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REVIEW ARTICLE

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Applications of artificial intelligence in dentistry: A comprehensive review

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Abstract

Objective: To perform a comprehensive review of the use of artificial intelligence (AI) and machine learning (ML) in dentistry, providing the community with a broad insight on the different advances that these technologies and tools have produced, paying special attention to the area of esthetic dentistry and color research.

Materials and methods: The comprehensive review was conducted in MEDLINE/PubMed, Web of Science, and Scopus databases, for papers published in English language in the last 20 years.

Results: Out of 3871 eligible papers, 120 were included for final appraisal. Study methodologies included deep learning (DL; $n = 76$), fuzzy logic (FL; $n = 12$), and other ML techniques ($n = 32$), which were mainly applied to disease identification, image segmentation, image correction, and biomimetic color analysis and modeling.

Conclusions: The insight provided by the present work has reported outstanding results in the design of high-performance decision support systems for the aforementioned areas. The future of digital dentistry goes through the design of integrated approaches providing personalized treatments to patients. In addition, esthetic dentistry can benefit from those advances by developing models allowing a complete characterization of tooth color, enhancing the accuracy of dental restorations.

Clinical significance: The use of AI and ML has an increasing impact on the dental profession and is complementing the development of digital technologies and tools, with a wide application in treatment planning and esthetic dentistry procedures.

KEYWORDS
artificial intelligence, deep learning, dentistry, machine learning

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1 | INTRODUCTION

Since its beginnings, the use of artificial intelligence (AI) has brought advancements of high importance, which have enhanced our daily life and everyday activities in many ways (facial recognition, self-driving cars, and image classification, among others). A growing number of fields can benefit from AI support, including the surgical field (e.g., intelligent systems for assisted surgery, and video-surgery)[1,2] automatic disease diagnosis (e.g., decision support diagnosis systems from images)[3–5] and the recently developed personalized medicine, which provided the predisposition to diseases, diagnosing, and selection of the best treatment for a given individual[6–11] Although, dentistry might not seem to be greatly impacted by the advances in AI, certain areas such as image-based automatic detection of diseases and other diagnosis-support systems,[12,13] image segmentation for automatic detection of oral traits,[14,15] and resolution enhancement of dentistry related images,[16] are undergoing significant improvements thanks to the use of AI.[17] On the robotics side, several advances are similarly enabling the utilization of robotic support in dentistry.[18] Either way, the door is still wide-open to AI techniques in many areas of dentistry, all under the emerging digital dentistry paradigm.

Several factors have contributed to this recent wave of AI revolution in biomedicine. First, data collection has increased exponentially over the last decades. Yet, data by itself is not enough. Thanks to the developments in high-performance computing (HPC), new powerful AI techniques have enabled a thorough and insightful extraction of information from collected data. This information extraction process is normally referred to as machine learning (ML), that is, the data-driven part of AI, whose objective is to allow the machines (algorithms executed in computer systems) to learn about a specific topic from a certain available dataset. This type of information extraction is usually performed by using supervised learning techniques, which have solved many problems with great success.[19] Supervised learning is the task of learning a function that maps an input sample to a desired output, all based on a database of examples of input–output pairs. Once this function has been learned by using training data, new predictions over new incoming samples can be performed.[19]

Within this dramatic expansion across all the biomedical sciences, ML has reached a number of important milestones. These include the resurgence in recent years of neural networks under the new paradigm of deep learning (DL), the incursion of fuzzy logic (FL) for the treatment of uncertainty and the labeling of numerical data through "linguistic" terms, and the boom in kernel methods (KMs) and other specific ML techniques such as XGBoost.

KMs revolutionized the ML field in the late 1990s and the beginning of the 2000s,[20] being a highly considered technique for pattern recognition tasks for middle sized datasets.[21] Other pattern recognition techniques that strongly impacted the ML field include random forest (RF) and XGBoost,[22,23] decision-tree based methods frequently applied to a wide range of biomedical problems, including dentistry.[24]

FL is a well-known paradigm, which has been widely used in the design of decision-making support systems and other applications.[25,26] Its main advantages are related to their capacity to deal with uncertainty in data and with its ability to provide interpretable solutions to the experts in the form of rule bases. Specifically, an area with important applicability to esthetic dentistry is the so-called color naming (i.e., color designation) technique. Early results indicate that bridging the gap between the computational representation of colors in digital devices and subjective human perception of color may be possible.[27] Fuzzy colors, defined as fuzzy sets, allow semantics to be introduced in the automatic operation and description of color.[28]

Finally, DL[29] has matched and improved human performance for very complex tasks in areas such as image processing (e.g., object detection, and facial identification) and sound processing (e.g., speech synthesis and processing). In dentistry, the first models based on convolutional neural networks (CNNs) and 2D and 3D photography are emerging for the 3D design of dental prostheses, with very encouraging results.[14,15] Industrial initiatives to store information virtually from a large number of cases for subsequent processing enable a knowledge base to be built to help with the design of optimized treatments based on big data and AI techniques.[30] Recently, several reviews have been published relating AI and ML with dentistry. They have approached the topic from a clinical point of view,[31–34] either focusing on specific dentistry research areas (AI for dental and maxillofacial radiology,[35] forensic odontology,[36] orthodontics,[37,38] dental caries[39]) or on specific AI working areas of dentistry (DL in dentistry,[40] AI for dental imaging).[39,41–43] Other review works have approached future trends and challenges.[44–48]

This comprehensive narrative review provides an insight into the different applications of ML in dentistry from a ML-focused approach to the problem. Special attention was paid to the area of esthetic dentistry and color research, and the great benefits that techniques such as DL and FL bring to this area.

The manuscript is organized as follows: Section 2 presents the methodology carried out to perform the present review. Then, the articleis organized based on the classification of ML techniques, on the three aforementioned main milestones and their application in dentistry. Section 3 presents the well-known and break-through paradigm of DL, which has dramatically changed the way computation and science is done, and summarizes the up-to-date dental applications that make use of deep neural networks (DNNs) to solve a variety of problems. An introduction to other ML techniques in provided in Section 4, such as KMs and gradient-boosting decision tree techniques, and their applications. Finally, Section 5 introduces the FL paradigm, including use of fuzzy systems for color naming in dentistry and fuzzy systems for diagnosing dental diseases. Section 5 is dedicated to some recent clinical assistance software initiatives, which have gained attention in the last few years, and that claim to apply AI techniques in their operation. Finally, Section 6 is dedicated to the future scope of data-driven AI techniques in dentistry, both from the computational and clinical points of view.

2 | MATERIALS AND METHODS

The review included studies that reported on AI and ML methodologies and applications in dentistry. In addition, the datasets and the comparison (expert opinion or reference standards) used for the model had to be indicated, and studies outcomes had to be quantified (predictive or measurable outcomes). In contrast, the exclusion criteria were as follows:

1. Type of study: animal studies, forensic studies, literature reviews of AI applications for dentistry, letter to editors, comments, questionnaire-based studies, and conferences abstracts.
2. Methodology: AI studies not applied to dentistry, robotics, AI model not described.
3. Outcome: studies that did not report numerical or measurable outcomes.
4. Studies using supervised learning that did not provide information on the data sets used for either training-test or cross validation for the assessment of the methodology

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 20 years, and the last search was performed on January 1, 2021. Table 1 shows the search strategy and the terms used for PubMed. The search strategy performed on Web of Science, and Scopus were adapted for each database.

TABLE 1 Structured search strategy carried out in MEDLINE/PubMed database. Searches on Scopus, and Web of Science were adapted according to the respective database

Search	Topic and terms
#1	Artificial Intelligence: "artificial intelligence" OR "machine learning" OR "neural networks" OR "deep learning" OR "Fuzzy logic" OR "computational intelligence" OR "machine intelligence" OR "computer reasoning" OR "Support Vector Machines" OR "generative adversarial networks" OR "color naming" OR "TSK fuzzy system" OR "Computer Vision Systems" OR "Supervised Machine Learning" OR "Fuzzy C-means" OR "Unsupervised Machine Learning" OR "Clustering" OR "Natural Language Processing" OR "TSK fuzzy system" OR "Computer Vision Systems" OR "Supervised Machine Learning" OR "Fuzzy C-means" OR "Unsupervised Machine Learning" OR "Clustering" OR "Natural Language Processing"
#2	Dentistry: "dentistry" (Mesh) OR "dentistry" OR "operative dentistry" OR "esthetic dentistry" OR "orthodontics" OR "pediatric dentistry" OR "oral pathology" OR "periodontics" OR "preventive dentistry" OR "prosthodontics" OR "oral surgery" OR "oral medicine" OR "endodontics" OR "oral cancer" OR "tooth segmentation" OR "prosthodontics" OR "dental materials" OR "tooth color" OR "orthodontics" OR "pediatric dentistry" OR "oral pathology" OR "periodontics" OR "preventive dentistry" OR "oral surgery" OR "oral medicine" OR "endodontics" OR "oral cancer"
#3	Search #1 AND #2

After searching each database, Mendeley software was used to eliminate duplicates. Two reviewers (FCP and OEP) independently selected the studies analyzing the title and abstract, according to criteria previously described. In case of disagreement, this was resolved by the consensus of a third reviewer (Luis Javier Herrera). During full text reading, the reasons for excluding any paper was recorded (Figure 1).

