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Ocena zaawansowania zapalenia przyzębia z wykorzystaniem sieci neuronowych

Rozprawa na stopień doktora nauk medycznych i nauk o zdrowiu w dyscyplinie nauki medyczne

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Wykaz skrótów

ANN	sztuczne sieci neuronowe (ang. artificial neural networks)
API	aproksymalny wskaźnik płytki (ang. approximal plaque index)
BoP	krwawienie przy zgłębnikowaniu (ang. bleeding on probing)
CAL	utrata przyczepu klinicznego (ang. clinical attachment loose)
CNN	konwolucyjne sieci neuronowe (ang. convolutional neural networks)
DL	uczenie głębokie (ang. deep learning)
MLP	Multilayer Perceptron
PPD	mierzalna głębokość kieszonki (ang. probing pocket depth)
SOM	mapa samoorganizująca (ang. Self Organizing Maps)
SVM	metoda wektorów nośnych (ang. Support Vector Machine)

1. Wykaz publikacji stanowiących rozprawę doktorską

1. **Ossowska, A**.; Kusiak, A.; Świetlik, D. Artificial Intelligence in Dentistry—Narrative Review. *Int. J. Environ. Res. Public Health* **2022**, *19*, 3449. https://doi.org/10.3390/ijerph19063449

(IF = 4.614; MEiN = 140)

2. **Ossowska, A**.; Kusiak, A.; Świetlik, D. Evaluation of the Progression of Periodontitis with the Use of Neural Networks. *J. Clin. Med.* **2022**, *11*, 4667. https://doi.org/10.3390/jcm11164667

(IF = 4.964; MEiN = 140)

3. **Ossowska, A**.; Kusiak, A.; Świetlik, D. Progression of Selected Parameters of the Clinical Profile of Patients with Periodontitis Using Kohonen's Self-Organizing Maps. *J. Pers. Med.* **2023**, *13*, 346. https://doi.org/10.3390/jpm13020346

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2. Streszczenie w języku polskim

Najważniejszym organem ludzkiego organizmu jest mózg, który składa się z sieci neuronów połączonych ze sobą za pomocą synaps. Naukowcy od wielu lat próbują zrozumieć i odtworzyć działanie mózgu w celu jego poznania oraz w celu tworzenia sztucznych sieci neuronowych będących częścią sztucznej inteligencji. Neuronauka komputerowa polega na tworzeniu obwodów komputerowych, które przypominają działanie sieci neuronów ludzkich. Procesy informatyczne, które imitują percepcję, myślenie i działanie człowieka są wykorzystywane przez sztuczne sieci neuronowe. Potrafią one być niezwykle szybkie oraz dokładne, co sprawia, że doskonale radzą sobie z bardzo dużą ilością danych. W działaniu sieci neuronowych można wyróżnić dwa etapy. Pierwszym z nich jest etap uczenia, w którym sieć jest trenowana pod kątem rozwiązywania konkretnych problemów. W drugim etapie sieć na podstawie zdobytych umiejętności jest w stanie sama wykonywać zadania do których została skonstruowana. Sieci neuronowe możemy podzielić na sieci uczące się z nadzorem (supervised learning) oraz bez nadzoru - nauczyciela (unsupervised learning). W poniższych pracach wykorzystano zarówno sieci uczące się z nadzorem, jak i uczące się bez nadzoru– sieci neuronowe Kohonena (ang. self organizing maps).

