DERLEME

Machine Learning Applications in Dentistry

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ÖZ

Diş Hekimliğinde Makine Öğrenimi Uygulamaları

Yapay Zekâ, diş hekimliği alanında karşılaşılan zorlu karar verme süreçlerini çözmek için yeni yaklaşımların kullanılabildiği tıp ve diş hekimliği dâhil birçok alanda bir atılım olarak ortaya çıkmıştır. Artan nüfus ve buna bağlı olarak artan diş tedavi ihtiyaçlarını çözmek için yapay zekâ bir karar destek mekanizması olarak kullanılabilir. Ayrıca uzman görüşü gerektiren teşhis ve tedavi planlama aşamalarında diş hekimlerine yardımcı olur. Bu mini inceleme, bu alandaki son çalışmalardan bazılarını kapsamakta ve diş problemlerinde makine öğreniminin kullanımına ilişkin gelecekteki yönergeleri öngörmektedir.

ANAHTAR KELİMELER

Diş Hekimliği, Makine Öğrenimi Uygulamaları

ABSTRACT

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Artificial Intelligence has emerged as a breakthrough in many fields including medicine and dentistry where new approaches can be employed to solve challenging decision making processes faced in the dental field. Artificial intelligence can be used as a decision support mechanism to solve the increasing population and consequently the increasing dental treatment needs. It also assists dentists in diagnosis and treatment planning stages that require expert opinion. This mini-review covers some of the recent studies in this area and envisions future directions on the use of machine learning in dental problems.

KEYWORDS

Dentistry, Machine Learning Applications

1. Introduction

The concept of artificial intelligence (AI) can be defined as the ability of machines to think like humans and to program machines such as human intelligence in a way that can imitate the actions of humans.[1] Machine learning (ML) is a subset of AI that can learn as a structural function and investigate the work and construction of algorithms that can make predictions over data. These types of algorithms work by building a model to make data-based predictions and decisions from sample inputs rather than following static program instructions strictly. Today, ML can employ classification, regression, rule extraction, association rule mining methods in order to tackle chal-lenges related to diagnosis or treatment planning in the medical research field and dental prob-lems is not an exception.[2-4] Highly complex relationships between parameters are under consider-ation in clinical decision-making processes. This requires the use of sophisticated approaches that can identify and distinguish patterns in such complex structures. In this study, we first briefly describe some of the widely employed approaches, then discuss application areas in the dental research field, and finally conclude the paper by presenting some future directions.

2. Methods Overview

Our review covers the following ML algorithms as a means to guide the decision-making process in dental challenges. Here we briefly outline some of the commonly used algorithms in ML, namely Logistic Regression,[5] Random Forest,[6] K-nearest Neighbours,[7] Artificial Neural Networks,[8] Fuzzy Logic,[9] Genetic Algorithms and Hybrid Systems.[10]

Logistic Regression

This algorithm performs machine learning and achieves classification performance by examining the relationship of the dependent variable with the independent variables. The logistic regression method, also known as the binary classification method, has low variance due to its simple nature of operation, so it is less prone to overfitting. The similarity between the dependent variable and the observation values is tried to be maximized.

Random Forest

It is one of the community learning models where new and stronger models can be obtained by combining multiple decision tree algorithms. The aim is to reduce the variance and increase the accuracy of the decision tree structure based on the community decision by preventing potential over-fitting. Since it provides learning, reliability validity is much higher and easy operation is an advantage. Besides, random selection of the sample is its disadvantage.

K-Nearest Neighbor (KNN)

The object to be classified or predicted within the scope of this algorithm is classified according to the majority of its neighbors and assigned to the most common class among the nearest k neighbors. Distance measurement is based on, and the most commonly used is the

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Euclidean distance measurement shown in the formulation above.

Artificial Neural Networks (ANN)

Inspired from the synaptic connections and the learning pro-cess in human brain, ANN has been one of the most widely employed methods. In neural net-works, learning takes place with the help of neurons. There are three types of neuron structures, namely input, output and hidden neurons, and each neuron has a weight storing the learning ex-perience. Input neurons receive stimulation from elements outside the network, output neurons enable their output to be used externally, while hidden neurons are placed between input and output neurons.

Fuzzy Logic (FL)

Based on Fuzzy Set theory, FL is capable of using words for computation in order to better model the uncertainty in the decision-making process. Generally used along with a rule-based expert system, FL can produce accurate diagnosis results very similar to those of a real expert.

