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TITLE

CLINICAL APPLICATIONS OF ARTIFICIAL INTELLIGENCE IN DENTISTRY. AN OVERVIEW OF SYSTEMATIC REVIEWS.

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Abstract

Aim: To do a comprehensive assessment of the application of artificial intelligence\s(AI) and machine learning (ML) in dentistry, to provide the dental community a wide perspective on the different achievements that these technology and techniques have achieved, giving specific attention to the field of esthetic dentistry and color research.

Materials and method: The systematic review was undertaken in MEDLINE PubMed, Web of Science, and Scopus databases, for research published in English language in the previous 15 years.

Results: Out of 3213 suitable articles, 103 were included for final review. Study techniques included deep learning (DL; n = 68), fuzzy logic (FL; n = 10), and other ML approaches (n = 24), which were largely used to illness detection, image segmentation, picture correction, and biomimetic color analysis and modeling.

Conclusion: The insight offered by the current investigation has reported exceptional outcomes in the construction of high-performance decision assistance systems for the aforementioned sectors. The future of digital dentistry goes through the construction of integrated techniques offering individualized therapy to patients. In addition, esthetic dentistry can profit from such improvements

by building models providing a comprehensive characterisation of tooth color, boosting the correctness of dental restorations.

In the field of dentistry, the usage of AI and ML is having an increasingly significant influence and complements the growth of digital tools and technology providing a wide range of applications in dental treatment planning and cosmetic operations.

INTRODUCTION

Artificial intelligence (AI) is gradually permeating our daily lives, and its influence on the modern world cannot be overstated. Artificial intelligence (AI) has established itself as a supporting technology in a wide range of fields, from industry to commerce to education, thanks to developments in processing power, methodologies and procedures and the explosion of data.

Despite the lack of a formal definition, artificial intelligence (AI) is widely understood to be the capacity of machines to mimic human cognitive functions. AI can accomplish activities at a level equivalent to or even better than that of humans because to an imaginative combination of computer science, algorithms, machine learning, and data science.[1]

This includes any system capable of sensing, reasoning, engaging, and learning that may be used to do many human-like duties, such as interpreting digital pictures and speech recognition, motion, planning and organizing, as well as other tasks. A branch of AI known as machine learning (ML) employs statistical approaches to give computers the capacity to learn and improve over time. AI technologies that can update their models to improve predictions, resulting in an increase in performance, are referred to as machine learning (ML). Data sets of any size can theoretically be used to train ML models, however the more data available, the better the model can be trained. By feeding these traits into computer models, ML hopes to gain insights into the data, such as grouping like observations or forecasting occurrences. Deep learning (DL) is a subcategory of machine learning in which algorithms may train themselves through the "self-learning" capacity obtained by a sequential chain of crucial characteristics from input data. DL is a subclass of ML. Deep neural networks (DNNs), which are capable of learning extremely complicated nonlinear mathematical functions, automatically master data representations. Neurons and iterations between input and output are referred to as "deep" when describing the number of layers (so-called neurons). To put it another way, input characteristics are fed into the first layer of neurons and transmitted to the output layer, which is inspired by the information processing principles of real neurons.[2] Figure 1 depicts the connection between AI, ML, and DL. Table 1 also provides a succinct overview of the most critical AI tool principles.

There has been a rise in the use of artificial intelligence (AI) in medicine and dentistry recently.

