ISSN: 2581-5989
PubMed - National Library of Medicine - ID: 101738774

International Journal of Dental Science and Innovative Research (IJDSIR)
IJDSIR : Dental Publication Service
Available Online at: www.ijdsir.com
Volume – 6, Issue – 3, May - 2023, Page No. : 74 – 88

Application of neural networks

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Citation of this Article: Dr. Theres James, Dr. Sruthy Prathap, Dr. Rajesh K.S., Dr. Shashikanth Hegde, Dr. Vinita Boloor, "Application of neural networks", IJDSIR- May - 2023, Volume – 6, Issue - 3, P. No. 74 – 88.

Type of Publication: Review Article

Conflicts of Interest: Nil

Abstract

Artificial intelligence is becoming increasingly important in medicine and dentistry. With recent advances in digitised data acquisition, machine learning, and computing infrastructure, artificial intelligence applications are expanding into areas previously thought to be reserved for human experts. Artificial intelligence encompasses machine learning, neural networks, and deep learning. Artificial neurons that are similar to human neural networks are used in neural networks to mimic the human brain in a mathematical non-linear model. Neural networks can simulate human cognitive skills like problem solving and thinking abilities such as learning and decision making. Artificial intelligence has enormous potential to improve patient care and revolutionise the health care field when applied to medicine and dentistry. It could be used to plan more effective therapies, prophylaxis, and treatment cost reduction. In many dental fields, computers can now provide second opinions. In dentistry, neural networks can be used to improve diagnosis accuracy, speed, and efficiency. The purpose of this review article is to provide an overview of the possibilities for using neural networks in modern dentistry.

Keywords: Artificial intelligence, Neural networks, Deep learning, Dentistry

Introduction

Ever since the field of science has originated, researchers and technologists have been working to understand the complexity of the human brain, which is a network of neurons that communicate with one another and send signals throughout the body.[1] For the scientific community, creating a model that closely resembles the human brain has remained a big challenge. Since many years, researchers have been working endlessly to promote "artificial intelligence."[2] The term "artificial intelligence" was first used by mathematician John McCarthy in 1955. McCarthy is widely recognized as the father of artificial intelligence. He used this term to describe how machines have the capacity to carry out operations that could be categorised as "intelligent" activities. [3] This field began in 1956 when John McCarthy organised the renowned Dartmouth conference that was on the artificial intelligence research project. The crucial period when in-depth research on AI was conducted, from the 1950s to the 1970s, was prompted by the conference..[4] Richard Bellman defined artificial intelligence in 1978 as the automation of activities associated with human thinking abilities, such as learning, decision making, and problem solving. The artificial neuron, which is a mathematical model system influenced by the human neuron, is the main component of any artificial neural network. A network capable of solving specific tasks such as image classification is created by assembling artificial neurons and connecting the layers of these artificial neurons using several mathematical operations.

Neural networks can "learn" how to make a diagnosis based on the data presented to them. Neural networks have been used since the mid-twentieth century. Although neural networks appear complex at first, they can be easily integrated into a medical environment. Today, specialists pay attention to smart tools and decision support systems in medical issues due to the development of knowledge in the medical field as well as the complexity of decisions related to diagnosis and treatment, and the use of various types of smart systems in medicine has been increasing. Using these tools and systems can help to reduce potential errors caused by medical specialists' fatigue or lack of experience in disease diagnosis and treatment. Furthermore, by utilising these systems, we can analyse the medical database in much less time and in greater detail.[6]

The purpose of this article is to review the current application of neural networks in dentistry especially in the field of periodontics. Additionally the future perspectives of neural networks in dental profession will be addressed.