A descriptive analysis of the findings was used to evaluate the data. As the selected studies had a large diversity of objectives and the objective of the present study is to analyze the different methodologies of ML applied in dentistry, a quantitative analysis was considered impractical. Therefore, a qualitative data synthesis was performed for this comprehensive narrative review based on a systematic search.

Table 2 shows the AI methodologies and applications in dentistry reported in the included studies (120), which are also organized based on their data type. Table 3 shows a glossary with AI and ML terms used along the manuscript.

3 | DEEP LEARNING APPLICATIONS IN DENTISTRY

Artificial neural networks (ANNs) are learning algorithms based on the functioning of biological neural networks. They can be used for supervised, unsupervised, and reinforcement learning problems and been used to solve many different problems. The basic structure of an ANN is a set of interconnected layers of operating neurons, and the term *deep* refers to ANN with a large (deep) number of both layers and neurons per layer.

Applications of DL in dentistry are probably the most promising area of research in this field. This type of techniques can contribute to the design of high-performance decision-making support systems since they allow the identification of specific patterns from large databases of images (although any type of biomedical signal or other data sources could be used).

3.1 | Basic operation of an artificial neural network

The most general type of ANN is the multilayer perceptron, also known as feed forward neural network (FFNN), wherein connections between the nodes do not form a cycle. In this type of networks, the information moves in only one direction, forward, from the input nodes, through the hidden nodes (if any) and to the output nodes.[162] The basic building blocks of ANNs (and FFNNs specifically) are the so-called neurons. The neuron is formed by a weight vector W, a unique value named 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 calculus, the activation function determines whether the neuron will activate or not. If the sum exceeds a threshold θ, it will return a one; if it does not, it will return a zero. Neurons are grouped in layers, which in the case of FFNNs are named as follows:

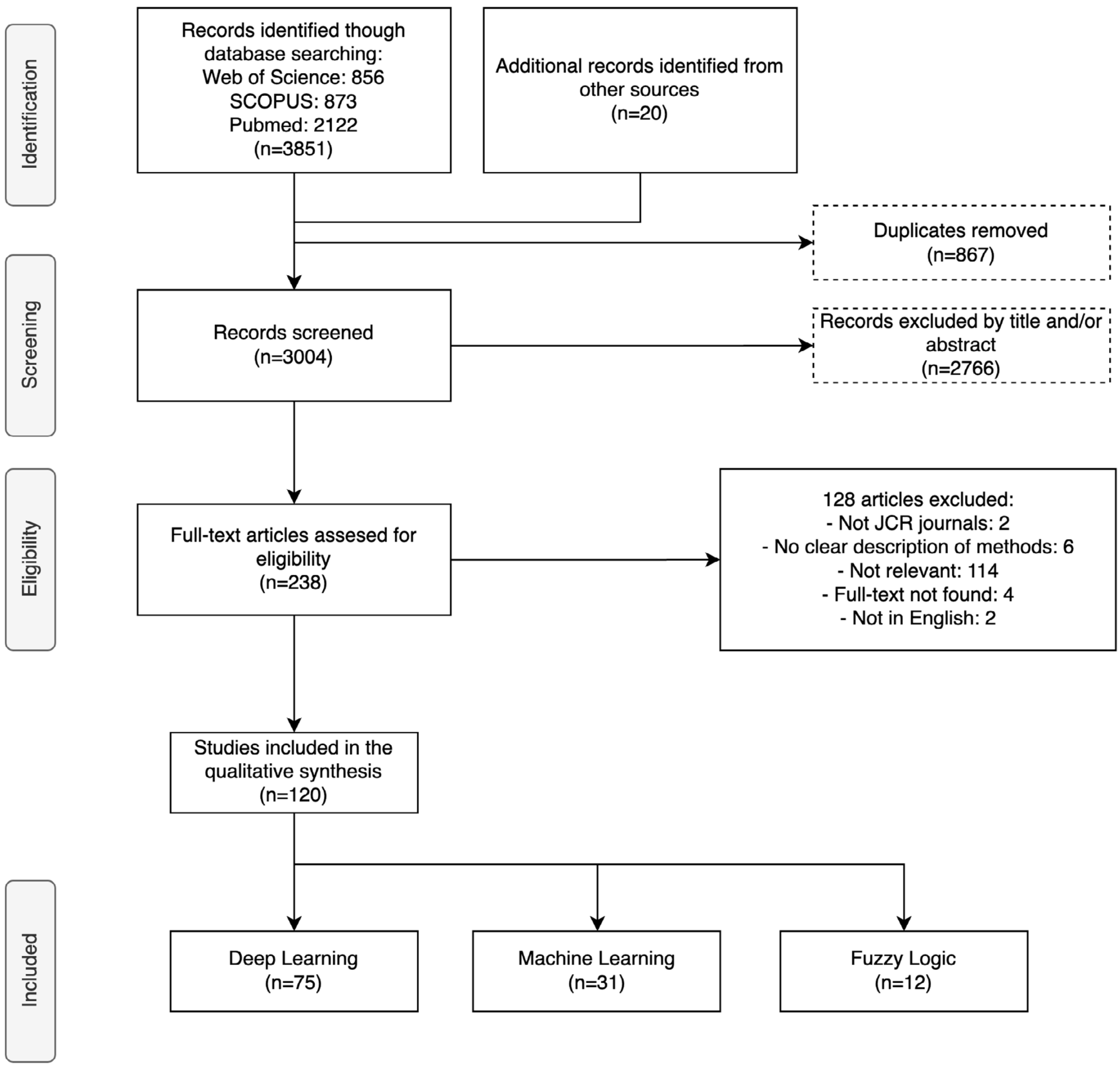

FIGURE 1 Flow diagram of the electronic search

- Input layer: Layer that receives the input data.
- Output layer: Layer that determines the output of the network. The output layer would have the same number of neurons and the number of classes in the dataset.
- Hidden layer: Layer (there can be one or several) that processes the information from the previous layer and calculates its output, which is taken as input by the next layer.

For a given problem, neurons weights need to be learned in order to properly approximate the function that would classify or predict an input. To accomplish this task, the backpropagation algorithm[163] was proposed. It uses a dataset of samples of a problem with known output, and in an iterative way updates the weights as follows:

$$w^{k+1} = w^k + \Delta w,$$

$$\Delta \mathrm{w_i} = -\eta \cdot \frac{\partial \mathrm{E}}{\partial \mathrm{w}},$$

where η is the learning rate and $\frac{\partial E}{\partial w}$ is the errors gradient in respect to the weights. The gradient gives how a function varies in respect to the variable is being derived. The negative sign is used since the error needs to be minimized. FFNNs were proven to be a universal approximator.[164] A basic scheme of an FFNN can be observed in Figure 2.

This basic operation of networks with a certain number of layers represents the building block for other more complex DL models, such as recurrent neural networks (RNN) or the next reviewed CNNs. These have been shown to be useful in solving in a number of specific problems.

3.2 | Convolutional neural networks

Based on the popularity of the multilayer perceptron, other neural network architectures have been proposed. One example is CNNs, with a strong impact in computer vision thanks to an architecture

TABLE 2 Included studies organized by the AI methods and techniques, target problems, and data type used

Technique	Application	Target problem and studies number	Data type used
Deep learning			
	Disease identification	Dental caries,[12,49–53] oral cancer,[54–62] gingivitis,[63,64] other diseases[65–80]	Radiography,[12,49,50,57,58,65–73,77] CT images,[59,74,76,80] Other image formats,[51,53–56,61,63,64,75,78,79] clinical data[52,60,62]
	Image segmentation	3D tooth segmentation,[14,15,81–84] 2D tooth segmentation,[85–89] teeth classification and numbering,[90–95] segmentation for disease diagnosis,[53,61,72,73,79,80] segmentation of other oral surfaces,[96–102] metal artifacts,[103–105] root morphology,[106] teeth alignment[107]	Radiography,[72,73,85–88,91–93,95,99–102,106] CBCT images,[14,80,82–84,89,90,94,98,103,104] other image formats[15,53,61,79,81,96,97]
	Image correction	Image enhancement[16,108,109]	CBCT images[16,108,109]
	Other applications	Dental implants classification,[110–112] landmark detection,[113–116] forecast cutting forces,[117] need of orthodontic treatment,[118,119] dental artifact status prediction.[105] Color matching[120]	Radiography,[110–112,115] CBCT Images,[105,116] clinical/other types of data,[117–120] other image formats[113,114]
ML techniques			
	Disease identification	Dental caries,[13,121,122] periodontal disease,[123–127] oral cancer,[128–135] dental pain,[136] oral malodour,[137] oral clefts detection.[138] Oral disease prevention[139]	Radiography,[122] other image formats,[121,128,129] clinical/biological data[13,123–127,130–139]
	Other applications	Dental restoration detection,[140] dental deformities,[141] failure of dental implants,[142] tooth segmentation and numbering,[143,144] predict implant bonelevels,[145] shade matching,[146] dental care and tooth extraction needs[24,147–150]	Radiography,[140,143] CBCT images,[144] clinical/biological data,[24,142,147–149] other image formats[141,146,150]
Fuzzy logic			
	Disease identification	Periodontal disease,[151] Candidiasis risk factor,[152] other diseases and applications[153–158]	Clinical/biological data,[151–154] radiography[155–158]
	Biomimetic color analysis and modeling	Color naming,[28] color threshold calculation,[159,160] shade guide optimization[161]	Tooth color measurements[28,159–161]

based on the convolution operation, which is applied as a matrix multiplication between a filter and the data. CNNs have been around for a long time. Although they were first proposed in 1980,[165] it was not until diverse modifications were applied to the learning algorithms, the quantity of data available was dramatically increased, and the necessary computing platforms were developed, that CNNs were revisited. One of the most important works from this new era of CNNs was proposed for solving a digit classification problem.[166] Since then, many studies have been published showing CNNs outperforming other established techniques (in some cases even outperforming human capabilities) in multiple computer vision problems,[167] including pattern recognition, image segmentation, and image generation.