Obecnie sztuczna inteligencja nabiera coraz większego znaczenia w medycynie oraz somatologii. W stomatologii zachowawczej algorytmy są coraz częściej używane do oceny zdjęć radiologicznych. Dokładność wykrywania zmian próchnicowych przez sztuczną inteligencję jest porównywalna, a często nawet wyższa od wykrywania tych zmian przez człowieka. Ponadto sztuczne sieci neuronowe mogą służyć do określenia rodzaju wypełnienia oraz do planowania kształtu opracowania ubytków. W endodoncji sztuczna inteligencja jest wykorzystywana do wykrywania zmian okołowierzchołkowych, złamań korzeni, oceny systemu kanałów korzeniowych, oceny długości roboczej, oceny położenia otworu anatomicznego oraz przewidywaniu potencjalnego sukcesu ponownego leczenia kanałowego. W powyższych sytuacjach sieci neuronowe wykazują często większą skuteczność niż tradycyjnie wykorzystywane metody. W ortodoncji sztuczne sieci neuronowe mogą pomóc lekarzowi w podjęciu decyzji o leczeniu ekstrakcyjnym lub bezekstrakcyjnym. Mogą one posłużyć do automatycznego nanoszenia punktów cefalometrycznych i analizy cefalometrycznej oraz do przewidywania rezultatów leczenia ortodontycznego. W chirurgii szczękowo – twarzowej coraz bardziej popularne stają się zabiegi z zakresu chirurgii ortognatycznej. Sieci neuronowe ułatwiają komunikację między lekarzem chirurgiem, ortodontą a pacjentem poprzez symulacje efektów leczenia ortognatycznego. Dodatkowo z użyciem sztucznej inteligencji można przewidzieć możliwe do wystąpienia parestezje po zabiegu ekstrakcji trzecich zębów trzonowych. W implantologii sieci neuronowe mogą wspomóc planowanie leczenia i przyczynić się do precyzyjniejszego umieszczania implantów. Mogą również służyć do oceny osteointegracji implantu oraz do oceny stopnia utraty kości w przypadku wystąpienia periimplantitis.

Choroby przyzębia są szeroko rozpowszechnione w społeczeństwie. Początkowym etapem jest zapalenie dziąseł, które charakteryzuje się zaczerwienieniem, obrzękiem, krwawieniem, dyskomfortem i bólem dziąseł. Nieleczone zapalenie dziąseł może prowadzić do zapalenia przyzębia, gdzie występuje utrata tkanek podtrzymujących ząb. Rozwój zapalenia dziąseł w kierunku zapalenia przyzębia głównie uwarunkowany jest odpowiedzią immunologiczno-zapalną gospodarza na obecność biofilmu bakteryjnego, stąd nie u wszystkich pacjentów rozwinie się w zapalenie przyzębia. Ponadto czynnikami mającymi wpływ na rozwój zapalenia przyzębia są wiek, płeć, uwarunkowania genetyczne, cukrzyca, nikotynizm, nadwaga, niska aktywność fizyczna i zaburzenia odżywiania. Aby zdiagnozować zapalenie przyzębia niezbędne jest dokładne badanie kliniczne oraz badania dodatkowe, najczęściej zdjęcia pantomograficzne. Sieci neuronowe mogą być użyte do oceny zdjęć radiologicznych i do procentowego oszacowania utraty kości. Mogą one również zostać użyte do oceny stadiów i stopni zgodnie z najnowszą klasyfikacją zapalenia przyzębia.

Celem poniższych prac była ocena zaawansowania zapalenia przyzębia z wykorzystaniem sieci neuronowych ze szczególnym uwzględnieniem parametrów klinicznych oraz czynników ryzyka, ocena skuteczności sieci w podziale na poszczególne stopnie zapalenia przyzębia oraz ocena wpływu poszczególnych parametrów na stopień zaawansowania zapalenia przyzębia.

Badaniem objęto 110 pacjentów, w wieku od 30 do 60 lat. Badania przeprowadzono w 2022 roku w Poradni Chorób Przyzębia i Błony Śluzowej Jamy Ustnej USC GUMed. Dane pozyskano z historii choroby pacjentów. Do analizy została włączona dokumentacja pacjentów z pełnymi danymi dotyczącymi badania klinicznego oraz stadiów i stopni zapalenia przyzębia wg nowej klasyfikacji z 2017 roku. Pacjenci zostali losowo podzieleni na dwie grupy. Do pierwszej grupy, gdzie sieci uczyły się włączono 90 osób, a do drugiej grupy testowej, gdzie dokładność sieci została sprawdzona włączono 20 osób.