Genetic Algorithms (GA)

These are nature-inspired optimization algorithms, developed based on the natural selection and survival-of-fittest paradigms. The fitness is a measure for the quality of a candidate solution. Starting with a random population of candidate solutions, these algorithms create generations using genetic operators with an aim to increase the overall fitness of the popu-lation.

Hybrid Systems

There are also hybrid approaches that make use of at least two different algo-rithms together in order to overcome weaknesses of individual algorithms. For instance, ANNs can be improved in terms of explanation capability using fuzzy logic (FL) or in terms of network architecture/topology using genetic algorithms (GA).

Deep Learning (DL)

These approaches have emerged with highly increased numbers of layers and therefore an enormous learning capability over traditional ANNs which had 3-5 hidden lay-ers. Methods have been developed to both extract features and perform model training over the input data using approaches as Convolutional Neural Networks (CNN).

3. Application Areas

Although the progress of the ML approaches is still at its baby steps for the dental field, we can say that there is a great potential to unveil by simply looking at some of the recent studies which employed diagnostic, predictive and prescriptive capabilities of such approaches. With the new technologies developed in recent years, great changes have been observed in dentistry. These automatized systems have been used for predicting the diagnosis, helping the clinicians in treatment planning and estimation of expected outcomes from treatment.[11]

Machine learning techniques are useful for medical diagnosis or prognosis and they are good for handling noisy and incomplete data, and significant results can be obtained despite a small sam-ple size. The mentioned systems used in diagnosis and treatment planning such as; making ortho-dontic diagnosis by analysis of cephalometric variables;[12] periodontal diseases by risk factors, periodontal data, and radiographically bone loss and detection;[13] diagnosis of dental caries on periapical radiographs;[14] and also the location and volume of lesions and detecting periapical pa-thology based on CBCT images with high success rate.[15-16]

One of the earlier studies employed NN for predicting dental pain by constructing a model that incorporates several parameters such as tooth brushing habits, use of dental floss and nutrition. The study achieved a fitness rate of 80% for the listed factors.[17]

Dental caries were detected and diagnosed using Deep Learning in using 304 bitewing radio-graph with 12-bit depth images.[18] The precision, recall, and F1-score were used to evaluate the performance of the model. The deep network yielded fairly accurate and consistent results re-garding the detection task of the dental caries.

Literature, also, presents studies include deep networks for measurement of bone mineral density from CBCT.[19] Similar techniques can be used to identify of the area to be implanted.[20]

Furthermore, various studies have been performed in the field of orthodontics with the use of AI algorithms to determine the growth and development stages of the cervical vertebrae.[21-22] It has been shown to be accurate with rates up to 90%. AI systems were also used for locating cepha-lometric landmarks[23] and to estimate the size of unerupted canines and premolars in mixed denti-tion[24], and to predict mandibular morphology through cranio-maxillary variables.[25]

Several studies have used these tools to determine the necessity of tooth extraction and treatment planning before orthodontic treatment and orthognathic surgery.[26-27] The prior study was per-formed over the data of 838 patients which includes 208 extraction samples. Random Forest and Multilayer Perceptron methods were used for prediction and the yielded results of accuracy was 75% to 96% for different settings.

The effect of orthognathic treatment using CNN on the facial attractiveness and apparent age of patients [28], a system for predicting color change after tooth whitening procedure 29 were present-ed in the literature.

Recent studies shows that oral cancer is a universal spread type of cancer.[30] Diagnosis and analy-sis of the tissue of a tumor in the oral cavity are essential for determining the degree of patholo-gy. For this purpose, in a study the grade of OSCC could be determined with an accuracy rate of 97.5%.[31] In another study, CNN was used for cancer diagnosis and lesion localization, and the detection sensitivity reached 93.14%.[32] In addition, ML-assisted fibre probes were used for the detection of cancer tissue margins in a study and random forest showed the best performance.[33] And another study employed ML approaches occult nodal metastasis prediction in early oral squamous cell carcinoma.[34] In another study, a machine learning-based algorithm was developed that can classify the survival rate for patients with advanced oral cancer.[35] Also, a hybrid of fea-ture selection and machine learning methods were used to predict oral cancer prognosis based on correlation parameters of clinicopathological and genomic markers and achieved the best accura-cy of 93.81% for the oral cancer prognosis.[36] In another study, it was also used in the evaluation of lymph node metastasis.[37] A Fuzzy logic application was used in oral cancer risk assessment and it was stated by the authors that it could be used as an important aid in oral cancer screen-ing.[38]

Here, the decision forest achieves the best performance from a set of various ML architectures including logistic regression, decision forest, kernel support vector machines and gradient boost-ing. Hybrid system of FL and evolution strategies were employed for detecting dental diseases including pulpitis, gingivitis, periodontitis in.[39] In this age where a lot of data needs to be evalu-ated; The importance of machine learning in individual patient risk estimation is emphasized by the authors.