What makes CNNs so special is their refined ability to automatically extract features from data. Previously, features needed to be extracted *by hand* from images for later processing.[168] Due to its complexity, this was considered as one of the toughest tasks in computer vision. Figure 3 shows the convolution basic operation. At its most basic, it can easily detect edges, lines, textures, and other simple patterns in an image. By using different layers together with an adequate learning algorithm, more complex filters can be learned. These more complex filters would not only be able to detect specific complex shapes in images or in the signals presented, which are more relevant to the problem tackled, but they would also improve the model performance when compared with other more traditional methods. In fact, in CNNs, by applying the convolution operation and through the backpropagation of the error for the weights update, those complex filters are learned in a straightforward manner.[29] By grouping the convolutional operation in convolutional layers, different specific features can be learned within the same layer. The use of multiple layers would lead to a hierarchical structure where the first layers will learn basic features

TABLE 3 Glossary

Acronym	Term	Definition
AI	Artificial intelligence	The theory and development of computer systems able to perform tasks normally requiring human intelligence, such as visual perception, speech recognition, decision-making, and translation between languages
	Supervised learning	ML approach where labeled data is used for predicting labels or outcomes
NN	Neural network	ML technique inspired in biological neurons where the input is fed to one or multiple layers to produce an output
FFNN	Feed forward neural network	ML technique inspired in biological neurons where the input is fed to one or multiple layers to produce an output
DNN	Deep neural network	NN with multiple hidden layers, allowing more complex feature construction
TL	Transfer learning	Technique for DNN that used the previously learnt weights from a bigger dataset to learn in an smaller one
CNN	Convolutional neural network	Special type of NN. It can extract spatial information by means of filters, which use the convolution operator
GANs	Generative adversarial networks	Methodology that is used to generate data similar to the input data. Make use of two different models that compete against each other
SVMs	Support vector machines	ML technique where for classification a maximum margin separating hyperplane is built so that the samples of different categories are divided by a clear gap that is as wide as possible
DT	Decision tree	Flowchart-like structure in which each internal node represents a "test" on an attribute, each branch represents the outcome of the test, and each leaf node represents a class label
	Bagging	ML methodology that combines the prediction of multiple weak classifiers in order to improve classification performance
	Boosting	ML methodology that builds classifiers sequentially based on the error of the previous classifier in order to improve classification performance
RFs	Random forest	Methodology that combines the prediction of a high number of weak decision trees, averaging their predictions to perform a final prediction
GB	Gradient boosting	Methodology that builds classifiers sequentially based on the error of the previous ones
FL	Fuzzy logic	A form of many-valued logic in which the truth values of variables may be any real number between 0 and 1 both inclusive. It is used to handle the concept of partial truth, where the truth value may range between completely true and completely false
	Fuzzification process	Converts the given numbered-valued inputs into fuzzy sets according to their membership functions for its later operation using fuzzy logic
	Knowledge database	Provides the definition of the linguistic values of each of the variables considered in a problem, together with the rules making up the rule base of the system
	Inference engine	Operates according to the input values provided and the rule base. It is itself the core of the fuzzy system and resembles the human capability to take decisions
	Biomimetic	Is defined as the examination of nature, its models, systems, processes, and elements to emulate or take inspiration from nature in order to solve human problems

(e.g., lines or corners) and will pass that information to the remaining layers in order to detect more complex features (e.g., numbers or traffic signs). In their operation, CNNs are formed by different kind of layers:

- Convolutional layer: As explained, these are based on the convolutional operation, which is applied to the whole data spatial domain (image or signal). Their main goal is to extract information from the data, transforming the input values into a different representation. Internally they are weight matrices that are learned during the training process (Figure 3).
- Pooling layer: Pooling layers reduce the dimensions of the data by combining the outputs of neuron clusters at one layer into a single neuron in the next layer. They are usually placed after the activation function.[29] This reduces the amount of information extracted by the convolution filters.
- Fully connected/dense layers: These are placed as final layers of the CNN. Fully connected layers connect every neuron in one layer to every neuron in another layer, and it is the same main component of FFNN. They operate over the features learned by the convolutional layers in order to perform the classification.

A general architecture for a CNN can be observed in Figure 4. The feature extraction operation is performed by a set of convolutional filters (in the form of convolutional layers). Later, those filters are used for predictive tasks, using fully connected layers.

An important aspect to be considered when using DL techniques is that they normally require large databases of high-quality images to

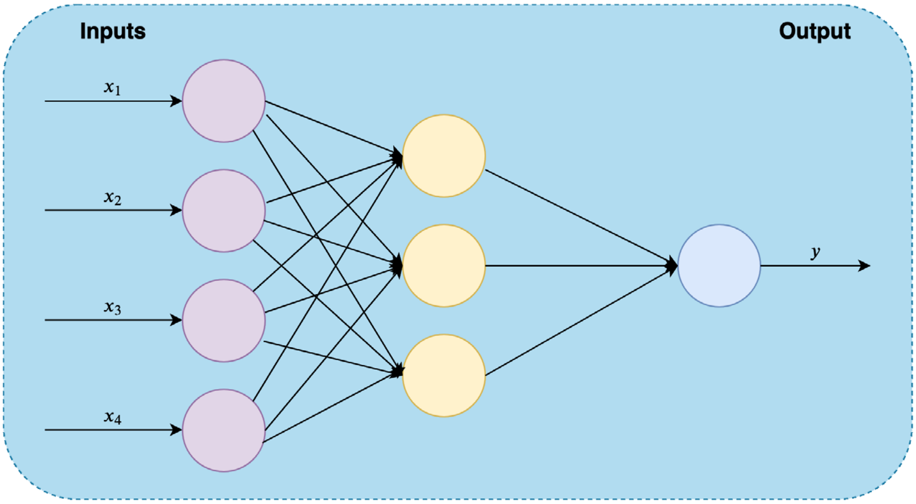

FIGURE 2 Example architecture of FFNN with four inputs and one output. FFNN, feed forward neural network

learn very specific patterns. This requires much computational time and powerful HPC systems. In order to avoid these possible drawbacks, transfer learning (TL) allows the use of a pretrained network (a DNN that has been trained on another dataset), which is able to identify complex patterns in image data, for a certain application. That network could be partially retrained (fine-tuning) with the application database (which is usually much smaller) in order to classify a set of moderately different patterns. This greatly expands the usability of DL models for specific tasks, by learning global image patterns in a sufficiently big database, but refining them with a smaller, more specific one. Several networks are commonly used by researchers to approach computer vision problems using TL, such as GoogLeNet Inception v3,[170] ResNet[171] in its various forms (Resnet-18, Resnet-34, Resnet-50, Resnet-101, and Resnet-152) or VGG net.[172] Details and examples of this general technique can be reviewed in several published papers.[173–175]

3.3 | Deep learning applications

Since large amounts of medical data are stored digitally, deep ANNs with computer-aided detection systems can be applied to several medical fields. In dentistry, the use of ANNs, and more concretely CNNs, has produced interesting results in diagnosis and prediction, especially in radiology and pathology, highlighting three application areas: disease or injury identification, image segmentation and their applications, and image correction through the use of Generative Adversarial Neural Networks. The next subsections expand on each of these application areas.

3.3.1 | Disease identification

ANNs have been successfully used for detection of dental caries from periapical radiographic images,[12,49,50] other types of radiographic images,[51] near-infrared transillumination images[53] or clinical features.[52] Similarly, oral cancer diagnosis has benefit from the use of DL, either from hyperespectral[54] or photographic[55] images, different types of medical images,[56–59,61] or through the use of clinical data.[60,62]

One group used a pretrained GoogLeNet Inception v3 CNN network[170] to detect and diagnose dental caries in premolar and molar teeth.[12] The dataset (3000 periapical radiographic images) was trained using TL. The diagnosis accuracy of dental caries was 89.0% for premolars and 88.0% for molars. More recently, it was reported that a CNN-based model (U-Net[176]) for caries detection was used, reaching an accuracy of 80% using radiographic images.[49] The use of clinical data on shallow FFNNs has also been inspected for caries presence estimation,[52] and for *post-Streptococcus* mutants estimation prior to caries excavation.[50]

For oral cancer diagnosis and prognosis, CNNs with hyperspectral images as input were used, reaching an accuracy of 91.4% in a 7-fold CV.[54] Photographic images and TL were used for oral cavity squamous cell carcinoma using a large database with more than 40.000 images to reach a 92.3% of accuracy.[55] Other works have focused on CNN models using other types of images (histopathological,[56] x-ray[57,58] or cone bean computer tomography-CBCT-scans[59]), or shallow ANNs[60,62] using clinical features, all with a more modest success.