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There are various domains where new technology may support and assist the human being. It wasn't until 1956 at a symposium in Dartmouth that John McCarthy coined the phrase "artificial intelligence." Artificial intelligence encompasses several subfields, including deep learning, neural networks, and machine learning. Prediction issues can be solved without human intervention if machines learn to create algorithms from data. Neural networks (NNs) imitate the human brain in a mathematical non-linear model by using artificial neurons that are comparable to human neural networks. Problem solving and human thinking abilities, including learning and decision making, may be simulated by neural networks. A basic neural network has three layers: an input layer (where data enter the system), a hidden layer (where processing occurs), and an output layer (where the system decides what to do). NNs can map any input to any output given a collection of mathematical models. Such NNs may be taught to reflect the data's underlying statistical statistics if an appropriate amount of data is supplied. Figure 3 in Swietlik D et al. shows the architecture of a basic artificial neural network (2004). Multilayer perception (MLP) neural networks, on the other hand, are more complicated artificial neural networks with additional hidden layers. Artificial neural networks (ANN), convolutional neural networks (CNN), and recurrent neural networks (RNN) are the three most prevalent forms of neural networks. A type of neural network known as deep learning is one in which the computer learns on its own how to analyze the input data. Between a few thousand and a few million neurons can be found in the hidden layer of a deep learning neural network. Artificial intelligence (AI) has the potential to improve therapeutic outcomes, prevent disease before it starts, and lower treatment costs.[3] Most of the medical applications of artificial intelligence (AI) may be found in oncology (using "Thermalitics" in breast cancer diagnosis), cardiology (helping ECG interpretation), and psychiatry (using "Thermalitics").

diagnosing and treating mental health issues), nuclear medicine, and a slew of other fields . Because of the limits of current research methodologies, we cannot examine the nervous system in natural settings and must instead rely on computer models of neural networks.[4,5]

Due to technology advancements and digitalization in dentistry, artificial intelligence is also becoming more prevalent. In many dental specialties, a second opinion may now be generated by a computer. It is possible to increase the precision, speed, and efficiency of diagnosis in dentistry by utilizing NNs. This narrative review was prompted by the rapid advancement and the emergence of new studies on dental neural networks. It was the goal of this research to provide a comprehensive picture of the potential applications of neural networks in current dental practice.

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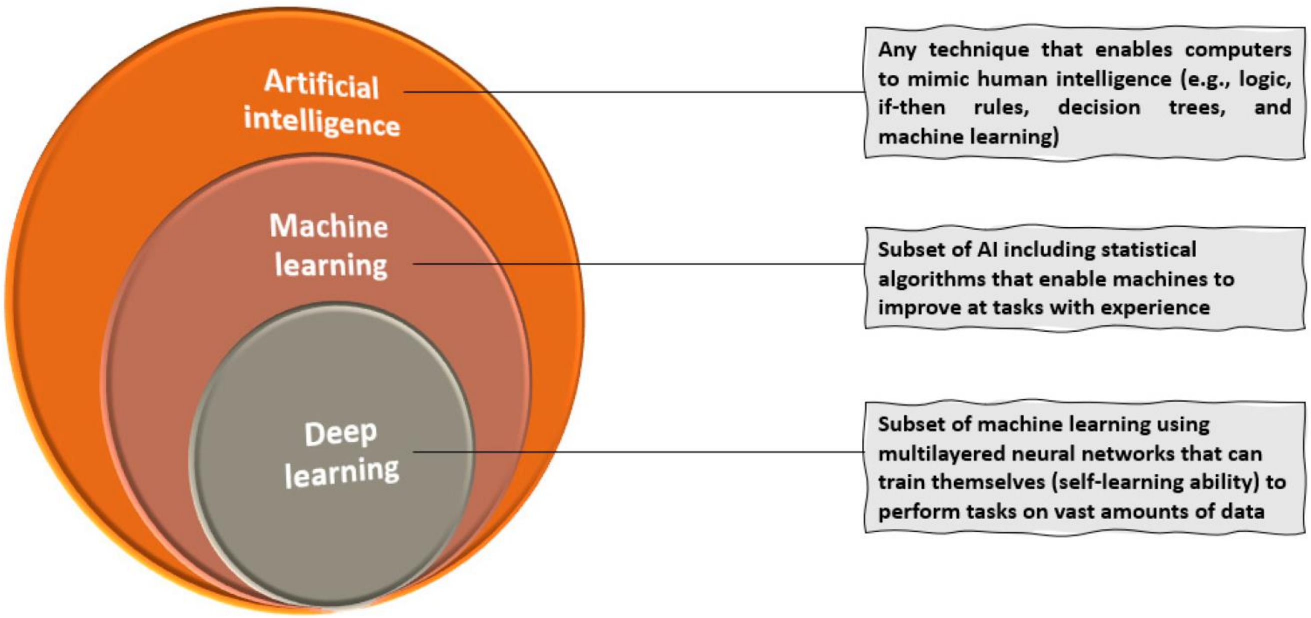

Figure 1. Relationship between AI, ML, and DL. Created based on information from [4,7,8].

