Review paper

Use of digital techniques in the diagnosis of oral diseases in children

Zastosowanie technik komputerowych w diagnostyce jamy ustnej dzieci

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Słowa kluczowe: sztuczne sieci neuronowe (SSN), sztuczna inteligencja, stomatologia dziecięca.

Abstract

Innovative computer techniques including artificial intelligence technique have been widely used in many areas, including dentistry. Increasing requirements in the field of diagnostics and dental treatment are conducive to the digitization of many areas of dentistry. The mentioned diagnosis and treatment are based on the knowledge of a specialist. The introduction of artificial neural networks (ANN) makes it possible to support the doctor's decision regarding the diagnosis and treatment plan. The article presents the possibilities offered by artificial intelligence in the field of paediatric dentistry, both in terms of diagnostics and in the treatment process. There are many publications and ongoing research on the use of machine learning methods for dental treatment. Various types of analysis are based on digital images such as intraoral photographs, panoramic images, computed tomography images, and cephalometric radiography.

Streszczenie

Innowacyjne techniki komputerowe, w tym możliwości, jakie daje sztuczna inteligencja, znajdują coraz szersze zastosowanie w wielu dziedzinach stomatologii. Coraz większe wymagania w zakresie diagnostyki i leczenia sprzyjają cyfryzacji wielu dziedzin stomatologii. Diagnoza i leczenie są oparte na wiedzy specjalisty. Wprowadzenie sztucznych sieci neuronowych pozwala na wspomaganie decyzji lekarza dotyczącej diagnozy i planu leczenia. W artykule przedstawiono możliwości, jakie daje sztuczna inteligencja w dziedzinie stomatologii dziecięcej zarówno w zakresie diagnostyki, jak i w procesie leczenia. Trwają aktywne badania nad zastosowaniem uczenia maszynowego opartego na sztucznych sieciach neuronowych do leczenia stomatologicznego poprzez analizę różnego rodzaju obrazów, takich jak fotografie wewnątrzustne, zdjęcia panoramiczne, obrazy tomografii komputerowej i radiografii cefalometrycznej.

The basic unit of the nervous system is a neuron, a nerve cell whose task is to receive and process stimuli both from the external environment and from the inside of the body, and to generate appropriate reactions. The human brain and nerve cells have become the inspiration to create a neural network. The first definition of an artificial neuron modelled on the structure of a human cell was by McCulloch and Pitts in the 1940s. They created a so-called unipolar model of a neuron that collected signals from other neurons and produced an output signal when triggered [1].

The artificial neural network is one of the state-of-the-art artificial intelligence techniques that have gained wide acceptance since the 1990s. Artificial neural networks, due to their adaptive abilities, i.e. the ability to learn by adjusting the parameters and structure of the network to the environment, are widely used in many fields of biological, and natural and medical sciences – where the characteristic of issue is nonlinear [2]. Therefore, artificial neural networks find application in medicine, especially in prophylaxis, diagnostics, and treatment. Many intelligent systems have been built to improve healthcare and offer better treatment at reduced costs. Intelligent computer systems can support doctors and patients by providing early and accurate diagnosis for better and more effective treatment [3].

Neural networks are systems modelled after the operation of the human nervous system and the brain. Artificial neural networks are a type of machine learning computer system that is designed to process data using artificial neurons grouped into layers. Such a model can map the processes in the human brain such as learning and drawing conclusions, data analysis, pattern analysis, and can support decision making [4].

An artificial neuron, or a mathematical neuron, is modelled on a human nerve cell. It has many inputs and usually one output signal. Each input has an appropriate weight, i.e. parameters that determine its properties and role in data processing. The set of weighted values set during network training (or self-learning) determines the knowledge held by the neural network. The structure of a neural network consists of layers of neurons where each layer has a specific function. An input layer, a hidden layer, and an output layer are identified. Such division determines the connections of neurons that connect between adjacent layers [5].