For other diseases, TL was used to train a CNN algorithm for the diagnosis and prediction of periodontally compromised teeth from radiographic images.[65] Analyzing the periapical dataset (N = 1840) with the DL algorithm, the diagnosis accuracy of periodontal disease was 81.0% for premolars and 76.7% for molars. Besides, different approaches have been followed for the diagnosis of the gingivitis disease, by employing shallow FFNNs[63,64] and CNNs.[79] An extreme learning machine (a simple way of training a model by using randomly assigned parameters) over a basic ANN architecture with manually extracted features was used to diagnose gingivitis.[63] The features extracted were based on contrast-limited adaptive histogram equalization (CLAHE) and the gray-level co-occurrence matrix (GLCM). The dataset used by the authors contained 93 digital images (58 images were from gingivitis cases and 35 images were from healthy patients used as control). The methodology was built upon previous work[64] and showed improvements in the results, reaching 74% accuracy, 75%

sensitivity, and 73% specificity. CNNs were also used for the early identification of the disease in intraoral images, reaching great results.[79]

New approaches, such as mobile health (mHealth) alternatives, are currently under development for the self-examination and identification of different oral conditions (diseases or early disease signals) using a smartphone camera and the internet-of-thing (IoT) approaches.[75] A smart dental health IoT platform, which uses the Mask-RCNN network[177] for the detection and classification of seven different oral diseases, reaching a mean accuracy of 93.6%, was proposed.[75]

DL has also been used in the detection and assessment of other diseases or lesions using different types of images. Radiographs have been found useful for periodontal bone loss,[66,73,77] ostheoporosis,[67] maxillary cyst-like lesions,[68] periapical disease,[69] apical lesions,[70] lesions detection[72] or the detection of root fractures.[71] Also, CBCT scans have been successfully used to diagnose Sjögren's syndrome,[76] periapical pathosis[74] or lesions detection.[80] Finally, the use of RGB images for plaque detection[78] has also been explored in literature.

3.3.2 | Dental image segmentation and applications

CNN models have been widely used for 3D[14,15,81–84] and 2D[85–89] tooth segmentation, including teeth classification and numbering,[90–95] using CBCT scans for the 3D evaluations.[14,82–84] A manually extracted set of geometry features as face feature representations from CBCT scans, and a manually labeled dental mesh dataset with 1200 samples were used as input for this task.[14] For tooth segmentation, a two-level hierarchical CNNs structure was used for teeth-gingiva labeling and inter-teeth labeling, reaching an accuracy of 99.1%. Similar approaches were taken, and authors used volumes of interest for the segmentation.[82] Some authors used the U-Net[176] architecture,[83] or a Multi-task 3D CNN,[84] all achieving remarkable results. Other types of three-dimensional data have been used for tooth segmentation. A separate approach used a CNN and 3D dental models in combination with a sparse voxel octree, reaching a high accuracy in the segmentation task.[15] 3D dental models were also successfully applied as input, using FFNNs for the segmentation task.[81]

The use of 2D images has also been explored in literature for tooth detection and segmentation, mainly by employing radiographs,[85–88] but also 2D images obtained from CBCT scans.[89] Periapical radiographs were used for tooth segmentation using a VGG-16 architecture, reaching a high precision and recall (95.8% and 96.1%, respectively).[85] Similarly, the Resnet-101 architecture was utilized for the same task, obtaining a precision in the tooth detection of 99.6%.[86] Two papers used similar approaches, reaching great results.[87,88] The U-Net[176] architecture and 2D images obtained from computer tomography (CT) scans were also used, reaching a dice similarity coefficient of 91.7%.[89]

The segmentation of oral diseases can increase the performance of the diagnostic process, as the algorithm can then focus on the identified regions of interest. Therefore, several works have segmented the disease prior to the diagnosis for a range of diseases and a range of image types. This approach has been useful, for instance,

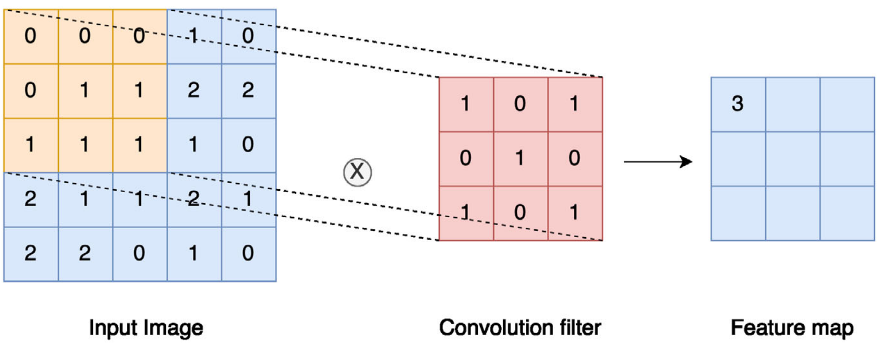

FIGURE 3 Example of convolutional operation in a convolutional layer

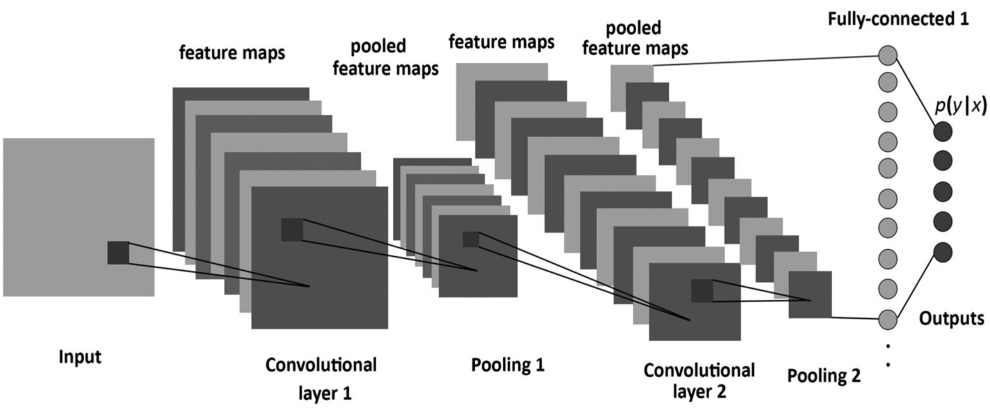

FIGURE 4 Example of a general CNN architecture.[169] CNN, convolutional neural network

in maxillary sinus lesions on panoramic radiographs,[72] oral squamous cell carcinoma segmentation in whole-slide imaging (WSI),[61] gingivitis segmentation in intraoral images,[79] the segmentation of periodontal bone loss and stage periodontitis classification using panoramic radiographs,[73] lesion segmentation using CT images,[80] or dental caries segmentation using near-infrared transillumination images.[53]

The segmentation of other oral surfaces has also been widely explored in literature by using dental radiographs,[99–102] intraoral ultrasound imaging,[97] 3D intraoral scans,[96] or CBCT Scans.[98] For instance, one paper used a U-Net based model for the segmentation of the third molar and the mandibular nerve.[99] Authors obtained a dice-coefficient of 0.95 for third molar, and 0.847 for nerve. CNNs have also been used for molar angulation measurement,[100] mandibular canal detection,[98,102] maxillofacial segmentation,[101] and alveolar bone segmentation.[97] FFNNs were also implemented for the segmentation and labeling of raw dental surfaces, reaching a mean dice-coefficient of 0.95.[96]

Finally, other problems have been addressed using the aforementioned DL techniques, such as: the segmentation of metal artifacts,[103–105] root morphology,[106] or segmenting for teeth alignment.[107]

3.3.3 | Image correction through generative adversarial networks

Generative adversarial networks (GANs) are an ANN framework based on a game theory scenario where two players—the generator network and the discriminator network—play against each other. The generator network produces samples based on what it learns from the training data, while the discriminator network tries to distinguish between samples draw directly from training data and those produced by the generator. The discriminator emits a probability for that sample being drawn from training data or produced by the generator. Therefore, the discriminator goal is to correctly classify samples as real or fake. At the same time, the generator tries to fool the classifier into believing its samples are real, learning from the data presented. At convergence, the generator's samples are indistinguishable from real data, and the discriminator outputs everything as real data. A diagram of a GAN can be observed in Figure 5.

Since the introduction of GANs,[178] several different applications have been presented, mainly for computer vision problems. Any kind of model can be used with GANs, but since GANs are mainly used in computer vision problems, CNNs have usually been the preferred model. In the case CNNs are chosen, the model is called deep convolutional GAN (DCGAN). These techniques have been mainly applied in dentistry for dental CT images.