Table 1. Important AI-related terms and definitions.

Term	Description	References
Machine learning (ML)	Process by which an algorithm encodes statistical regularities from a database of examples into parameter weights for future predictions	[11]
Deep learning (DL)	Multilayered complex ML platform comprised of numerous computational layers able to make accurate predictions	[6]
Supervised learning	Training an ML algorithm using previously labeled training examples, consisting of inputs and desired outputs provided by an expert	[7,11]
Unsupervised learning	When an ML algorithm discovers hidden patterns or data groupings without the need for human intervention	[11]
Reinforcement learning	Learning strategies towards acting optimally in certain situations with respect to a given criterion; such an algorithm obtains feedback on its performance by comparison with this criterion through reward values during training	[7]
Model	A trained ML algorithm that can make predictions from unseen data	[11]
Training	Feeding an ML algorithm with examples from a training dataset towards deriving useful parameters for future predictions	[11]
Features	Components of a dataset describing the characteristics of the studied observations	[1]
Decision tree	Nonparametric supervised learning method visualized as a graph representing the choices and their outcomes in the form of a tree; each tree consists of nodes (attributes in the group to be classified) and branches (values that a node can take)	[12,13]
Random forest	Ensemble classification technique that uses "parallel ensembling", fitting several decision tree classifiers in parallel on dataset subsamples	[13]
Naïve Bayes (NB)	Classification technique assuming independence among predictors (i.e., assumes that the presence of a feature in the class is unrelated to the presence of any other feature)	[12]
Logistic regression	Algorithm using a logistic function to estimate probabilities that can overfit high-dimensional datasets, being suitable for datasets that can be linearly separated	[13]
K-nearest neighbors (KNN)	"Instance-based learning" or a non-generalizing learning algorithm that does not focus on constructing a general internal model but, rather, stores all instances corresponding to the training data in an *n*-dimensional space and classifies new data points based on similarity measures	[13]
Support vector machine (SVM)	Supervised learning model that can efficiently perform linear and nonlinear classifications, implicitly mapping their inputs into high-dimensional feature spaces	[12]
Boosting	Family of algorithms converting weak learners (i.e., classifiers) to strong learners (i.e., classifiers that are arbitrarily well-correlated with the true classification) towards decreasing the bias and variance	[12]
Artificial neural network (ANN)	An ML technique that processes information in an architecture comprising many layers ("neurons"), each inter-neuronal connection extracting the desired parameters incrementally from the training data	[6,11]
Deep neural network (DNN)	A DL architecture with multiple layers between the input and output layers	[11]
Convolutional neural network (CNN)	A class of DNN displaying connectivity patterns similar to the connectivity patterns and image processing in the visual cortex	[11]

MATERIALS AND METHOD

AI and ML methods and applications in dentistry were covered by the review. An indication of the comparison (expert opinion or reference standards) employed in the model was required, as were quantitative measurements of the study findings.

Exclusion criteria included

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1)Forensic investigations and literature reviews on AI applications for dentistry

2)Artificial intelligence (AI) research that have not been used in dentistry or robotics in any way.

3)Research that did not report numerical or quantifiable results.

A systematic search was conducted in three different databases (MEDLINE/PubMed, Web of Science and Scopus). All studies have been published in the English language within the last 15 years. Data sets used for training-test or cross-validation in supervised learning studies that did not offer information about the data sets utilized. KEYWORDS USED WERE ‘AI, artificial intelligence, fuzzy logic,machine learning,algorithm.

Mendeley software was used to delete duplicates after each database had been searched. According to the criteria previously specified, two reviewers independently chose the research based on their evaluation of the title and abstract. A third reviewer's opinion was sought in the event of a split decision. Any papers that were excluded from the full text reading were documented. PRISMA 2020 statement was followed to create PRISMA FLOW DIAGRAM (Table 3).

The data was assessed using a descriptive analysis of the findings. A quantitative analysis was deemed unrealistic since the selected studies had a wide range of aims and the purpose of this study is to examine the different methods of ML utilized in dentistry. For this complete narrative review, a qualitative data synthesis was undertaken based on a systematic search.