Dane dotyczące badania klinicznego obejmowały: liczbę zębów zachowanych oraz liczbę zębów utraconych z powody choroby przyzębia, aproksymalny wskaźnik płytki (API), krwawienie przy zgłębnikowaniu (BoP), głębokość kieszonek (PD), utratę przyczepu klinicznego (CAL). Użyto następujących sieci neuronowych - sieci Kohonena oraz wielowarstwowe sieci neuronowe typu Multilayer Perceptron – zostały one stworzone przy użyciu programu Statistica Automated Neural Networks, TIBCO Software (Palo Alto, CA, USA, 2017).

Na podstawie przeprowadzonych badań stwierdzono, że dokładność oceny zaawansowania zapalenia przyzębia z użyciem sieci neuronowych może być porównywalna z oceną doświadczonego lekarza periodontologa. Ocena stadiów i stopni zapalenia przyzębia przez sieci neuronowe z wykorzystaniem dużej liczby danych jest znacznie szybsza niż ocena przeprowadzana przez klinicystów, co może pozwolić na wdrożenie odpowiedniego leczenia dla poszczególnych pacjentów.

3. Streszczenie w języku angielskim

The most important organ of the human body is the brain, which consists of a network of neurons that are connected with synapses. Computational neuroscience creates computer circuits that resemble the operation of human neuronal networks. IT processes can imitate perception and thinking by human what is used by artificial neural networks. They can be extremely fast, which makes them great at handling very large amounts of data. There are two stages in the use of neural networks. The first one is the learning stage where the network is trained for problems. Secondly, the network is checked if it is possible to perform the tasks for which it had been created. Neural networks can be divided into supervised learning neural networks and unsupervised learning neural networks, like the Kohonen neural network (self-organizing maps).

Nowadays artificial intelligence is becoming more and more important in medicine and dentistry. In conservative dentistry algorithms can be used to evaluate radiographs. The accuracy of detecting carious lesions by artificial intelligence is comparable and often even higher than the detection of these lesions by humans. Moreover artificial neural networks can be used to determine the type of filling and to plan the shape of cavity preparation. In endodontics artificial intelligence is used to detect periapical lesions, root fractures, assess the root canal system, assess working length, assess the position of the anatomical opening and predict the potential success of root canal retreatment. In the above situations neural networks are often more effective than traditionally used methods. In orthodontics artificial neural networks can help the doctor in deciding about the way of the treatment. They can be used to automatically put cephalometric points and carry out cephalometric analysis, as well as to predict the results of orthodontic treatment. Orthognathic surgery procedures are becoming more and more popular in maxillofacial surgery. Neural networks facilitate communication between the surgeon, orthodontist and the patient by simulating the effects of treatment. Additionally using artificial intelligence it is possible to predict the possible occurrence of paresthesia after the extraction of third molars. In implantology neural networks can support treatment planning and contribute to more precise implant placement. They can also be used to assess implant osseointegration and to assess the degree of bone loss in the event of periimplantitis.

Periodontal diseases are widespread in society. The initial stage is gingivitis, which is characterized by redness, swelling, bleeding, discomfort and pain in the gums. If left untreated gingivitis can lead to periodontitis, where there is the loss of tissue that supports the tooth. The development of gingivitis towards periodontitis is mainly determined by the host's immune-inflammatory response to the presence of bacterial biofilm, hence not all patients will develop periodontitis. Additionally factors influencing the development of periodontitis include age, gender, genetic predispositions, diabetes, nicotine addiction, overweight, low physical activity and eating disorders. To diagnose periodontitis a thorough clinical examination and additional tests are necessary, most often panoramic X-rays. Neural networks can be used to evaluate radiographs and to estimate the percentage of bone loss. They can also be used to assess stages and degrees according to the latest classification of periodontitis.

The aim of the following work was to assess the severity of periodontitis using neural networks with particular emphasis on clinical parameters and risk factors, assess the quality of the network in dividing into individual degrees of periodontitis, and assess the impact of individual parameters on the degree of advancement of periodontitis.

The study included 110 patients, aged 30 to 60. The research was carried out in 2022 at the Periodontal and Oral Mucosa Diseases Clinic of the Medical University of Gdańsk. Data were obtained from the patients' medical records. The analysis included patient records with complete data on the clinical examination and the stages and degrees of periodontitis according to the new classification from 2017. The patients were randomly divided into 2 groups. The first one, which included 90 people, where the neural networks were trained, and the second - test group, which consisted of 20 people. The goal of the test group was to check the accuracy of the previously trained neural network.