In dentistry GANs have been used to improve low resolution or defective images. One study presented a DL-based method for enhancing the resolution of dental CT images using two CNN architectures (a subpixel network and the U-net network).[16] Different metrics (peak signal-to-noise ratio [PSNR], structure similarity index, and other objective measures estimating human perception) were used to evaluate the model. The CNN approach improved the CT images, allowing better detection of features, such as the size, shape, and curvature of the root canal. Similarly, Wasserstein GANs were used for artifact correction of low-dose dental CT imaging.[108] The authors trained a GAN with Wasserstein distance (WGAN) and mean squared error (MSE) loss, called m-WGAN, to remove artifacts and obtain high-quality CT dental images. The metrics used to assess performance were PSNR and structural

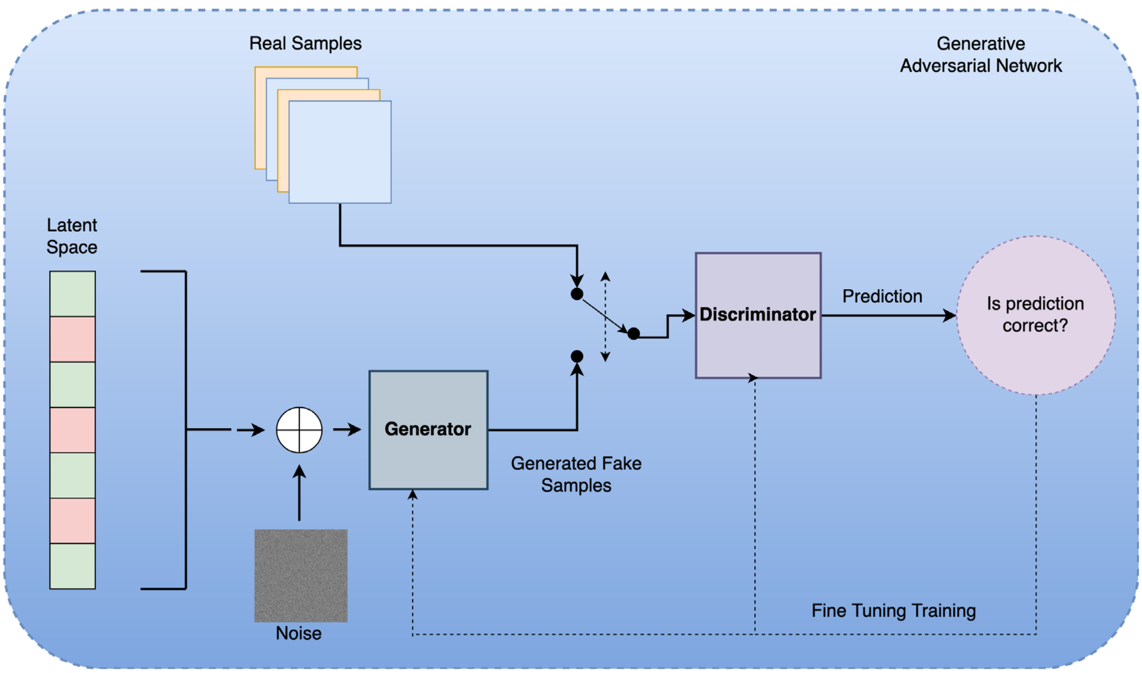

FIGURE 5 Example architecture for a GAN. GAN, generative adversarial network

similarity (SSIM), and statistical properties were used for metrics. The proposed m-WSGAN model outperformed general GAN. Another team used GANs for imaging denoising of dental CT, obtaining a PSNR of 24.0 and a SSIM of 0.96.[109]

3.3.4 | Other DL applications

DL techniques have been widely used in other related problems, such as dental implants classification.[110–112] When TL and periapical radiographs were used as input for implant identification, an accuracy of 98% was reported.[110] Similar results were obtained with the same methodology, except for the use of x-ray images.[111] Another study utilized CNNs and radiograph images for predicting dental implants from different manufacturers.[112]

Literature also addressed landmark detection for orthodontic treatments.[113–116] Cephalograms were used on a multi-head attention ANN for cephalometric landmark prediction, reaching an accuracy of 87.6%.[113] Similarly, a 3D CNN was used for surgery landmark prediction using CT images, achieving a mean error of 5.8 mm in comparison to the original landmark.[116] X-ray images have been used as inputs for the landmark detection task with an encoder-decoder architecture[114] or Bayesian CNNs.[115]

Within the color research area, shallow FFNNs were used to design a color matching system identifying the pigments needed to match a specific color.[120] Authors used a database with 43 samples using pigments combinations for the body layer of metal-ceramic specimens. In comparison with a visual approach, they reduced the average ΔE from 3.54 ± 1.11 to 1.89 ± 0.75. More interesting problems that have been explored are the need of orthodontic treatment,[118,119] dental artifact status prediction[105] or forecasting of cutting forces of different ceramic prostheses employing different manually selected features.[117]

4 | OTHER ML APPLICATIONS IN DENTISTRY

Using manually extracted features to design automatic decision support systems has also been an interesting area of research in dentistry. Several well-known ML methodologies can be found in the reference literature of AI, including basic techniques such as k-nearest neighbors, decision-tree, Naive-Bayes classifier, and logistic regression, as well as more advanced and powerful-contrasted methods, such as kernel-methods, RFs, and XGBoost. In this section, the focus is only on the three because of their comparative importance and modeling power.

4.1 | Support vector machines

KMs, and more specifically support vector machines (SVMs),[179,180] are an important family of learning algorithms. They gained popularity in the mid-1990s, and since then they have been applied to multiple problems in a variety of areas with remarkable results.[6,181,182]

In linear SVM classification, a maximum margin separating hyperplane is built so that the samples of different categories are divided by a clear gap that is as wide as possible. For that, the learning process automatically identifies a certain number of training samples (called support vectors) that define such hyperplane. New examples are then mapped and predicted to belong to a category depending on which side of the gap they fall. Although on its basis SVM is a binary classifier, it can also be applied as a multi-class classifier by following a one-against-one (OVO) set of classifiers methodology. Under OVO classification, *K(K1)/2* binary classifiers are trained. At prediction time, a voting scheme is applied: all *K(K1)/2* classifiers are applied to an unseen sample, and the class with the highest number of "$+1$" predictions is predicted by the combined classifier.[183]

The success of KMs, and SVMs in particular, has been related to their effectiveness in performing a nonlinear classification using what is called the kernel trick, implicitly mapping their inputs into high-dimensional feature spaces. The kernel trick internally operates the inner product in that so-called dual space. In practice, the kernel function can be seen as a similarity measure between samples, so that when a new sample arrives, it is applied to the incoming sample with respect to the support vectors in order to select the final class of the sample.

4.2 | Random forest

RFs[22] are an ensemble learning methodology based on decision trees. The popularity of individual decision trees lies in their straightforward interpretability, from which it is easy to check the decisions of the classifier. A decision tree is formed by a group of nodes, branches, and leaves. In each node a specific feature is tested. Each branch represents the outcome of that test and each leaf would represent a class. An example of a decision tree can be observed in Figure 6A. However, decision trees suffer from a significant performance bias in comparison with other well-known methodologies.

RFs, on the other hand, are formed by a vast number of decision trees, each making a prediction, and the class with the most votes is the RF classifier prediction. Interpretability is mostly lost, but they present a very precise behavior. Their power relies on having uncorrelated trees, since the trees—being uncorrelated—will protect each other from individual error. While some trees may be wrong, many other trees will be right, so, as a group, the RF can move in the correct direction. This technique can be enclosed in what is called bagging, a simple assembling technique in which many independent predictors/models/learners are built and combined using some model averaging techniques (weighted average, majority vote, or normal average). An example of a RF schema when predicting can be observed in Figure 6B.

4.3 | Gradient boosting

Unlike RF, gradient boosting (GB)[185] can be classified within the boosting ensemble techniques, in which the predictors, typically also decision trees, are determined sequentially rather than independently. In this case, the subsequent predictors (also known as weak models within GB terminology) learn from the mistakes of the previous classifiers. Therefore, errors do not propagate through iterations since the subsequent models are correcting them, and each additional weak model reduces the MSE of the overall model. The applied tweaks are based on the computed error, named direction vector. Based on that, the tweak is computed by using gradient descent, which gives a magnitude and a direction. The training process can be summarized as:

1. Fit a classifier on data.
2. Calculate error residuals. Actual target value, minus predicted target value.
3. Fit a new model on error residuals as a target variable with the same input variables.
4. Add the predicted residuals to the previous predictions.
5. Fit another model on residuals that are still left, and repeat steps 2–5 until it starts overfitting or the sum of residuals becomes constant. Overfitting can be controlled by consistently checking the accuracy of validation data.

4.4 | ML techniques applied to dentistry

The aforementioned algorithms have been used in the literature to solve a range of different problems in which specific significant features were manually identified/extracted by experts for a group of patients/cases.

ML methods were utilized to select the most relevant variables to classify the presence and absence of root caries in a study that included a total of 5135 volunteers.[13] Several variables fed the ML models, and it was determined that the age of individual was the most relevant variable. Comparing the methods used in the study, SVMs showed the best performance for the detection of root caries, with an accuracy of 97.1%, precision of 95.1%, sensitivity of 99.6%, and specificity of 93.3%. Other approached have been proposed in literature by using features extracted from photographic color images[121] and x-ray images,[122] achieving similar results.