PICO format was used for framing foreground research question (Table 2)

TABLE 2	**Description of PICO (Population, Intervention, Comparison, Outcome)**
Research question	What are the clinical applications, performance of AI in dental practice
Patient Population	Applications in endodontics, Imaging, oral and maxillofacial surgery, orthodontics
Intervention	AI based models, edicting the need for treatment, plannig the treatment, predicting the outcome of treatment
Comparison	Expert opinionsMeasurable or predictive outcomes such as specificity, sensitivity, accuracy,positive and negative predictive values.

RESULTS

Results are depicted in Prisma flow diagram (Table 3). Out of 3213 suitable articles, 103 were included for final review. Study techniques included deep learning (DL; n = 68), fuzzy logic (FL; n = 10), and other ML approaches (n = 24), which were largely used to illness detection, image segmentation, picture correction, and biomimetic color analysis and modeling.

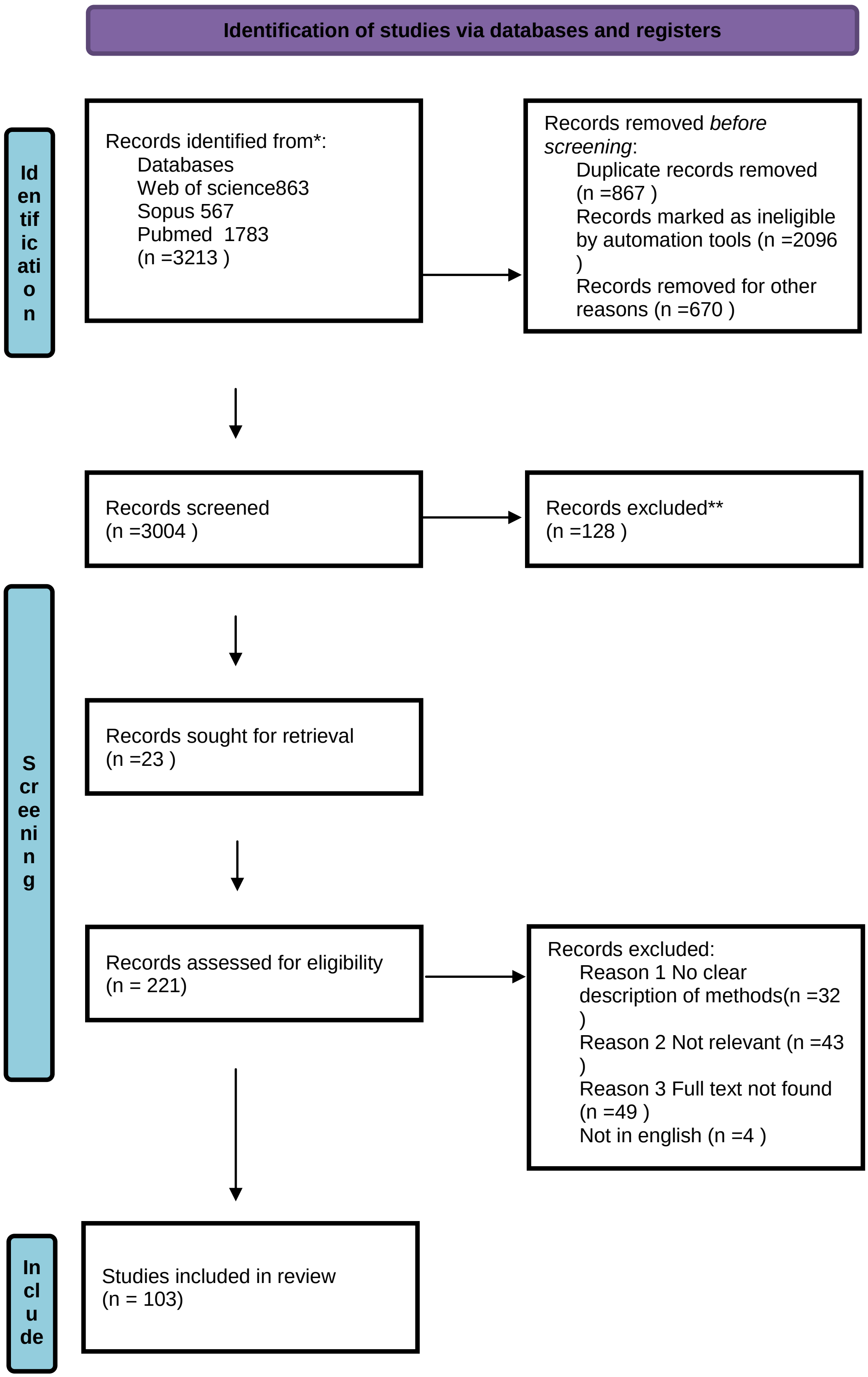

Table 3-PRISMA 2020 FLOW-DIAGRAM

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From: Page MJ, McKenzie JE, Bossuyt PM, Boutron I, Hoffmann TC, Mulrow CD, et al. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. BMJ 2021;372: n71. doi: 10.1136/bmj. n71

DISCUSSION

Deep Learning in Dentistry

Based on biological neural networks, artificial neural networks (ANNs) are algorithms for learning. They have been used to tackle a wide range of issues, including those requiring supervised, unsupervised, and reinforcement learning. When it comes to neural networks, the term "deep" refers to an ANN with a significant number of both layers and neurons per layer, which is what an ANN's core structure is.

Dentistry is one of the most promising areas of research for DL applications. High-performance decision-making support systems can benefit from the use of these approaches since they allow for the discovery of particular patterns from massive databases of pictures.

Artificial neural Network

Multiple layers of feed-forward neural networks (FFNNs), also known as multilayer perceptrons, are the most common type of artificial neural network (ANN). There is only one way in which information goes in these networks: forward, from the input nodes through the hidden nodes to the output nodes.

The basic building blocks of ANNs and FFNNs especially are the so- termed neurons. The neuron is made up of a weight vector W, a unique value called bias b, and the activation function. The neuron calculates the inner product of its inputs and the weight vector plus the bias and given this mathematics, the activation function determines whether the neuron will activate or not. If the total exceeds a threshold zero, it will return a one; if it does not, it will return a zero. There are several layers of neurons.