Clinical examination data included: number of teeth retained and number of teeth lost due to periodontal disease, proximal plaque index (API), bleeding on probing (BoP), pocket depth (PD), and clinical attachment loss (CAL). The following neural networks were used - Kohonen networks and Multilayer Perceptron neural networks - they were created using the Statistica Automated Neural Networks program, TIBCO Software (Palo Alto, CA, USA, 2017).

Based on the conducted research, it was found that the accuracy of assessing the severity of periodontitis using neural networks can be comparable to the assessment by an experienced periodontist. Assessment of stages and degrees of periodontitis by neural networks using large amounts of data is much more faster than assessment by clinicians, which may allow the implementation of appropriate treatment for individual patients.

4. Wstęp

4.1. Sieci neuronowe

Najważniejszym organem układu nerwowego człowieka jest mózg, który odpowiada za ciało i umysł człowieka, a także za jego osobowość i świadomość. Komórki z których składa się mózg są nazywane neuronami, a każdy z neuronów może być połączony z innymi komórkami nerwowymi za pomocą wypustek zwanymi dendrytami. Daje to możliwość połączenia odległych od siebie komórek, co jest unikatowe dla układu nerwowego [1]. Typowe prędkości przenoszenia potencjału czynnościowego wzdłuż aksonu wynoszą od 10 do 100 m/s i są one znacznie mniejsze niż prędkości impulsów prądowych w układzie elektronicznym. Położenie i efektywność synaps, czyli zdolność do przekazywania potencjałów czynnościowych zmienia się w czasie pod wpływem procesu uczenia [1-4]. Wyższe czynności nerwowe, którymi są percepcja, zapamiętywanie oraz świadomość przebiegają w obszarze kory mózgowej [1]. Choroby degeneracyjne układu nerwowego, takie jak choroba Alzheimera, powodują ogromne zmiany w działaniu neuronów, prowadzące do zmiany bądź nawet utraty osobowości [5-10]. Do niedawna uważano, że liczba sprawnych neuronów w czasie życia człowieka stale maleje, jednak badania wskazują na to, że jest możliwe pojawienie się nowych neuronów [1]. Mózg ma strukturę mającą charakter sieci, a hipotetyczna mapa wszystkich połączeń nosi nazwę konektomu. Wielu badaczy próbuje odtworzyć strukturę mózgu, co na razie najlepiej się udaje przy pomocy rezonansu magnetycznego, dzięki czemu możliwe jest nieinwazyjne odtworzenie głównych szlaków komunikacyjnych mózgu. Mimo, że działanie mózgu zawdzięczamy aktywności miliardów neuronów oraz reakcjom chemicznym, to neuronaukowcy twierdzą, że najważniejszą cechą jest sieciowy charakter tej struktury [11].