There are two methods of artificial neural network (ANN) learning. In the first one, involving the teacher, the so-called training set, i.e. the set of data used to carry out the analysis, includes a set of features (feature vectors, indicators) and responses. The second method, without a teacher, does not provide correct answers to the network. The network learns by itself and finds the optimal solution. Today, there are many types of artificial neural networks that have developed and changed over the years. In the 1950s, Frank Rosenblatt and Charles Wightmann at the Cornell Aeronautical laboratory created a so-called perceptron, a network that classifies images and is able to learn by modifying the connections that lead to threshold circuits [6].

The Adaline network (Adaptive Linear Neuron) proposed in 1960 by Widrow and Hoff is a linear network able to learn under supervision [7].

In the years 1982–1984 Hopefield introduced a reccurent architecture of neural memories. The neurons of the network are connected in a graph shape with closed-loop cycles. Such architecture is represented in the Hopefield network and its modification, the Boltzmann machine. They constitute a system of connected neurons and are used as a memory to recognize images and speech or to solve problems of minimization and finding the optimal solution [8].

Self-Organized SOM maps, Self-Organized Feature Map (SOFM), or Kohonen network learning without a teacher were proposed by Tuevo Kohonen in 1982. The network is coupled to the coordinates on a straight line, plane, or in any space and learns as the coordinates change so that the neurons follow a pattern with the structure of the analysed data [9].

In the Multi Layered Perceptron (MLP) network according to Rumelhart's and McClelland's 1986 concept, neurons are arranged in multiple layers, and each layer has a sum of inputs determined by weight and is a unidirectional structure [10].

In the Radial Based Function (RBF) network presented by Broomhead and Lowe in 1988, the stimulation of neurons depends on the distance of the input signal from the centre. The neuron responds to stimuli similar to a stimulus fixed in the neuron. The network comprises any number of inputs, a certain number of hidden layer neurons with radial function, and output neurons with linear function, which implement a weight sum of signals from the hidden layer. The advantage of this network is a fast and simplified learning process [11].

In paediatric dentistry, a system for detecting dental plaque, currently defined as biofilm, on deciduous molars has been developed. Biofilm is a sticky and colourless mass of bacteria and carbohydrates that constantly forms on the teeth, mainly at the gingival margin and in the interdental space. Biofilm in children can be identified using a dental probe or staining, which is sometimes difficult, especially in non-cooperating patients. Efficient biofilm detection is important because it is a precursor to dental and periodontal disease.

The neural network was trained, based on the analysis of intraoral photographs, to detect biofilm. In the training of the network, photographs of the cheek surfaces of deciduous molars were used before and after the use of the plaque-staining agent. The created artificial intelligence model was characterized by effectiveness in detecting biofilm comparable to the examination performed with the use of a dental probe by a specialist doctor. The use of such a tool in paediatric dentistry may be beneficial, given the difficulties in assessing posterior parts of the dentition in children.

The authors of the study plan further research on the use of an artificial neural network to identify biofilm on permanent and deciduous teeth using an intraoral camera at home to control children's oral hygiene. It is assumed to create a mobile application that, based on the photograph taken, will help in locating the sediment and mark areas that require greater hygiene [12].

An artificial neural network is also applied in paediatric dentistry to automatically detect and classify the presence of fissure sealants on permanent molars. It is important to control the presence of a well-preserved molar seal for caries prevention. The loss of part of the sealant may result in the development of caries on the tooth with the damaged material. The research material was a collection of intraoral photographs. The photographs were divided into 2 groups: training and testing. The photographs were analysed by computer and catalogued according to the principle: 0 – no sealant on the occlusal surface; 1 – occlusal surface with intact fissure sealant, without the loss of 1/3 of the seal on the periphery of the fissures; 2 – occlusal surface with the seal remaining in the deepest part of the fissure; and 3 – insufficient amount of fissure sealant. Each of the categories has been combined with a treatment proposal to be applied in a given situation. The research showed that the accuracy of the diagnosis made by artificial intelligence was high and amounted to 98.7%, and therefore it can be very helpful in the dentist's work [13].