Caries Detection

Periapical radiography images, other radiographic images, near infrared transillumination images and clinical characteristics have all been effectively employed to train ANNs for the diagnosis of dental caries. As in the case of oral cancer, the use of DL, either from hyperespectral or photographic 55 pictures, other forms of medical imaging or clinical data has been beneficial.

Dental caries may be detected and diagnosed using a pre-trained GoogLeNet Inception v3 CNN network.

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TL was used to train the dataset, which consisted of 3000 periapical radiography pictures. For pre-molars, the diagnostic accuracy of dental caries was 89.0% and for molars, it was 88.0%. Using radiographic pictures, a CNN-based model (U-Net176) was able to detect caries with an accuracy of 80%, according to recent reports. Clinical data on shallow FFNNs has also been examined for the assessment of caries presence,52 and for the estimate of post-Streptococcus mutations prior to caries excavation.

Digital Image Application

For training neural networks (ANNs) to detect dental caries, various radiographic pictures, near infrared transillumination images, and clinical data have all been used. When it comes to detecting oral cancer, the use of DL, either from hyperspectral or photographic55 photos or other medical imaging or clinical data, has been effective.

It is possible to identify and diagnose dental caries using a Google Net Inception v3 CNN network that has been pre-trained. The dataset, which included 3000 periapical radiography images, was trained using TL. Dental caries diagnosis accuracy was 89.0 percent for pre-molars and 88.0 percent for molars. According to recent research, a CNN-based model (U-Net176) was 80 percent accurate in detecting caries using radiographic images. Caries presence and post-Streptococcus mutations in shallow FFNNs have been assessed clinically and estimated prior to caries excavation using clinical data. By using two-level hierarchical CNNs, we were able to achieve a 99.1 percent success rate in the segmentation of teeth. Authors employed interest volumes for segmentation in similar ways. The U-Net architecture or a multi-task 3D CNN were utilized by certain writers, all with impressive results. For tooth segmentation, other three-dimensional data has been employed. It was possible to achieve a high level of accuracy in the segmentation job with the usage of an octree-based sparse voxel network and 3D dental models. FFNNs were used to segment 15 3D dental models for use as input in the analysis.[5’6]