Neuronauka komputerowa polega na tworzeniu obwodów komputerowych, które przypominają działanie sieci neuronów ludzkich. Procesy informatyczne, które imitują percepcję, myślenie i działanie człowieka są wykorzystywane przez sztuczne sieci neuronowe. Modele komputerowe neuronów i sieci neuronowych to dwie metody służące zrozumieniu funkcjonowania układu nerwowego [12-14]. W roku 1943 Warren McCulloch i Walter Pitts stworzyli teoretyczną podstawę dla pierwszych sztucznych sieci neuronowych, tworząc jeden z ważniejszych matematycznych modeli pojedynczego neuronu z bodźcami wchodzącymi i wychodzącymi [15]. Nowe algorytmy uczenia zostały stworzone już w latach 70. Modele, które zostały stworzone, pomagają opracować nowe technologie oparte na biologii i poprawić rozumienie funkcjonowania ludzkiego mózgu. Obecnie naukowcom zależy na stworzeniu nowych rodzajów architektury sztucznych sieci neuronowych, by jeszcze wierniej naśladowały one działanie mózgu [16-18]. Nowe drogi do stworzenia maszyn obliczeniowych, które mogłyby naśladować biologiczne procesy żywego układu nerwowego otworzył Donald Hebb, kanadyjski psycholog, który stworzył teorię neuronauki. Wprowadzając koncepcję synapsy hebbowskiej, która mówi o tym, że neurony, które jednocześnie wysyłają impulsy nawiązują ze sobą głębszą łączność oraz pojęcie zespołów komórkowych pokazujące, że grupy neuronów aktywują się w określonych i sobie wiadomych sekwencjach, co umożliwia uczenie się, myślenie, postrzeganie, zapamiętywanie [19]. Do dnia dzisiejszego odkrycia Hebba stanowią podstawę osiągnięć robotyki, nauk komputerowych, sztucznej inteligencji, inżynierii, neuronauki i psychologii rozwoju [20,21]. Jednym z jego ważniejszych dzieł było opublikowanie w 1949 roku książki o działaniu pamięci, a zawarte w niej teorie mówią, że pamięć krótkotrwała jest nietrwała i mało odporna [20]. Sztuczne sieci neuronowe potrafią być niezwykle szybkie oraz dokładne, co sprawia, że doskonale radzą sobie z bardzo dużą ilością danych [22].

W działaniu sieci neuronowych można wyróżnić dwa etapy. Pierwszym z nich jest etap uczenia, w którym sieć jest trenowana pod kątem rozwiązywania konkretnych problemów. Po pierwsze należy zastanowić się czym jest uczenie się. Jest ono najczęściej definiowane jako zmiany w zachowaniu wynikające z doświadczenia [22,23]. W drugim etapie sieć na podstawie zdobytych umiejętności jest w stanie sama wykonywać zadania do których została skonstruowana. Najogólniej sieci neuronowe możemy podzielić na sieci uczące się z nadzorem (supervised learning) oraz bez nadzoru - nauczyciela (unsupervised learning) [24,25].

W sieciach uczących się z nadzorem dane wyjściowe, czyli wyniki znane są nauczycielowi i służą one do trenowania sieci. Ten typ sieci używa zarówno wektorów wejściowych jak i wyjściowych [22]. W sieciach uczących się bez nadzoru wyniki nie są znane sieci lub nie są jej one podane. Sieć sama musi odkryć prawidłowe mechanizmy, bez pomocy nauczyciela. To może być niezwykle istotna cecha, szczególnie w przypadku dużych i/lub złożonych zestawów danych, które byłyby czasochłonne lub trudne do obliczenia dla człowieka. Ten styl uczenia się jest wykorzystywany przez samoorganizujące się mapy (SOM) [22].

Konwolucyjne sieci neuronowe zdobywają coraz większą popularność w wielu dziedzinach, a główną cechą odróżniającą je od pozostałych sieci jest włączenie części konwolucyjnej. Konwolucyjność to matematyczne działanie na dwóch funkcjach, które powoduje powstanie trzeciej funkcji [26]. Sieci te mogą być z sukcesem użyte do np. oznaczenia stadiów i stopni zapaleń przyzębia na podstawie zdjęć pantomograficznych [27]. Na podstawie zdjęć pantomograficznych możliwe jest określenie położenia brzegu kości względem połączenia szkliwno-cementowego i postawienie właściwej diagnozy [28]. Wysoka wydajność konwolucyjnych sieci neuronowych spowodowała wyróżnienie kilku ich podtypów [29].