Artificial intelligence has also been used to diagnose dental caries. Several different X-ray images were used in the research, including pantomographic, occlusal, dental, and intraoral photographs with the use of transillumination.

Caries is a chronic dental disease leading to serious complications, pain, and premature tooth loss. Detecting minor carious lesions as soon as possible is crucial in clinical practice, allowing for the use of non-invasive treatment. The simplest method of detecting carious lesions is the visual-touch method with the use of a dental mirror and a probe during a dental examination. The second most common way is to analyse panoramic or occlusal X-rays [14].

The use of imaging data for the method of deep learning of the neural network is a technique that helps doctors in the diagnosis of non-advanced caries lesions.

In their research, Lian *et al.* used pantomographic images, which were initially assessed by a trained team of specialist doctors. The photographs show carious lesions, and on this basis, a reference data set was created, used as training data of the neural network. The nnU-Net has been trained as a caries detection tool, while the Dense-Net has been trained to classify caries by depth and extent. The performance and accuracy of the neural network have been compared with the results obtained by 6 experienced dentists. Research has shown that the deep learning method in neural modelling can be used to detect and classify carious lesions on panoramic radiographs, with the effectiveness of the method comparable to the assessment of lesions by a team of specialist doctors [15, 16].

In another study, researchers Bayraktar and Ayan used occlusion photographs to teach an artificial neural network and then used them as a diagnostic tool. Occlusion photographs are a very efficient tool for caries detection; they are characterized by high sensitivity, much higher than pantomographic images [17], therefore constitute a good basis for training artificial neural networks.

In the described study, occlusal radiographs were analysed by 2 experienced specialists who marked the carious lesions on the radiographs. The marked data were used as material for training the neural network according to the YOLO principle (you look only once). In the study the high effectiveness of the neural network as a tool for the diagnosis of dental caries was proven [17].

Occlusal images were also used in the deep learning method by the Korean authors Lee *et al.* to create a tool for the early diagnosis of dental caries. The study used the U-Net model of a neural network trained to detect caries on the contact surfaces of molars. In the first stage, 3 clinicians independently marked carious lesions on radiographs. In the next stage, the radiograms prepared in such a way were used for deep learning of the neural network.

When clinicians referred to the diagnostic results showed by the neural network, the sensitivity of such results in detecting carious lesions on occlusal radiographs turned out to be higher. It may be helpful for clinicians to refer to the results of caries detection by the deep learning model as an additional opinion when analysing occlusal images in caries diagnosis. It should be remembered that occlusal images may also give false positive or false negative results where radiographs show places of overlapping enamel or other abnormalities in the structure of the hard tissues of the tooth. The final decision about the presence of caries must be verified by a doctor [18].

Cantu *et al.* obtained similar results in his research, showing that the support of an artificial neural network can be particularly helpful for dentists in detecting the initial carious lesions in occlusal radiographs. Cantu explored the use of artificial intelligence in the diagnostic process in clinical practice. In his research, he used a U-Net convolutional neural network, which proved to be an effective tool to enhance the detection of carious lesions. More than 3500 occlusal radiographs were used to train and validate the neural network, and the accuracy and sensitivity of the SSN were observed to be high, proving it to be an effective tool in the decision-making process. He also indicated that further research is needed in this area as well as the need to build a more extensive database to achieve more stable and accurate results [19].

Near infrared transillumination (NIRT) is a non-ionizing imaging method used to detect carious lesions, which is particularly useful in the diagnosis of side teeth. This technique takes advantage of the fact that the optical properties of mineralized and non-mineralized tissue differ significantly upon the use of long-wave light. The mineralized tissues are transparent, while the structure of demineralized tissues causes light scattering and absorption in the tissues. It is possible to visualise carious lesions using this technique. There is a DIAGNOcam (KaVo) system available on the market that uses this technology to provide greyscale images with useful information on early enamel caries and dental caries. The image of the transilluminated tooth is captured by the sensor and displayed on a standard monitor [20]. High-contrast enamel caries can be visualized, while carious lesions of dentin can only be visualized indirectly. This technique is aimed at detecting primary caries. Specific classification criteria are required in clinical practice for the purpose of reproducible documentation and monitoring of treatment outcomes. The interpretation of these images, as with any diagnostic imaging technology, is limited and characterized by divergent assessments. For this reason, it is justified to use computer image analysis supporting diagnostic procedures.