The use of 2D images from radiographs and CBCT scans has also been studied in the literature for tooth identification and segmentation.[7] The VGG-16 design was utilized to segment teeth from periapical radiographs, resulting in good accuracy and recall (95.8 percent and 96.1 percent, respectively). For the identical objective, the Resnet-101 architecture was used to achieve a precision of 99.6 percent in the detection of teeth. The authors of two articles that took a similar approach to the problem had excellent outcomes. Also used were the U-Net176 architecture and 2D CT scan pictures to achieve an impressive dice similarity coefficient of 91.7%.[8]

Dental Implants

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DL approaches have been widely applied in other related situations, such as the categorization of dental implants. An accuracy of 98 percent was obtained when implant identification was based on TL and periapical radiographs. Except for x-ray pictures, the same process yielded similar findings. Dental implants from different manufacturers were predicted using CNNs and radiological images in another investigation.[9,10,11]

Orthodontic Applications

Literature also addressed landmark detection for orthodontic treatments.[10-16] Cephalograms were used on a multi-head attention ANN for cephalometric landmark prediction, reaching an accuracy of 87.6%. Similarly, a 3D CNN was used for surgery landmark predic- tion using CT images, achieving a mean error of 5.8 mm in comparison to the original landmark.[17] X-ray images have been used as inputs forthe landmark detection task with an encoder-decoder architecture[18] or Bayesian CNNs

Prosthodontic Considerations

A technique for finding the pigments that go well with a certain hue was devised using shallow FFNNs in the field of color research. The body layer of metal-ceramic specimens was studied by 120 authors utilizing a database of 43 examples with pigment combinations. A reduction in the average E was achieved from 3.54 to 1.11 when using the visual technique. There have been a lot more fascinating issues.[19-21]

Orthodontia, dental artifact state prediction, and cutting force forecasting for various ceramic prostheses using various manually selected characteristics are some of the topics being investigated.

ML applications in Dentistry

For a variety of various challenges, specialists manually identified/extracted certain relevant features for a set of patients/cases using the techniques outlined above.

A total of 5135 people participated in the study, and ML approaches were used to pick the most relevant characteristics to categorize the presence and absence of root decay.[22]

The age of the individual was shown to be the most important factor in the ML models. With 97.1 percent accuracy, 95.1 percent precision, 99.6 percent sensitivity, and 93.3 percent specificity, SVMs outperformed the other techniques utilized in the study in the diagnosis of root caries. Similar findings may be achieved by extracting characteristics from color pictures and x-ray images, which have been proposed in the literature and have been shown effective.

The application of these approaches in conjunction of diverse data sources for the detection of periodontal diseases has been widely investigated in literature. In a 10-fold cross-validation (CV) employing 300 samples, SVMs and clinical factors were used to diagnose periodontal disease with an accuracy of 88.7 percent. A biomarker com- parison between gingivitis and periodontitis using salivary gene expression patterns, obtained an accuracy of 78 percent . Other forms of biological or clinical data, such as rRNA, microbial profiles, or other clinical markers, have been utilized to detect illness.[23]

Oral cancer detection and survival prediction using ML algorithms have been the subject of several theoretical proposals in the literature. For survival prediction, an accuracy of 76 percent was attained utilizing a decision tree and clinical characteristics for a global, recurrence-free 5-year survival,1similar to prior results. The RMSE (root mean square error) for forecasting survival time was 22.1 using extreme learning machines and clinical data.[24] aspects of the human body gene expression were integrated for prognosis prediction, using the ElasticNet method. WSIs were utilized in conjunction with several algorithms and manually derived features to get a high-classification performance for oral cancer classification. Another study examined several machine learning algorithms on this problem using clinical data as the input.[25] For this particular assignment, an RF was used in conjunction with DNA data from the mucosal microbiome, and the results were excellent.

A regression model with LASSO feature selection and other approaches were also used to predict the need for dental care.