The use of these techniques in combination of different data types for the diagnosis of periodontal diseases has been extensively explored in literature.[123–127] Using SVMs and clinical variables to detect periodontal diseases, an accuracy of 88.7% was reached in a 10-fold cross-validation (CV) using 300 samples.[124] A biomarker comparison between gingivitis and periodontitis using salivary gene expression profiles, reached an accuracy of 78%.[127] Other types of biological or clinical data have been used for the disease detection, such as rRNA,[123] microbial profiles,[125] or other clinical features.[126]

Several approaches have been proposed in literature for oral cancer diagnosis[128–131] and survival prediction[132–135] using ML algorithms. For survival prediction, an accuracy of 76% was achieved using a decision tree and clinical features for a global, recurrence-free 5-year survival,[134] similar to other results.[133] Extreme learning machines and clinical data, achieved a root mean square error (RMSE) of 22.1 when predicting the survival time.[132] Clinical features and gene expression were combined for prognosis prediction, using the ElasticNet algorithm.[135] For oral cancer classification, WSIs was used in combination with different algorithms and manually extracted features, achieving a high-classification performance.[128,130] Another paper tested different ML algorithms on this task using as input clinical data.[130] Interestingly, the use of DNA data from mucosal microbiome was explored for this task in combination of a RF, and heeded great results.[131]

Predicting the need for dental care was also studied using clinical features in combination with a regression model with LASSO feature selection[147] and other methods.[148,149] For dental care prediction, eight features were selected, and the most relevant were the following: gingival health, demographics, healthcare access, and general health variables.[147] These variables were used as input for different models, such as logistic regression, SVM, RF, and classification and regression tree. RF outperformed the other models in terms of accuracy (84.1%). In addition, predicting the necessity of tooth extraction has also been explored in literature by using different types of photographic images[150] or clinical data.[24]

The prevention of oral diseases based on oral hygiene behavior has also been reported. A novel method, based on wrist-worn inertial sensors to detect brushing and flossing behaviors, was proposed.[139] Using sensor data, the authors were able to predict if the user was brushing their teeth and the start and end of the toothbrushing action. Their brushing model achieved 100% median recall with a false positive rate of one event for every 9 days of sensor wearing. Dental pain was estimated using selected pain parameters and naive bayesian classifier.[136] Also, the use of omics information has been explored in literature for the prediction of oral malodour (using gene expression data),[137] and oral clefts (using single nucleotide polymorphisms data).[138]

Further problems have benefit from the use of ML algorithms and different types of data. Radiographs and SVMs have been used for dental restoration detection,[140] and tooth segmentation and numbering.[143] Images from CBCT scans have been useful also for tooth segmentation and numbering using RF.[144] Cephalometry images in combination with SVMs have been used for diagnosing deformities,[141] and the task of shade matching has been performed using RGB images.[146] Finally, clinical and SVMs or trees models have been used for predicting implant bone levels[145] and the failure of dental implants using bagging.[142]

5 | FUZZY LOGIC

FL arose as a way of dealing with uncertainty in the operation and representation of knowledge.[26,186] Fuzzy systems enable a more approximate human-like information processing than other well-known computational paradigms for to two main reasons: the core units of their operation are the fuzzy sets which may correspond to human-understandable quantifying terms such as *high* or *low* for instance, for a temperature variable in a problem. The solution makes use of IF-THEN rules, easily interpretable by experts, having fuzzy

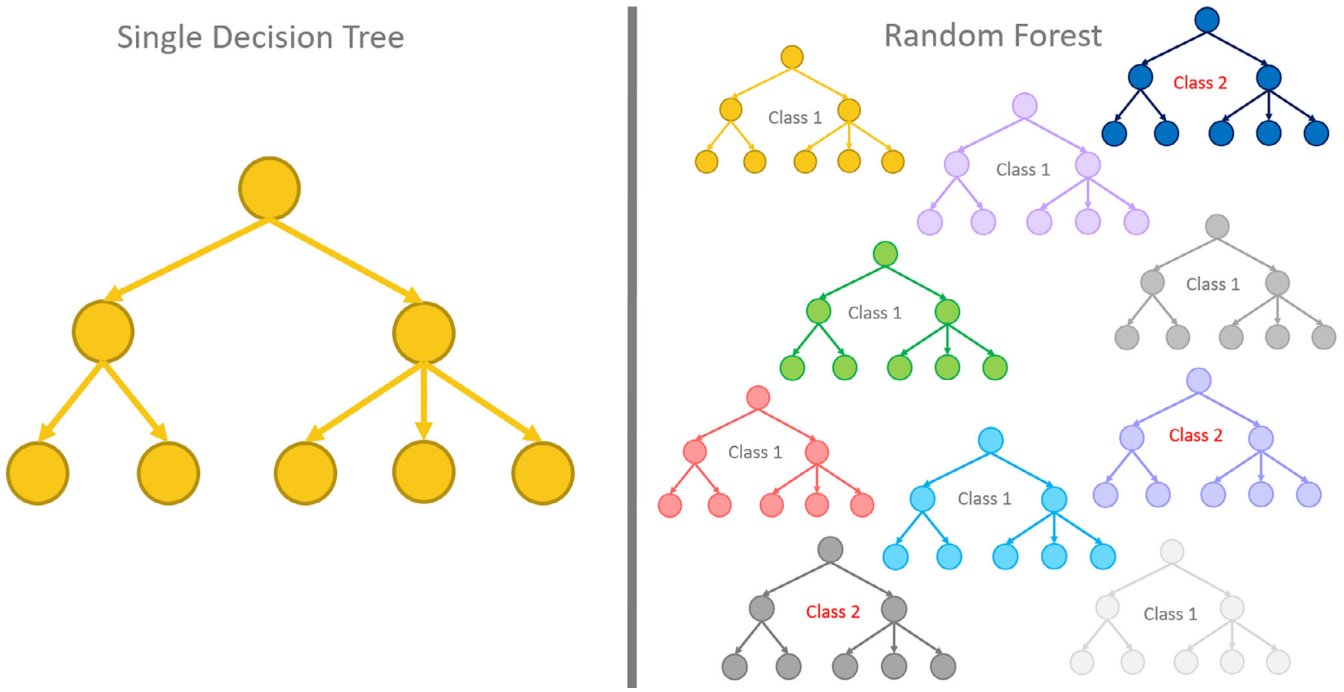

FIGURE 6 (A) Example of a decision tree predicting one class. (B) Example of a random forest method, where each tree predicts a class and then the overall majority predicted class is taken[184]

sets in their antecedents and consequent (such as: “IF Temperature is *low* THEN Heating should be *high*”). The design of fuzzy systems can be driven either by learning from available data on a given problem, or by expert-provided prior knowledge.

5.1 | Definitions and operation

In FL a truth value can range from 0 to 1, opposite to traditional (Boolean) logic in which the true or false concepts are strict ones. More specifically, bringing it to fuzzy set theory, it allows an element to have a membership value in a specific set that ranges from 0 to 1. This provides a more human-like reasoning and operation in which one can take complex decisions and perform complex control tasks based on sometimes imprecise or vague (fuzzy) information.

FL defines the set of operators allowed between fuzzy sets: Union, Intersection, Negation, among others, and provides the needed mechanisms for a reasoning engine based on fuzzy rules. These are IF-THEN rules in which the antecedents and consequents are fuzzy sets. For instance.

IF temperature is *low* and humidity is *high* THEN chances of rain are *high*.

IF temperature is *high* and humidity is *low* THEN chances of rain are *low*.

One of the most best-known successful application areas of FL is the control system used to control the Sendai Subway since the late 1980s. In this perspective, it is to be mentioned that there are two main types of fuzzy systems, depending on the consequent side of the rules: the more interpretable Mamdani systems,[187] which use fuzzy sets as consequents and the Takagi-Sugeno-Kang fuzzy systems,[188] which provide a more powerful way to solve certain problems requiring numerical precision. However, in the biomedical area, it is of crucially important its use in computer-aided diagnosis in medicine as it can provide interpretable solutions in which either the experts can intervene in the design of the rules that bring the solution to a given question, or the automatic learning from the available data provides a set of rules which can be easily understood by the experts.

In the basic structure of a fuzzy system, several blocks can be distinguished (see Figure 7). First, the so-called fuzzification process which converts the given numbered-valued inputs into fuzzy sets according to their membership functions, for its later operation using FL. A knowledge database defines the linguistic values of each of the variables considered in a problem, together with the rules that make up the rule base of the system. Then the inference engine operates according to the provided input values and the rule base. This is the core of the fuzzy system and resembles the human capability of decision-making. The final step aggregates the outputs of all the activated rules and converts the outputs into a single numerical or categorical value.