History

There are several internal tributaries in the history of artificial intelligence formulation, research, and development. Some scholars point to Aristotle as the first person to present the concept of AI. He did not offer a direct view of the emergence of machinery capable of replacing human thought. His attempt to identify man's way of thinking as a type of logic based on syllogism, on the other hand, has since become a source of belief that computing can completely replace human thought mechanisms.[7] Ramon Llull, a 14th century Catalan poet and great missionary theologian, published Ars generalis ultima (The Ultimate General Art) in 1308 based on Aristotle's idea. The author devised a mechanical method of recreating the mind of man in this book through a logical combination of concepts based on Aristotle's logic.[8] Gottfried Leibniz, a German mathematician and philosopher, published Dissertatio de arte combinatoria (On the Combinatorial Art) in 1666. The author stated that every human thought is implemented with a relatively simple combination of simple concepts. [9] In 1854, George Boole asserted that logical reasoning is performed in the same way as solving equations with a set of systems, implying that complete replacement of logical thinking and computing is possible. Warren McCulloch and Walter Pitts published a paper in 1943 proposing neural networks as a way to mimic human brains. [10] In 1951, Minsky and Dean Edmunds created the stochastic neural analogue reinforcement calculator, which is regarded as the first neural network in history. [11] For the first time in history, Allen Newell and Herbert Simon created AI programmes in 1955. [12] The Logic Theorist programme proved 38 of the first 52 axioms of Whitehead and Russell's Principia Mathematica. [8]

Components Of Neural Network

A neural network is made up of a variable number of small, very limited computing elements, each of which can only perform one mathematical function. A representation of each element, known as a neuron, as well as formation inputs (i.e. data input to the network) or connections from other neurons in the network, known as synapses. Synapses are not direct connections, but they do have a 'resistance' that reduces the size of the signal from the connecting neuron crossing that synapse. This resistance is represented by a weight between 0 and 1 that is multiplied by the input signal to give the proportion of the input signal that actually affects the neuron.

Each synapse can be excitatory (meaning the input signal is positive) or inhibitory (in which case the value of the input signal is negative). The output of each neuron, referred to as 'activity,' is derived by running the total input to the neuron through a mathematical algorithm known as the transfer function, which is typically a logarithmic regression function. The transfer function specifies how the output of a neuron varies with the sum of its inputs. A typical transfer function approximates the all-or-nothing firing response of a biological neuron, with a critical level above which output is near maximal and below which output is nearly zero.