Gingival health, demography, access to healthcare, and overall health were the most important factors in predicting dental care.

A variety of models, including logistic regression, SVM, RF, and classification and regression trees, were able to use these data as inputs. According to accuracy, RF outperformed the others (84.1 percent). Tooth extraction need prediction has also been investigated in literature utilizing several types of photographic images150 or clinical data.[26]

Oral cleanliness has also been linked to a reduced risk of oral illnesses. A new approach for detecting brushing and flossing habits, based on wrist-worn inertial sensors, was suggested. They were able to anticipate if the user was brushing their teeth, as well as the start and finish points of the brushing operation, using sensor data. With a false positive rate of one incident for every nine

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days of sensor usage, their brushing model obtained a median recall of 100%. naïve bayesian classifier and chosen pain factors were used to estimate dental pain. Also, gene expression data has been used in the literature to predict oral malodor and oral clefts, respectively (using single nucleotide polymorphisms data).[27,28]

The application of ML algorithms has helped solve further issues as well, notably

many kinds of information For example, dental restoration identification and tooth segmentation and numbering have been accomplished using radiographs and SVMs. A CBCT scan's images have also proved used for RF-based tooth segmentation and numbering. SVMs with RGB pictures have been utilized to diagnose deformities,[29]and shade matching has been accomplished using RGB images.[30-32] Implant bone levels have been predicted using clinical and SVMs or trees models, as well as the failure of dental implants using bagging.

Fuzzy Logic

FL was born out of the need to cope with the inherent ambiguity that exists in both the functioning of knowledge and the representation of it. Since fuzzy sets may be used to represent human-understandable quantification words, such as "high" or "low" for a temperature variable in a problem, fuzzy systems can be used to handle more human-like information than other well-known computer paradigms. When the temperature drops, "IF Temperature is low, then Heating should be turned up" is an example of an IF-THEN rule that can be clearly understood by professionals.[33-36] Expert-provided previous knowledge or accessible data can be used to drive the design of fuzzy systems.

Clinical prospects

The dentistry sector and dental care providers can benefit from the use of AI-generated dental models. Biomimetic approaches to dental materials research and development, diagnostic tools (e.g., for the detection of caries, periapical lesions, and periodontal disease), treatment planning, and the administration of oral health care services are all potential uses. AI may be used to construct CAD systems that can help diagnose specific illnesses by evaluating pictures (photographs and radiography). There will be a substantial influence on dentistry due to the present trend and quick growth of AI, especially in the field of digital dentistry.

protocols. Pre-appointment (AI Patient Manager, AI Patient History Analyzer, AI Scientific Data Library), inter-appointment (AI Problem Detector, AI Treatment Proposals, AI Instant Feedback), and post-appointment (AI Laboratory Work Designer, AI Patient Data Library, AI Clinical Evaluation) dental care can benefit from AI data collection. 44 Patients' preferences (day and time of appointments, music, calming smells, and room temperature) should be considered prior to the dental session. Preparation for the visit should include a thorough review of the patient's medical history (vital signs, allergies, health conditions, current medicines, and drug interactions). The diagnostic and treatment suggestions are generated during the dental session. Predicting the outcomes and prognosis of therapy is essential. Immediately following the dentist appointment, a digital workflow is created, and dental restorations are manufactured in a timely and correct manner. 44 It's important to remember that artificial intelligence (AI) assists dentists, not replaces them. Diagnosis and treatment planning in dental clinics are increasingly being done digitally and using AI. Although just a small fraction of dental clinics has completely incorporated AI, this is changing. "Smart dentistry clinics" are another name for this method of operation.

Cone beam computed tomography, intraoral and face scans, and other 3D dental imaging techniques have sped up the development of artificial intelligence (AI) systems based on 3D images. An automated, high-quality diagnostic and treatment planning might be provided by these models' advancements. 41 Dental professionals and industry leaders throughout the world have expressed an interest in AI, indicating that it is both the present and the future of dentistry.

CONCLUSION

Artificial intelligence models depicted in the studies exhibited tremendous potential for clinical applications in dentistry and more advancements in relation to this is inevitable with a AI being the way forward.

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