Fuzzy systems have been researched deeply since their appearance, and it is still one of the main areas of research within intelligent computing. As mentioned before, their main strength is not so much the accuracy (or either sensibility of specificity) attained in a given problem, but the interpretability of the computer-aided solutions they provide.[189,190] Latest research advances include for instance genetic fuzzy systems[191] and other automatic optimization techniques[192] of a fuzzy system from a specific dataset, and type-2 fuzzy systems, which are providing a more flexible management of the uncertainty in the data.[193]

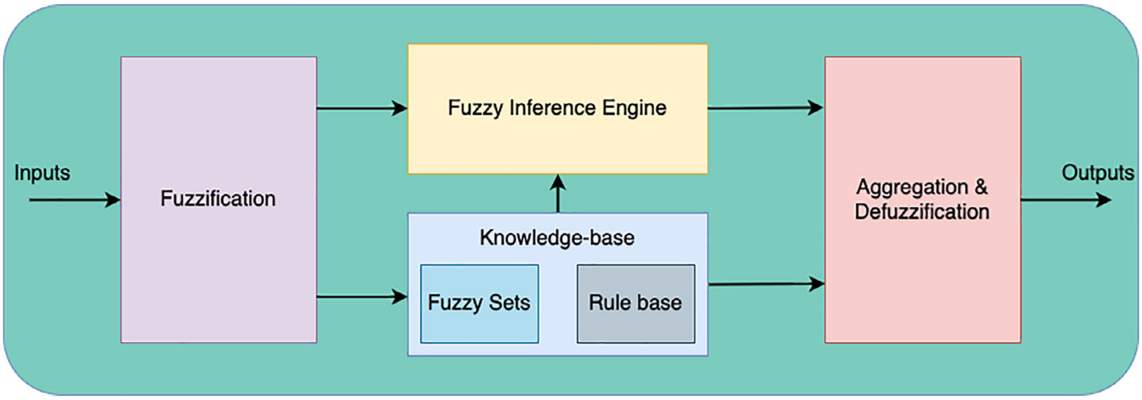

FIGURE 7 Structure of a fuzzy system

5.2 | Applications of fuzzy logic in dentistry

A novel framework called dental diagnosis system (DDS) was proposed to assist in the diagnosis of five oral diseases (root fracture, impacted teeth, caries, missing teeth, and resorption of alveolar bone) based on 87 radiographs images as inputs.[155] Three different steps were performed in the presented method: segmentation, classification, and decision-making. In this work, a semi-supervised fuzzy clustering method was used for the segmentation task. Once this process was finished, a new graph-based clustering algorithm combining the dental image dataset with the previously obtained segment's features, was used for the classification task. The DDS accuracy was 92.7%, which is better than other methods, such as the fuzzy inference system (89.7%), fuzzy k-nearest neighbor (80.1%), Prim spanning tree (58.5%), Kruskal spanning tree (58.5%), and affinity propagation clustering (90.9%).

One study proposed a hybrid approach combining FL and evolution strategies for diagnosing periodontal diseases.[151] This approach used as input the disease symptoms gathered by observations and interviews with experts. The considered symptoms were plaque, gingival inflammation, pain, gingival swelling, easy gingival bleeding, breath odor, and mobile teeth. The diseases considered were pulpitis, gingivitis, periodontitis, and advanced periodontitis. The presented method was named hybrid FIS ES (FIS-Fuzzy inference system, and ES- evolution strategies), where FL was used to calculate the fitness of the individual. This method obtained an accuracy value of 82%, which was higher than the Tsukamoto FIS method (70%) alone.

FL was also used to study the risk factors for oral candidiasis (OC). One study presented a twofold approach using FL and traditional statistics on 89 patients microbiologically diagnosed with OC infection and 98 healthy individuals.[152] An adaptive network-based fuzzy interference system (ANFIS) was used to evaluate the most significant predisposing factors and their connections with OC. For the statistical traditional method, the chi-square test was used to assess statistical differences among categorical variables. The association level, the crude odds ratio and the 95% corresponding test-based confidence interval were calculated. Socio-demographic variables were also considered, with age, gender and smoking habits being the most relevant. The following local and systemic predisposing factors for OC were also investigated: hyposalivation/xerostomia, denture wearing, antibiotic therapy, local or systemic corticosteroid therapy, diabetes mellitus, other endocrine disorders, non-HIV related immunodeficiency (e.g., organ transplants) and previous malignancy. Significant associations between OC onset and its chronic maintenance were found for denture wearing and hyposalivation or xerostomia as local risk factors, and for age and female gender as socio-demographic variables. Tobacco smoking was not found to be a risk factor.

Fuzzy techniques have also been used the automatic computation of mandibular indices in dental panoramic radiographs for early osteoporosis detection. A Fuzzy k-means classification algorithm has been presented for identifying artificial structures.[157] Then, different image preprocessing techniques are used to determine porosities for an early diagnosis of osteoporosis in significant bone structures. The study was carried out on a set of 370 dental panoramic digital radiographs with an image resolution of 1536×2573. The proposed method was validated against the criteria of expert dentists and its validity was verified with statistical studies based on the analysis of deterioration of bone structures with different levels of osteoporosis.

Other papers on the use of FL technologies include disease identification using fuzzy rules,[156] the prediction of oral squamous cell carcinoma through fuzzy decision trees,[153] the selection of headgear types through fuzzy rules,[154] and Fuzzy clustering for segmentation tasks on images.[154,158]

5.3 | Color naming for automatic dental color processing

Color perception by the human visual system is eminently fuzzy.[194] Color in dentistry is usually represented using the CIELAB color space (CIE1976).[195] However, the association of a specific color (represented as a single point in this three-dimensional space) to a known color name as perceived by a human (such as VITA Shades: A2, A3, etc.) may not always provide a single answer.[196,197] The subjectivity of the human color perception depends both on the observer and on the environmental conditions (e.g., illuminant and geometry of the illuminant).

Visual color matching is the most popular dental color assessment method, and most esthetic dental materials use the VITA shade designations. However, color assessment and color standardization in dentistry face two main problems: first and already commented upon, the subjectivity of human color perception; and second, that different manufacturers present material colors that differ from the original VITA shades.[198,199]

Initial approaches to solving these issues by means of color naming processes in which a fuzzy set design was carried out to identify the dental color space defined by the VITA shades within the CIELAB color space have been reported.[200] By performing psychophysical experiments, sets of dental materials from different manufacturers were assessed using the VITA shades. Then, the colorimetric measurements were associated to the VITA shades using fuzzy sets with the subjective information from the psychophysical experiments. Later the applicability of the color designation system to clinical dentistry was verified by using colorimetric measurements of composite resin samples from two different manufacturers.

A different study aimed to describe the efficacy of a bleaching treatment using a set of fuzzy rules.[28] These rules used VITA shades as antecedents and consequents, which were obtained through subjective associations of the objective (spectroradiometer) measurements of tooth color before and after bleaching to the VITA bleached guide shades. The fuzzy rules provided had the following form: "if the prebleaching shade is *SHADE1* then the post-bleaching shade will be *SHADE2*," where *SHADE1* and *SHADE2* were VITA shades fuzzy sets obtained as aforementioned. This methodology was able to deal with the uncertainty of the subjectivity of the color designation of the pre- and post-bleaching colors, providing different possible post-bleaching shades and the respective confidence values, while being able to estimate the efficiency of the treatment beforehand.

5.4 | Fuzzy technologies in biomimetic color analysis and modeling

One important area of implementation of fuzzy technologies is color processing and analysis in dentistry based on biomimetic principles. Biomimetic or biomimicry is defined as the examination of nature, its models, systems, processes, and elements to emulate or take inspiration from nature to solve human problems.[201,202] When it comes to color in dentistry, it is essential to provide answers to the following questions:

1. What color are the teeth/gingiva and what are their color ranges, distribution, and age-gender-ethnicity variations?
2. How do we interpret color match/mismatch in dentistry? What are the visual color discrimination thresholds, starting from the 50:50% acceptability threshold?
3. What is the coverage error ΔE_{COV} of existing shade guides and corresponding dental materials to the color of human teeth/healthy gingiva, and how does it compare with respective visual thresholds?
4. Can the mentioned coverage errors be reduced through colorimetric/spectral computer modeling (fuzzy C-means -FCM-, optimization)?

Learning from the nature as to what should be mimicked begins with the creation of databases on the fundamental optical properties of human teeth (permanent and primary) and gingiva.[203–205] The FL and TSK fuzzy system exhibits great potential for approximating color perception in the calculation of color difference thresholds in the realm of dentistry. The capability of this type of universal approximators for regression provided a better fit than previously used S-shaped approximators for evaluation of color difference formulas[206] and the calculation of visual thresholds for tooth color.[159,160,207]

Although not related to the fuzzy inference process, the FCM algorithm, a clustering technique based on fuzzy membership of the samples available to the cluster centers, has recently been used to optimize gingiva shade guide models. The spectral modeling and optimization, performed for the first time in this study, aimed at providing shade guide models with the coverage error to healthy human gingiva at or below the 50:50% acceptability threshold in two senses: (a) by assuring a reduced mean color difference of any point to its nearest shade in the database of human gingiva, that is, the lowest (best) coverage error of the color space of human gingiva, and (b) by confirming a reduced most considerable difference of any gingiva sample to the closest shade.[161]

The obtained results convincingly outperformed corresponding data on coverage error of some existing gingival shade guides and gingiva-colored dental materials as compared with healthy human gingiva.[208] Gingival shade guide models with only four tabs exhibited a CIEDE2000 coverage error of 2.4 (1.1), which is lower than the acceptability threshold for gingival color.