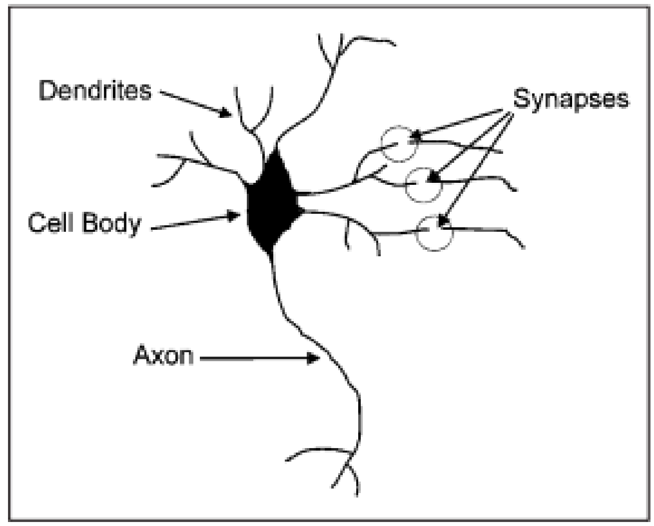


Fig 1: The biological neuron

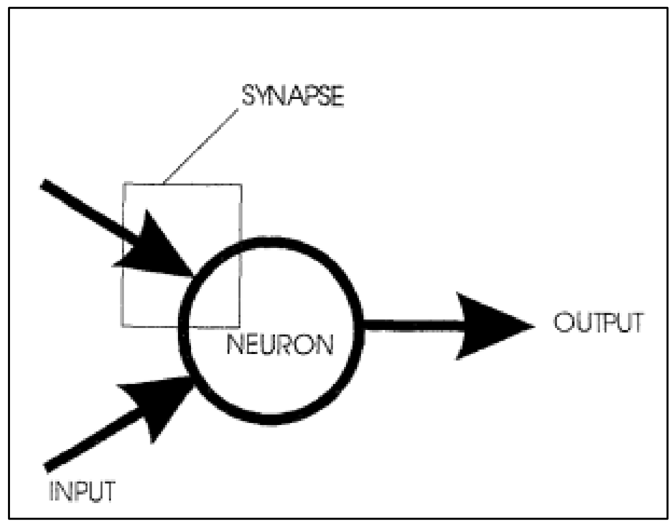


Fig 2: A neuronal network 'Neuron'.

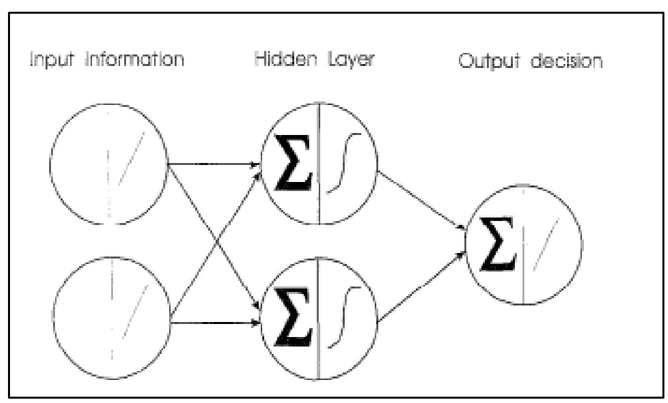


Fig 3: A basic neural network

Properties of A Typical Neural Network

A single neuron, whether artificial or biological, is useless without network interconnections. When multiple networks are linked together, the resulting network can have significant and powerful properties:

(1) After training, neural networks can recognise important patterns in input data and respond with an appropriate output. A neural network trained to recognise pathology on radiographic images, such as that developed by Gross et al, could, for example, have numerous applications in dental radiology.

(2) Neural networks are capable of dealing with missing and uncertain input data while still making the best decision.

(3) While neural networks require training, they frequently perform well even when trained with incomplete data.

(4) Unlike other decision support programmes, neural networks do not require a set of rules to be made explicit; rule derivation by questioning an expert is a difficult and imprecise process.

A typical neural network has an input layer with one or more neurons for each input variable (for example, patient age or periodontal probing depth), one or more intermediate 'hidden' layers that do not connect directly to either inputs or outputs, and an output layer with one or more neurons producing a graded output that is the network's output. The archetypal neuron as defined so far is altered when used in the input or output layer. Neurons in the input layer only have one input and simply scale the input data to produce a value in the O-l range. The output layer neurons do not have an all or nothing response, but instead have an output that directly reflects the sum of their outputs; this allows the network as a whole to give a graded output rather than an all or nothing response, allowing the network to represent ordinal data. Data are coded for neural network entry by assigning a numerical value to them. A typical network has 'one way' synapses that allow signals to flow only from the network's input end to the output (termed feed forward) and connect the output of every neuron in one layer to the input of every neuron in the layer below (termed 'fully connected'). The 'architecture' of the network refers to its overall structure. A given architecture can be built in hardware, but it is usually simulated in software on a standard desktop computer.

Development of Neural Network

The creation of a neural network begins with the design of a network architecture and is followed by neural network training. Validation is the final stage. The network architecture is chosen through trial and error by varying the number of hidden layers and the number of neurons in each hidden layer. A single hidden layer with two to three neurons is a good starting point. If validation demonstrates that the network performance is poor, the numbers can be changed. In general, increasing the number of hidden units or layers improves the network's ability to make subtle inferences while decreasing individual result accuracy. The best compromise is to start with more neurons than needed and gradually prune the network until performance is optimal. Following the completion of the architecture, the network must be trained to produce usable results. This is accomplished through the use of a training set of data for which the optimal output is known.