W roku 1982 Teuvo Kohonen zaproponował nowy algorytm sztucznych sieci neuronowych znany jako sieci Kohonena [30]. Sieci neuronowe Kohonena (Self-organizing maps) są przykładem sieci neuronowych uczących się bez nadzoru, bez asysty zewnętrznych źródeł. Wykonują one grupowanie wzorców treningowych bez znanych wyników [31]. Sieci Kohonena używane są do grupowania danych, niskowymiarowej reprezentacji danych wejściowych. Model samoorganizujących się sieci bardzo przypomina uczącą się kwantyzację wektorową (LVQ) i opiera się na konkurencyjnym uczeniu się, w którym uczy się tylko zwycięski neuron [32]. Sieci neuronowe Kohonena wyewoluowały z wczesnych modeli sieci neuronowych, a przełomowym odkryciem było wyjaśnienie przestrzennej organizacji funkcji mózgu, obserwowanej zwłaszcza w korze mózgowej. Uczenie się jest ograniczone przestrzennie do lokalnego sąsiedztwa najbardziej aktywnych neuronów. Zasadę działania sieci Kohonena można przedstawić czysto matematycznie z pominięciem aspektów chemicznych, biologicznych czy neurologicznych. Pierwszymi elementami danych są n- wymiarowe wektory euklidesowe, jednak matematyczna teoria SOM jest bardzo skomplikowana i tylko jeden przypadek jednowymiarowy został w pełni przeanalizowany [33-38].

Obecnie sztuczna inteligencja nabiera coraz większego znaczenia w medycynie i w stomatologii. W medycynie sztuczna inteligencja jest używana najczęściej w takich dziedzinach jak radiologia, patomorfologia, onkologia, kardiologia, czy psychiatria [39-48]. Sztuczna inteligencja może być użyta w planowaniu bardziej efektywnych terapii oraz w profilaktyce wielu schorzeń. Może ona przyczynić się także do redukcji kosztów leczenia [49-53].

4.2. Zastosowanie sieci neuronowe w stomatologii

Sztuczna inteligencja ma zastosowanie w wielu dziedzinach stomatologii. W dziedzinie stomatologii zachowawczej sieci neuronowe zdobywają bardzo szybko dużą popularność, chociaż wciąż jeszcze nie są często używane w codziennej praktyce [54]. Dzięki algorytmom możliwe jest rozpoznanie struktur anatomicznych oraz patologicznych na zdjęciach radiologicznych, które mogą być trudne do odróżnienia dla ludzkiego oka z powodu zbyt małego kontrastu, ich podobieństwa, a także artefaktów [55]. Dokładność działania sztucznej inteligencji w wykrywaniu zmian próchnicowych na podstawie zdjęć zębowych według przeprowadzonych przez Geetha badań wynosi nawet do 97,1% [56]. Ponadto przy użyciu zdjęć pantomograficznych na podstawie różnic kształtów i odcieni szarości możliwe jest wykrycie i rozróżnienie wypełnień stomatologicznych [57]. Sztuczna inteligencja może być także pomocna w planowaniu leczenia zachowawczego i w planowaniu opracowania kształtu ubytku. Sieci neuronowe pozwalają zaprojektować również kształt ubytku dla konkretnego pacjenta, tak aby w największym stopniu wyeliminować próchnicotwórcze bakterie z rodzaju Streptoccocus mutans i jednocześnie uniknąć nadmiernego opracowania zębiny czy obnażenia miazgi [40].

Sztuczna inteligencja zdobywa coraz większą popularność w endodoncji, gdzie może być pomocna przy wykrywaniu zmian okołowierzchołkowych, złamań korzeni, ocenie systemu kanałów korzeniowych, ocenie długości roboczej, ocenie położenia otworu anatomicznego oraz przewidywaniu potencjalnego sukcesu ponownego leczenia kanałowego [58-60]. W powyższych sytuacjach sieci neuronowe wykazują często większą skuteczność niż tradycyjnie wykorzystywane metody. Dużego znaczenia nabiera również możliwość wykrycia zmian okołowierzchołkowych w badaniu CBCT z wykorzystaniem sztucznej inteligencji, a czułość sieci neuronowych jest zbliżona do doświadczonego praktykującego lekarza dentysty [61].

W ortodoncji najczęściej używanymi rodzajami sieci neuronowych są sztuczne sieci neuronowe (ANN), konwolucyjne sieci neuronowe (CNN) oraz maszyny wektorów nośnych [62]. Sztuczne sieci neuronowe mogą pomóc lekarzowi ortodoncie w podjęciu decyzji o leczeniu ekstrakcyjnym lub bezekstrakcyjnym i dzięki temu dokładniej zaplanować leczenie [63]. Sztuczna inteligencja może wspomóc lekarzy ortodontów w analizie cefalometrycznej poprzez automatyczne naniesienie punktów i wyznaczenie kątów potrzebnych do dokonania pomiarów i oceny kierunku wzrostu twarzy [64]. Wiek oraz płeć mogą być również oznaczone podobnymi metodami z użyciem zdjęć radiologicznych nadgarstka oraz kręgów szyjnych [65]. Sieci neuronowe mogą także w pewnym stopniu przewidzieć rezultaty wybranego planu leczenia, co dodatkowo może wspomóc komunikację między lekarzem a pacjentem.