(ΔE_{00}),[207] and was a 50% reduction as compared with the corresponding coverage error of 4.8 (1.1), recorded for "pink" shade guides and dental materials.[208] The studies on gingiva provided further justification for the biomimetic approach. The spectral modeling utilizing the FCM algorithm was in essence a continuation and upgrade of previous work that used hierarchical clustering and nonlinear constrained optimization for the development of shade guide models for permanent and primary teeth.[209,210]

Compared with the traditional empirical methods of developing dental shade guides and corresponding restorative materials, the implementation of fuzzy technologies is a large step forward. Their role in biomimetic color analysis and modeling is significant, and their importance will only grow in the future.

6 | SOFTWARE INITIATIVES IN DENTAL CARE

This section presents a quick overview of some of the most popular dental software within digital dentistry used by dental professionals:

Digital Smile Design (DSD), 3Shape software (3Shape Design Studio and 3Shape Implant Studio), Exocad, and Bellus 3D. Their main objective was treatment predictability and treatment planning using digital dentistry and communication among different dental professionals. Although almost no information is available about the functionality of these software programs, DSD claims to use AI algorithms. While no information is available for the other software programs, all of them present segmentation or automatic generation tasks that imply the use of ML techniques in some way.

DSD in its 2D version uses digital photographs of the patient's smile, usually combined with visualization tools such as Keynote and PowerPoint. In the 3D version, photographs, intraoral scans, and computed tomography scans can be used for treatment planning. This software program allows the manual segmentation and measurement of teeth, as well as the superposition of the new desired teeth.[211] Part of this workflow can be automated by means of AI techniques, as can be appreciated in their iPhone app. The automation is mainly focused on the segmentation and the tooth generation elements. This type of segmentation can be performed using CNNs trained in a similar way as in other studies.[85] The manual workflow of DSD involves creating bounding boxes around the teeth so that the manual annotations that naturally arise in the process can be used as training data for the AI procedure. Since the prediction is shown as a polygon, the network can predict the vertices as a whole or one by one using RNNs. Similar tooth generation may be provided using GANs in a similar way to the way artifacts are corrected.[108] In addition to the automation capabilities, the app has multiple parameters that can be changed by the user to achieve the final desired result, notably reducing the design time, and can be used to design a set of teeth according to expectations. This software has been mentioned several times in the literature, many claiming that it presents advantages over traditional planning methods, but it is often not enough for the patient to observe and understand the proposed changes.[212] It is also helpful in the process of dental rehabilitation.[213,214]

3Shape has developed multiple specialized software programs that allow a full digital workflow for treatment and the design of the prosthetic procedures (3Shape design studio) and implants (3Shape implant studio), as well as for visualizing the result of the design. In addition, it allows enough versatility for the dental clinician to make any changes. These software programs work with digital images and videos that are obtained using an intraoral digital scanner. The digital model of the teeth can be easily moved, and its geometry can be modified by adding or removing part of it. It is also able to automatically generate an optimal alignment for the teeth from the 3D model, which can be also manually fine-tuned if necessary. These types of functionalities can be mimicked using 3D CNNs to obtain an accurate segmentation[14,15] and/or GANs[108,178] to correct the 3D model and generate the alignment. Apart from tooth visualization and modification, the software supports the design of 3D implants with a large built-in variety of manufacturers and options. It also integrates with some dedicated printers to obtain the desired physical product.

Exocad is a computer-aided design (CAD) software program that allows a full digital workflow for the design of implants and other dental applications. Many options are available for building a tooth set from scratch by importing a single tooth or a full set of teeth from multiple dental libraries. It can also work using stl 3D files generated by a 3D scanner. As for 3Shape, the 3D model can be easily modified, allowing operations such as scaling and displacement or rotation of the teeth. It also contains some semi-automatic segmentations, such as the detection of the edge line of the teeth by selecting a point over it, which can be reproduced using 3D CNNs over the imported model to add the extra feedback. The software also allows for the design of implants with an interface that guides the user through the many advanced options presented in the process.

Bellus 3D Dental Pro Integration can make a 3D scan of the full face. The main purpose of this software is to integrate the dental treatment plan with the face configuration, providing a visualization of the final results in full 3D, shortening the process of patient acceptance, and making the treatment easier. Bellus 3D provides automatic detection of the patient's teeth and their removal, with the possibility of manually modifying the segmentation. An automatic segmentation like this one can be done using 3D CNNs as presented in other studies.[15] A new tooth set can be chosen and superposed with the model in the correct place. This final aligned 3D scan can be imported into other software programs such as 3Shape software or Exocad.

7 | A GLANCE TO THE FUTURE

7.1 | Technology issues

DL is one of the most revolutionary groups of techniques in the area of AI in recent decades, and it provides solutions to problems that were previously thought as unapproachable. As it has been presented throughout this work, DL techniques have been successfully applied to dentistry, facilitating arduous tasks such as tooth segmentation,[14] or helping clinicians by automatically identifying disease.[12] Although DL techniques have shown outstanding results in a variety of fields, even surpassing results obtained by humans,[215–219] they are still prone to errors that humans are much less likely to make, such as misclassification of adversarial examples.[220,221] By no means should this diminish the great accomplishments that have been reached using these techniques, but they should also guide new efforts toward robustness and interpretability. The cooperation between human experts and computational models addresses these challenges and, first and foremost, they can achieve better performance than either individually.[222,223]

That said, with the rise of dental data gathering, its combination with DL would enhance in future years the already impressive results that have been obtained. As previously mentioned, DL requires large amounts of data to achieve its best performance, and the initiatives to gather more data are a crucial starting point for the enhancement of the actual models. Storing data in local servers would not scale once data size increases, which makes sharing the data a tedious task. A solution to this problem might be provided by cloud services, which have been rapidly increasing both among users and providers during the last decade. Given the costs of maintaining and improving local servers and computing platforms once they have become obsolete, companies have started to migrate their data platforms to cloud computing and storing services. This migration to the cloud opens the door to a wider range of data analysis and data mining pipelines, including complex DL approaches to learn specific and very complex tasks, all also thanks to the use of HPC cloud services.

In addition, thanks to this gathering of data, different sources of information can be available for the same patient (e.g., x-ray imaging, clinical information, genomics information). Integrating these sources into ML algorithms would provide more robust and enhanced predictions than using each source of information separately, as shown for other biomedical problems.[224–226] Having all these sources of information and the refinement of the aforementioned techniques would allow a precision medicine approach to be taken to each patient. For instance, with genomics information, patients can receive enhanced diagnoses and monitoring and more personalized treatment. This would reduce the patients' time of recovery and improve the treatment outcome.

All these advancements can also be extrapolated to color processing and characterization in esthetic dentistry. Further characterization of tooth color should address the characterization of the chromatic map, mainly for the labial surface of teeth, for different gradients and the association of different objective color measurements to subjective assessments. As was the case for DL problems, a complex data collection first needs to be performed. Once it is completed, colorimetric map modeling using intelligent systems (e.g., diffuse models, CNNs) needs to be carried out. Then, using a color designation process, it will be possible to characterize the tooth chromatic map using dental images. This will allow the development of methodological solutions to efficiently obtain accurate information from dental restorations, enhancing communication between dentists and dental laboratory technicians. Another application of high interest would be obtaining the necessary chromatic map and thicknesses for restoring a given composite resin based on one or several images. Since both problems require dental images, how to obtain them is a crucial factor. As smartphones with cameras capable of high-quality images are ubiquitous, their use for obtaining dental images is of great interest. Therefore, providing tooth color and other parameters from a picture taken from a smartphone would greatly enhance dentists' restoration processes.

7.2 | Clinical issues

The combination of models that can be generated by AI has the objective of helping the dental industry and dental care providers. Possible applications extend from the research and development of new dental materials based on the biomimetic approach to diagnostic tools (e.g., to detect caries, periapical lesions, and periodontal disease), to treatment planning and oral health care delivery, to the post-treatment monitoring and follow-ups. By analyzing images (photographs and radiographs), AI allows the building of CAD systems to help detect certain diseases.

With the current trend and rapid development of AI, a significant impact on dentistry can be expected shortly, especially on digital protocols. Three main types of data collection using AI can be used to improve patient care: pre-appointment (AI Patient Manager, AI Patient History Analyzer, AI Scientific Data Library), interappointment (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.[44] Before the dental appointment, the preferences of patients (day and time of appointments, music, relaxing fragrances, room temperature) should be considered. Information about the patient (vital signs, allergies, health condition, current medications, and drug interactions) should be carefully evaluated prior to the appointment. During the dental appointment, the diagnosis and recommendations for treatment are generated. The final outcomes and treatment prognosis should be predicted as accurately as possible. After the dental appointment, the digital workflow is generated, and dental restorations are fabricated quickly and accurately.[44] It needs to be underlined that AI facilitates but does not substitute for the work of dental professionals. An increasing number of dental practices use a digital workflow and AI for diagnosis and treatment planning. Still, there is a relatively low percentage of dental practices with fully integrated AI modus operandi, also referred to as "smart dental clinics."

The rapid development of 3D imaging in dentistry such as cone beam computed tomography or intraoral and facial scan, have generated the development of 3D image-based AI systems. The improvements of these models could provide an automated, high-quality diagnosis, treatment planning, and predictable treatment outcomes.[41] AI is a science that is here to stay, and the worldwide interest of the dental industry and professionals alike demonstrates that it is the present and future of dentistry.

DISCLOSURE

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

No data are associated with this article.

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