In pilot studies on the use of ANNs, extracted human teeth mounted in diagnostic dummy head models were used, and then near-infrared light transillumination was used. The images generated by DiagnoCam (Kavo) were described by dentists who marked carious lesions on the images that were used in the deep learning method. Two types of networks: Resnet 18 and Resnext 50, were used in this study. The obtained results were verified and validated. Both network models had a similar level of caries detection, which proves the usefulness of ANN for the diagnosis of teeth with the use of transillumination [21].

Similar studies were carried out by Casalegno *et al.*, who used greyscale images of the molars and premolars obtained from the DiagnoCam system (Kavo). These images were manually marked by experts, which is essential for training and evaluation of the neural network model. In the examination, the tooth was divided into 3 areas: mesial, distal, and occlusal surfaces, and each surface was marked as healthy or diseased if changes were observed that might correspond to enamel demineralization. The data prepared in this way were used to train the mIOU artificial neural network, which can effectively learn to provide information about the presence of lesions in the hard tissues of the tooth. The authors themselves indicate the shortcomings in the conducted research resulting from the overexposure or underexposure of the image and admit that the system requires further research. On the other hand, the results of the analysis indicate that the dentists' work can be supported with a computer used to assess the image of transillumination [22].

The artificial neural network was also used to create the application to facilitate the selection of a tool for preparing cavities in children to reduce the risk of developing secondary caries. Caries and periodontal diseases currently count among the most common bacterial diseases of the oral cavity. *Streptococcus mutans* is the initiator and the main microorganism causing the development of caries, and therefore it is justified to prepare the cavity in such a way that there is no risk of secondary caries developing. In their work, Javed *et al.* describe the use of an artificial neural network in such a way as to facilitate the preparation of carious cavities in children. The samples of material from the cavities were collected before and after the cavity was prepared using various methods: manually with an excavator, with a carbide drill, and with a polymer drill. The samples were cultured in a bacterial medium. It was assessed whether Streptococcus bacteria were present after the cavity preparation, which could be the cause of development of secondary caries. On the basis of the collected data, an application was developed to assist in selecting the method of preparing carious cavities which ensures the lowest risk of developing secondary caries. The effectiveness of assessing carious cavity clearance by means of vision or staining agents was also tested [23].

Trained neural networks have found application in the diagnosis of periodontal diseases and as a support in making decisions about periodontal treatment.

Gingivitis is a common oral disease with symptoms such as reddening of the gums, swelling, and bleeding. The main cause of gingivitis is tartar and dental plaque, and this pathology is easy for a dentist to recognize.

A study conducted by Li *et al*. consisted of analysis of photographs of the oral cavity (teeth and mucosa) of patients and was aimed at creating an application that would allow patients to self-assess the condition of the oral cavity. Nearly 4000 photos taken with different cameras were described as gingivitis, calculus, and soft deposits. The photos of the oral cavity were entered as input to the neural network designed for multi-task learning (MTL). The dataset contained an image with a description of the pathology involved. The study showed that on the basis of a photo taken with a mobile telephone, factors predisposing to periodontal disease can be located and the risk of gingivitis can be assessed. The effectiveness of the artificial neural network in detecting gingivitis, calculus, and soft deposits was estimated at 87.11%, 80.11%, and 78.57%, respectively. This means that the periodontal disease diagnosis system based on artificial intelligence can help users to self-assess the condition of the oral cavity and help in taking appropriate pro-health measures and hygiene procedures, which will be of importance to public health [24].

