vertical root fractures in teeth with multiple roots.

Shah et al. [22] made second molar splits and evaluated these using wavelets and artificial data. These operations in mathematics make it possible to recover weak signals from noisy environments in a machine learning technique. Despite the small sample size, cracks in high-quality CBCT images were reliably detected using steerable wavelets.

In a study conducted outside of the body, Vicory et al. [23] made microfractures in 22 teeth. When using wavelets and machine learning to identify broken teeth, the researchers discovered that micro-computed tomographic pictures were more precise than CBCT images. Although there was room for improvement, authors claimed that the machine learning's positive predictive utility outperformed the observers' explanation. According to the authors, a larger sample size should be used in future studies.

### *C. Working Length Determination*

An important part of root canal therapy is figuring out the root canal system's apical limit. Determining the system's apical limit is a critical step in root canal therapy. Thorough mechanical and chemical disinfection of the root canal system is made possible by an accurate working length (WL) calculation.[24] Furthermore, the appropriate WL lessens post-operative pain, stops debris from extruding, and shields the periodontal tissues from instruments that extend past the canal terminus.[26] When it comes to infected root canal systems, it has been shown that a millimeter loss in WL can cause the success rate to be lowered by 12–14% [26, 27] Additionally, the treatment plan may suffer if the canals are obturated past the radiographic apex.[27]

The quality of the image is crucial for accurately interpreting the anatomy of the root canal system in digital radiography. But a lot of other things can influence how radiographs are interpreted, which could result in a wrong diagnosis.[28] It is therefore crucial to create computer-based techniques for precisely calculating working lengths.

Saghiri et al. [29] claim that ANNs can be used as a second opinion to locate the apical foramen on radiographs, improving the correctness of determining working length. The quality of an ANN's working length determination in a human cadaver model that replicated a clinical setting was examined by Saghiri et al. [30] in a different investigation. When comparing an ANN with the exact measurement following extraction, they found no differences in the measurements of root length.

They added that the ANN (96%) performed better than an endodontist (76%) in identifying small anatomic constriction using periapical radiographs. A correct method for figuring out working length can be ANN.

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*D. Morphology of the Root and Root Canal System*

Knowing the differences between the root and the it's system is important for the success of root canal therapy. For this, CBCT imaging and periapical radiography have been used. It has been demonstrated that when evaluating the root and root canal configurations, CBCT imaging is more accurate than radiography. But in normal clinical practice because of risk of radiation these are not advised.

According to Hiraiwa et al. (2017),[31] the deep learning system using panoramic radiographs showed excellent accuracy in differentiating between one or more roots in the distal roots of mandibular first molars. Image patches from panoramic radiographs were taken out and fed into deep learning systems to generate learning models. The algorithm developed with AI and information analysis demonstrated the ability to measure the root canal curvature and its three-dimensional change after the instrumentation. Nevertheless, additional research is necessary to validate the findings of this investigation.

A CNN-based automatic 3D teeth segmentation technique was introduced by Lahoud et al. [32]. Authors had checked 433 CBCT segmentations of teeth in radiograph in an efficient and useful reference and discovered that AI performance was faster and accurate when compared to a normal human operator. The authors matched two deep CNNs with professional enhancement using panoramic radiography in another study.[33] In this 153 panoramic radiographs were checked the researchers demonstrated that the AI had recognized and segmented teeth with excellent specificity and sensitivity in a very short amount of time.

*E. Predictions*

- *Retreatment Predictions*

A paradigm for case-based reasoning was described by Campo et al.[34] as a way to forecast the risks and advantages of nonsurgical root canal retreatment. Essentially, the approach showed whether retreatment was required or not. Data from domains such as effectiveness, statistical probability and recall are involved in this. One of the system's advantages is its ability to accurately predict retreatment outcomes. The disadvantage was that the system's performance depended on the data quality.

A new method for formulating answers to problems by drawing on knowledge related to past problems is called Case-based reasoning. Valuable knowledge and information can be included by collecting the same situations. This system might be heterogeneous because of the problem in variability and prevalence of various methods.[35]

Further research must take into consideration the variability of a human method and possibly expand the sample size in order to improve sensitivity, specificity, and accuracy.

- *Predicting the Survival of Stem Cells*

To assess the extracted dental stem cells, Bindal et al. [36] used the neuro-fuzzy inference system from the pulp of the teeth in various regenerative treatments. The viability of the stem cells was examined using this technique following treatment with lipopolysaccharides produced by bacteria. One technique for forecasting cell survival was the neuro-fuzzy inference system following different regenerative regimens, which is hindered by microbial infection.

Following lipopolysaccharide therapy, the authors assessed the dental pulp stem cells' vitality to cause an inflammatory reaction. [36] Next the authors looked at the correct level of the results, predicting these stem cells' capacity to withstand microbial invasion using adaptive neuro-fuzzy interferences.

## IV. GAPS BETWEEN ENDODONTIC THERAPY AND AI

Till now, there is no:

- AI has to plan the treatment for patients depending on ongoing requirements and acquired medical information because scheduling, making appointments, assigning tasks, and decisions to recall are revised often to satisfy the healthcare system's requirements. This includes programming technology for patient management, appointment scheduling, and recall.

- As the population grows and life expectancy rises, more people are taking more medications. Using the available electronic health record, this procedure is used to inform the physician of medication interactions and/or changes to the course of treatment. If medical records are made public, AI might be able to predict drug-drug issues unique to a patient.

- AI may improve staging and diagnosis and forecast results based on gathered data. This would involve figuring out the risk of prognosis and deciding the final result.

- The endodontist has access to precise physical and robotic microsurgical procedures; in the implant technology field, the use of robotics in dental surgery can help the surgeon in correctly navigating the placement of the implant.[37]

Naturally, the same system should help endodontists navigate during endodontic procedures. According to the authors, the average deviations of the robotic implant placement was just as precise as both dynamic and static navigation, although no similar cohort studies that compare robotic surgery to conventional endodontic surgery or therapy have been used up to this point. Future studies should use a robotically assisted placement to evaluate the accuracy and safety of the different approaches.

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## V. DRAWBACKS OF AI

- To manage patients, schedule appointments, and perform periodic recalls, the healthcare system needs a standard programming technology. Additionally, this system needs to be updated frequently to reflect changes in the healthcare industry.

- It would be too expensive to install an AI-based system in separate clinics.

- Patient information based on individual health records can be used to notify dentists about adverse reactions associated with the use of particular medications and the required adjustments to the treatment protocol. However, this can also be a drawback because AI channels can potentially be used to misuse information.

- As of yet, no method has been developed to offer an accurate diagnosis that could influence prognostication or outcome prediction. The clinical results would determine how clear this diagnosis would be.

- AI can be used to enhance dynamic navigations in endodontic surgery. Few studies have examined these methods, and more research is strongly advised to examine and evaluate robotically guided placement in endodontics.

- People and dentists who have not had AI training may misunderstand the apps' intricacy.

- In endodontics, data is frequently utilized for evaluation and instruction, which can result in "data snooping bias."

- Because AI can provide a single response when there may be several possibilities, its results in endodontics are not immediately significant.

## VI. CONCLUSION

AI may be useful in clinical endodontic applications, particularly in periapical pathosis, working length evaluation, disease prediction, and root fracture diagnosis. AI is seen as a great adjunct for dentists, despite obstacles that must be addressed due to data collection, interpretation, processing capacity, and ethical concerns. AI has the potential to be transparent, reproducible, unbiased, and easy to use with careful design and long-term clinical validation.

As AI becomes more proficient at handling large amounts of data, its main goal should remain to serve human interests.

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