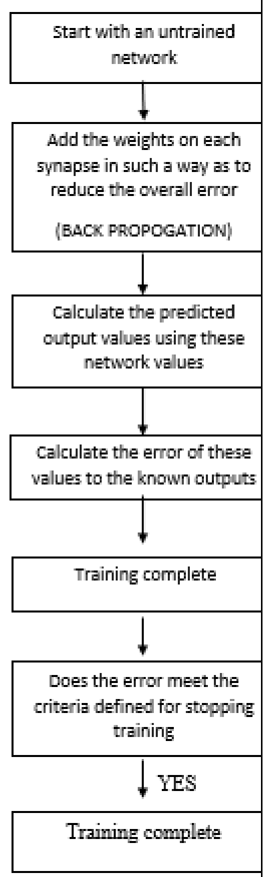
The most common method for training a network is back-propagation which involves changing the weights in the network's layer(s). The network may be undertrained, in which case it will perform poorly, or overtrained, in which case it will lose its ability to generalise. A network of this type will perform well with the training set but poorly on some other data. Over-training can be avoided by using a technique known as cross validation, which involves testing the neural network after each training cycle on a separate set of data (the validation set) for which the optimal outputs are also known, and calculating the network's error for this set. When this error is minimised, the neural network will be optimally trained. It is impossible to determine the optimal point at which training should stop until it has been proven, which is why it is necessary to train twice. The majority of software programmes automate the entire process. Thus, a neural network can learn to mimic, for example, clinical decisions made by a human expert using only a series of clinical histories and diagnoses.[1]

Application of Neural Networks in Medicine

Over the last few years, the number of research papers published globally demonstrating the applications of ANNs in medicine and the complex drug discovery process for various purposes such as pattern recognition, classification, prediction, data analysis, medical diagnosis and prognosis, controlling drug delivery systems, drug design, and quantitative structure activity relationship studies has increased. [13] Radiographs have been interpreted using neural networks. The neural network accepted more often with two human operators than they did with each other. Neural networks have also been applied to the assessment of cytological smears. A network trained using cervical smears as the model correctly classified 98% of 524 test cell images as either normal or abnormal monitoring systems, which are relevant to dentistry.[14]

Table 1: Application of artificial intelligence in medicine

Discipline	**Application field**
Cardiology	Diagnostics, Prognostics
Intensive care	Prediction
Gastroenterology	Prediction
Pulmonology	Diagnostics
Oncology	Diagnostics, Prognostics
Paediatrics	Diagnostics
Neurology	Signal processing, Modelling
Otology-Rhinology-Laryngology	Signal processing, Modelling
Obstetrics and Gynaecology	Prediction
Ophthalmology	Signal processing, Modelling
Radiology	Signal processing
Clinical Chemistry	Signal processing, Diagnostics
Pathology	Diagnostics, Prognostics



Cytology	Diagnostics, Re-screening
Genetics	Diagnostics
Biochemistry	Protein sequencing, structure

Table 2: Studies on application of neural networks in medicine

Medical Speciality	Applications
Cardiology	
• Baxt et al[15] (1991)	- trained the neural network for the prediction of acute myocardial infarction from the cardiac enzyme levels - found 100% diagnostic accuracy with an 8% false positive rate
• Baxt et al[16] (1992)	- developed an integrated decision support system in which neural network was trained not only by enzymatic data, but also by electrocardiogram data, subjective symptoms and changes after administration of nitroglycerine - showed that the ANN was superior to physicians for the clinical diagnosis of myocardial infarction in terms of diagnostic sensitivity and specificity
• Baxt and Skora[17] (1996)	- demonstrated the use of a computer-based neural network decision support system (called WeAidU) for automated interpretation of diagnostic heart images
• Ohlsson et al[18] (2004)	
Intensive care	
Mylrea et al[19] (1993)	- discussed the potential of integrated monitoring with ANN to detect incidents and reduce false alarms - estimated that half the anesthesia-related events could be detected with integrated monitoring with ANN - the necessary responses could be initiated within 17 seconds instead of the 45 seconds average by clinicians which improves the healthcare quality and efficiency
• Mobley et al[20] (1995)	- created an ANN model which predicted the length of hospital unit stay - their results showed that ANN has the capacity to utilize common patient admission characteristics to predict lengths of stay
Gastroenterology	
• Hamamoto et al[21] (1995)	- determined preoperatively the early prognosis of the hepatectomized patients with hepatocellular carcinoma with a perceptron-type neural network - the outcomes of the hepatectomy were predicted prospectively with 100% precision
• Banerjee et al [22] (2003)	- evaluated the role of the ANN in predicting one-year liver disease-related mortality - concluded that ANN can accurately predict one-year mortality in cirrhosis