A similar study concerning periodontal tissue examination was also carried out in patients undergoing orthodontic treatment. Intraoral photographs were taken before treatment, 1 week after starting orthodontic treatment, and after 4 weeks. The teeth in the photos were divided into 6 areas.

The patients were examined by dentists who determined the Silness and Loe index for individual areas of the dentition, and on this basis classified individual areas as healthy or inflamed. The research used 2 types of artificial neural networks into which the created images were entered: the Faster R CNN network was used to detect and locate objects, and the second network algorithm was trained to detect gingivitis. The tooth detection model was 100% effective, while the gingivitis detection model was 77.12% effective. Traditional diagnostic methods are used as the standard practice; however, because of the need for periodontal probing, the methods are invasive and often unpleasant for the patient. Due to the fact that the efficiency of the neural network diagnostics of periodontal assessment is high, it can be concluded that this technique is beneficial for the patient. Gingivitis is the first and the mildest stage in periodontitis, which, if left untreated, becomes periodontitis and may lead to complications. With such serious consequences, it is important to diagnose the disease in the early stages. The results of the study suggest that diagnosing gingivitis with intraoral imaging is a non-invasive method that may help reduce the complications of untreated gum disease [25].

The main goal of periodontal prophylaxis is to control the risk factors of occurring of periodontal disease, such as dental plaque and calculus. The key to healthy periodontium is the effective removal of calculus in the dentist's office. Depending on their location, supragingival calculus and subgingival calculus are distinguished, which generate rapid disease progression and loss of the gingival attachment. Effective diagnosis of the subgingival calculus is a very important step in periodontal treatment [26–29].

Hsiao *et al*. described the use of modern imaging techniques and artificial neural network for better imaging of the subgingival calculus. Optic coherence tomography (OCT) is a high-resolution technique that uses light with a wavelength close to infrared light. Thanks to this technique of image reception and processing, we can obtain accurate 3-dimensional images of scattering media, such as biological tissues. It is possible to test soft tissues using this method. This imaging technique was first used in 1998 to examine the tissues of the oral cavity and teeth, and it turned out that OCT provides good opportunities for imaging enamel cracks, caries, and calculus [30]. In these studies, images from coherence tomography showing subgingival calculus were used to train the neural network to enable quick diagnosis of the presence of a subgingival calculus.

In the study the OCT imaging technique was combined with an artificial neural network. The examination was performed outside the oral cavity on extracted teeth with subgingival calculus and on teeth without calculus. The teeth were covered with a tissue imitating gums and artificial skin, and then imaged using optical coherence tomography. The OCT images were then imported into the neural network and used for training, validation, and testing. In the experiment the detection of subgingival calculus using ANN on optical coherence tomography images was 94.95% efficient. The results of such research performed so far outside the oral cavity are very promising, and it seems that the combination of OCT imaging technique and an artificial neural network for assessing the presence of a subgingival calculus is an objective, efficient, and quick method [30].

A panoramic image is an image that perfectly adapts for use in deep learning of artificial neural networks. In their study, Tuzoff *et al.* proposed simple use of a neural network to recognize and classify teeth visible on a radiograph. Every dentist can easily interpret such a photograph without problems. However, it seems that assistance in the form of automatic analysis of the photograph by a computer can be very useful and significantly facilitate the work of clinicians, especially young doctors with less experience [31].

The ability to adapt, the ability to process large amounts of information, and the reduced probability of overlooking important data mean that artificial intelligence has gained enormous interest as an aid used in dental practice. Artificial neural networks have been increasingly used in dentistry. The resulting software is mostly used on an academic basis for research and teaching purposes. The above examples prove that artificial intelligence is an excellent tool operating as an advisory system supporting the clinical decisions of doctors. Clinical evaluation and treatment are carried out by a specialist, while artificial intelligence plays a supporting role. A good diagnosis supported by a computer system will allow for determining a better treatment plan, and thus more beneficial results of therapy [32].

Conflict of interest

The authors declare no conflict of interest.

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