The success of endodontic treatment depends on several factors, the anatomical configuration of the root and the location of the AF are the main factors affecting the success.[40] For this reason, artificial neural network systems have been used to locate different mandibular first molar distal root forms and minor apical foramen.[41-44]

Our recent work focused on a variety of challenges ranging from diagnosis, through oncological applications to treatment planning. One of the studies [45] aimed to support the dentists at early stages of the careers in the decision-making process for dental traumas. We aimed to incorporate the gold standard IADT guideline in a knowledge-based ANN in order to provide learning capa-bility. Our next study investigated the use of proton therapy for tumors in the mandibular plate.[46-47] We performed Monte Carlo simulations to analyze and find the efficient application depths for the radiotherapy with aims of administering the maximum dose to the tumor while protecting the adjacent healthy tissues. We are currently investigating a larger set of ML methods for orthodon-tic treatment planning. Our unpublished results have shown that alternative methods can yield superior performance over ANN.

4. Challenges for Wider Adoption of ML in Dentistry

The literature presents very interesting studies and promising approaches that show the potential of ML methods for the dental field. On the other hand, there are still some challenges to over-come for adoption of such techniques. Some of the major problems are related to interpretability of the systems, socio-cultural perceptions and economic factors and ethical problems.[48-51]

First of all, explanation facilities of ML approaches are still a common problem and this makes them difficult interpret the obtained results from them.[52] An efficient system should be capable of explaining the reasoning process to reach a conclusion in addition to merely reporting the re-sult. Failure to do so, undermines the adoption of these approaches by the practitioners since they may not feel fully confident on how a diagnosis was made.[53] An extra effort should be made here in order to improve the inner inference mechanisms for ML/AI approaches, rather than leav-ing them as working black-boxes. Data visualization can play an important role in explaining the inner processes of these systems.[54]

A second problem here is the socio-cultural perception by the practitioners and the patients.[55] The practitioners may not like the idea of entering the inputs and then simply reading reports of the system in front of the patients which may give the impression that the practitioner cannot diag-nose on their own, rather the system does the job for them. The surprised look on the patient's eyes can elevate the problem in this case. It must be clear to both sides, the practitioner and the patient, that such systems are a provider of second opinion in order to aid dentists in decision making for diagnosis and prognosis processes.

Thirdly, economic factors also come into consideration.[56] It is known that the most recent AI applications require a considerable amount of computational power and it may not be the case that every clinic has this infrastructure for employing AI based systems. If the perceived benefit of such approaches or systems developed using these approached are less than the perceived cost, then managers will be reluctant to make any investment decision. The authors believe that all these barriers will eventually be overcome, through the changes in people's perception of the world which is directed towards an AI-supported one.

Finally, standardization and establishment of ethical rules are required to govern the use of such approach in a clinical environment. Currently, according to many jurisdiction processes in differ-ent countries AI and ML approaches cannot be held responsible for errors, the main responsibility is still on the practitioners for diagnosis and prognosis processes. The same situation diagnosis and prognosis processes. The same situation holds for conducting clinical experiments, where normally practitioners use ethical approval forms clearly identifying how the information will be used and a consent form is filled by the patients approving how their information will be used and to what extent.[57] It is not clear how this information will be collected and used in case of a completely autonomous processes are in practical use.

5. Conclusion and Future Directions

We have covered some of the recent work on application of ML in the dental field. A deeper look at the current literature, one can observe that ANN has been the most widely employed method for a number of problems. One problem with ANN is the explainability of the system, since such systems are considered as black boxes which do not describe how a particular decision was reached.

Recently, there is a trend towards Explainable AI (XAI) to overcome this weakness. On the oth-er hand, other ML algorithms can achieve superior performance over ANN.[58]

Another future direction of the authors will be employing different spectroscopic models, such as Fourier Transform infrared (FTIR), together with ML algorithms for further analysis in the dental cavity.[59] With the increasing use of AI methods such as ML, we can confidently foresee that there will be an increase in the number of applications from diagnosis to treatment planning in the dental field.

One should consider ML and AI applications in dentistry as a tool that is used to facilitate the diagnosis and prognosis processes, rather than replacing the practitioner. AI systems relieve den-tists so that they can perform more valued tasks, such as integrating patient information and im-proving professional interactions.[60] Also, pedagogy for dental students should walk hand-in-hand with AI development.

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