Pulmonology	
• Perchiazzi et al[23] (2003)	- evaluated the performance of an ANN based technology in assessing the respiratory system resistance and compliance in a porcine model of acute lung injury - results suggested that ANNs can learn to assess the respiratory system mechanics during mechanical ventilation
• Banner et al[24] (2006)	- determined work of breathing per minute or power of breathing noninvasively using ANN without the need for an esophageal catheter in patients with respiratory failure.
• Heckerling et al[25] (2003)	- used ANN to predict the presence or absence of pneumonia among patients presenting to the emergency department with acute respiratory complaints - results showed that ANN accurately discriminated patients with and without pneumonia
Oncology	
• Ball et al[26] (2002)	- developed a prototype approach which uses a model system to identify mass spectral peaks whose relative intensity values correlate strongly to tumor grade - results suggested that applications of ANN-based approaches can identify molecular ion patterns which strongly associate with disease grade
Obstetrics and Gynaecology	
• Benesova et al[27] (1995)	- used neural networks to determine the teratogenity of perinatal administrated drugs
• Lapeer et al[28]	- compared multilayer perceptrons with Multivariate Linear Regression in predicting birth weight from nine perinatal variables which were thought to be related
Ophthalmology	
• Brigatti et al[29]	- assessed the ability of neural networks to discriminate between normal and glaucomatous eyes by using structural and functional measurements - concluded that analysis of several optic nerve and visual field variables by ANN can help identify early glaucomatous damage and assign an estimated probability of early damage in individual patients
Maeda et al[30]	- applied neural networks for automated videokeratography pattern interpretation in the diagnosis of shape abnormalities of the cornea. - concluded that the neural network based computer-assisted interpretation for objective classification of videokeratography may become a useful tool in the diagnosis of corneal topographic abnormalities.

Application In Dentistry

Oral and maxillofacial radiology and diagnostics

Zhank et al. used AI-based CNNs to evaluate effective teeth recognition by relying on the label tree and cascade network structure. The model had a high precision of 95.8%. [31] Chen et al. used CNNs to detect the number of teeth in intraoral periapical films and then identify the tooth. The model demonstrated a high level of precision. According to the findings, AI technologies make it easier for clinicians to do their jobs. They are not required to manually enter the information. Dentists can enter their dental charts digitally using these automated systems, resulting in greater efficiency.[32] AI technology has demonstrated excellent results in the detection of dental caries, as proven by the study conducted by Lee et al., who reported the application of CNN algorithms for the detection and diagnosis of dental caries on periapical radiographs. [33]

Orthodontics and dentofacial orthopaedics

In a study conducted by Xie et al., an artificial neural network (ANN) model was used to determine whether extractions are required using lateral cephalometric radiographs. The outcomes were quite promising. [34] Jung et al. demonstrated 92% accuracy in deciding on permanent tooth extraction using lateral cephalometric radiographs using an AI expert system. Both studies' findings indicate that artificial intelligence modes were effective and accurate in predicting the need for extraction. These models can be used as a decision-making tool in clinical practice. [35] Muraev et al. used ANN to place cephalometric points on cephalometric radiography in their study. The ANN's CP placement accuracy was compared to three groups of doctors: expert, regular, and inexperienced. The findings revealed that ANN had the same accuracy in planning cephalometric points as an experienced dentist, and in some cases, they may be even more precise than new doctors.[36]

Restorative Dentistry and Endodontics

Dental caries is the most common dental disease, so detecting it at an early stage is critical. Dentists use dental probes to screen and diagnose dental caries, and by observing the texture and discoloration, they can determine whether the tooth is sound or not. [37] Neural networks may aid in the detection of dental caries on radiological images, making the examination faster and more precise. Geetha et al. used an artificial neural network to determine whether or not there were caries in the 105 radiograph images. The input nodes were sixteen feature vectors extracted from the segmented image. There were two output nodes, one for caries and one for sound tooth. Caries detection accuracy was 97.1%, with a false positive rate of 2.8%. This study suggested that neural networks may be much more accurate than traditional dental examinations in detecting tooth decay.[38]

In a study by Javed et al artificial neural networks were used to predict post-Streptococcus mutans prior to dental caries excavation using an iOS App developed on an artificial neural network (ANN). 45 primary molars with occlusal caries were used in the study. Pre- and post-Streptococcus mutans colony forming units were counted. The study shows that ANN can predict which excavation method is best for a specific patient. ANN had a 99.03% accuracy rate and was microbiologically tested. The prediction of post-Streptococcus mutans avoids post-Streptococcus mutans examination, re-excavation, and re-examination, as well as pulpal trauma with the excavated cavity.[39] Artificial intelligence is becoming increasingly important in endodontics. It can be used to detect periapical lesions and root fractures, evaluate the anatomy of the root canal system, predict the viability of dental pulp stem cells, determine working length measurements, and predict the success of retreatment procedures.[40] Setzer et al. used deep learning to detect periapical lesions on cone-beam computed tomographic (CBCT) images in their study. The lesions were found with 93% accuracy. [41] Endodontic files were used in a study by Saghiri et al to determine the length of canals on radiology images, both with and without artificial neural networks. The measurements were taken using stereomicroscopy both before and after the teeth were extracted. The correct assessment made by the endodontics was strict in 76% and by the artificial neural network in 96%. This demonstrates that artificial neural networks can be used to assess apical foramen localization more precisely than humans..[42]

Periodontics

Periodontitis is a widespread disease that affects billions of people worldwide, causing tooth mobility and, in severe cases, tooth loss. To avoid this, early disease detection and effective treatment must be implemented. A thorough physical examination is required to obtain a reliable diagnosis. As a result, dental probing is used to determine pocket depth and clinical attachment loss. Because of the individual examiner's assessment, periodontal probing has limited accuracy. Dental radiographs are a common additional examination, and their evaluation is also dependent on the examiner's experience. Some authors have used neural networks to reduce diagnostic errors. Krois et al. used convolutional neural networks to analyse panoramic radiographs to detect periodontal bone loss as a percentage of tooth root length. The findings were compared to measurements taken by six experienced dentists. Convolutional neural networks detected periodontal bone loss with greater accuracy (83%) and reliability (80%) than dentists. [43]

Peri-implant bone loss can be detected using dental periapical radiographs, but the margins of bone around the implants are usually unclear or overlap. As a result, on dental periapical radiographs, convolutional neural networks can assess the marginal bone level, top, and apex of implants. The bone loss percentage was calculated and classified by an automated system in the study by Jun-Young Cha et al. This method can be used to determine the extent of peri-implantitis. [44]

Lee et al. used a deep convolutional neural network to analyse radiographs and calculate radiographic bone loss (RBL) for each tooth in their study. RBL percentage, staging, and presumptive diagnosis based on CNN's new periodontitis classification were compared to measurements taken by independent examiners. The neural network had an accuracy of 85%. As a result, neural networks could be useful tools for assessing radiographic bone loss and obtaining image-based periodontal diagnoses.[45] Chang et al. of ten used panoramic images and convolutional neural networks to detect periodontal bone level (PBL), cementoenamel junction level (CEJL), and teeth, and thus made a periodontitis stage diagnosis.[46] Vadzyuk et al. used psychological characteristics to predict the development of periodontal disease. They concluded that anxiety and stress hormone levels in patients had an effect on periodontitis. The use of neural networks to assess the condition of teeth hard tissues, oral hygiene, and psychophysiological features can effectively predict the risk of periodontal disease development in young people.[47]

Challenges

Despite their potential, AI solutions have yet to make their way into routine medical practise. Convolutional NNs, for example, were only used in research settings beginning in 2015, primarily on dental radiographs, and the first applications involving these technologies are now entering the clinical arena. This is all the more surprising given that dentistry is uniquely suited to applying AI tasks:

1) In dentistry, imagery is important and is at the epicentre of most patients' dental journeys, from screening to treatment planning and execution.

2) Dentistry routinely employs various imagery materials from the same anatomical region of the same individual, which are frequently accompanied by non-imagery data such as clinical records and general and dental history data, including systemic conditions and medications. Furthermore, data is frequently collected at multiple time points. AI is well-suited to effectively integrate and cross-link these data in order to improve diagnostics, prediction, and decision-making.

3) A wide range of dental conditions (caries, apical lesions, periodontal bone loss) are common. Building datasets with a large number of "affected" cases can be accomplished with minimal effort.

There are three main reasons why AI technologies in dentistry have not yet been fully adopted. Addressing these issues will help to improve dental AI technologies and facilitate their adoption in clinical care. First, due to data protection concerns and organisational barriers, medical and dental data are not as available and accessible as other data. Data is frequently locked within compartmentalised, individualised, and limitedly interoperable systems. Datasets lack structure and are frequently small in comparison to other datasets in the AI realm. Each patient's data is complex, multidimensional, and sensitive, with few options for triangulating or validating it. Medical and dental data, such as that from electronic medical records, have low variable completeness, with data missing systematically rather than at random. Individuals who are overly sick (e.g., hospital data), overly healthy (e.g., data collected by wearable devices), or overly affluent (e.g., data from those who can afford dental care in countries without universal healthcare coverage) are frequently over-represented in sampling. AI applications built on such data will be biased by definition.

Second, in dental AI research, data processing, measurement, and validation are frequently insufficiently replicable and robust. It is unclear how the datasets were chosen, curated, and preprocessed. When data is used for both training and testing, "data snooping bias" occurs. A "hard" gold standard is rarely defined, and there is no agreement on how many experts are required to label a data point or how to merge different labels of such "fuzzy" gold standards.

Third, the outcomes of AI in dentistry are not always immediately applicable: The single information provided by the majority of today's dental AI applications will only partially inform the required and complex clinical decision-making. Furthermore, concerns about accountability and transparency remain. [1]

Conclusion

AI is not a myth, but rather our future in dentistry. Its applications in every field are expanding on a daily basis. While it cannot replace the role of a dentist because dentistry is not about disease diagnosis, it does include correlation with various clinical findings and provides treatment to the patient. Nonetheless, a thorough understanding of AI techniques and concepts will undoubtedly be advantageous in the future.[48] This review demonstrates that artificial intelligence has advanced rapidly in recent years, and it may soon become a standard tool in modern dentistry. The benefits of this process include increased efficiency, accuracy and precision, improved monitoring, and is time saving.

To clinicians accustomed to a traditional ('reductionist') approach to clinical problem solving, neural networks may appear computationally complex and 'foreign' at first. The skills required to develop and use networks, on the other hand, are no more complex than those developed by any clinical student learning to take a clinical history. Neural networks have numerous potential applications in dental decision making and disease classification. Neural networks are important enablers in the process of rationalising care and should be studied further. The availability of insufficient and inaccurate data is currently the only limitation to the use of AI. As a result, dentists and clinicians must focus on collecting and entering authentic data into their database, which will be fully utilised for AI in dentistry in the near future. [49]

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