W chirurgii stomatologicznej i szczękowo – twarzowej coraz bardziej popularne stają się zabiegi z zakresu chirurgii ortognatycznej. W celu łatwiejszej komunikacji między lekarzem chirurgiem, ortodontą a pacjentem oraz dokładniejszego planowania zabiegów ortognatycznych można tworzyć symulacje efektów leczenia z użyciem sieci neuronowych [66]. Najczęściej wykonywanym zabiegiem z zakresu chirurgii stomatologicznej są ekstrakcje trzecich zębów trzonowych, a parestezje po zabiegu zdarzają się dość często. Dzięki sztucznej inteligencji zarówno pacjent jak i lekarz mogą być lepiej przygotowani na ewentualne powikłania. Na podstawie zdjęć pantomograficznych z użyciem konwolucyjnych sieci neuronowych można przewidzieć czy ekstrakcja trzeciego dolnego zęba trzonowego może skutkować parestezjami po zabiegu. W implantologii sieci neuronowe mogą wspomóc planowanie leczenia i przyczynić się do precyzyjniejszego umieszczania implantów. Mogą również służyć do oceny osteointegracji implantu oraz do oceny stopnia utraty kości w przypadku wystąpienia perimplantitis [67-70].

4.3. Zastosowanie sieci neuronowych w periodontologii

Choroby przyzębia są bardzo szeroko rozpowszechnione i dotyczą znacznej części społeczeństwa, nieleczone mogą prowadzić do ruchomości zębów i ich utraty. Aby zapobiec konsekwencjom chorób przyzębia profilaktykę oraz leczenie należy wprowadzić już na najwcześniejszym etapie [71]. W celu postawienia najwłaściwszej diagnozy u indywidualnego pacjenta należy przeprowadzić dokładny wywiad oraz badanie periodontologiczne. Aparat zawieszeniowy zęba składa się z dziąsła, kości wyrostka zębodołowego, cementu i więzadeł przyzębia. Najłagodniejszą formą chorób przyzębia i jednocześnie najczęściej obserwowaną jest zapalenie dziąseł spowodowane płytką bakteryjną. Wśród objawów zapalenia dziąseł można podać zaczerwienienie, obrzęk, krwawienie, dyskomfort, ból. Do czynników ryzyka modyfikujących zapalenie dziąseł należą zmiany hormonalne, hiperglikemia, palenie, zaburzenia odżywiania, substancje farmakologiczne, zaburzenia hematologiczne, nawisające wypełnienia i suchość jamy ustnej [71,72]. Zapalenie dziąseł może poprzedzać zapalenie przyzębia, które charakteryzuje się utratą przyczepu łącznotkankowego i kości. Rozwój zapalenia dziąseł w kierunku zapalenia przyzębia głównie uwarunkowany jest odpowiedzią immunologiczno-zapalną gospodarza na obecność biofilmu bakteryjnego, stąd nie u wszystkich pacjentów rozwinie się w zapalenie przyzębia. U niektórych pacjentów zapalenie ma przebieg szybko postępujący w krótkim czasie, a u innych przebiega umiarkowanie lub łagodnie przez całe życie. Dodatkowymi czynnikami mającymi wpływ na rozwój zapalenia przyzębia są wiek, płeć, uwarunkowania genetyczne, cukrzyca, nikotynizm, nadwaga, niska aktywność fizyczna i zaburzenia odżywiania [73]. Aby zdiagnozować zapalenie przyzębia niezbędne jest dokładne badanie kliniczne, a pomocne bywają również badania dodatkowe. Dokładność pomiarów periodontologicznych w dużym stopniu zależy od umiejętności oraz doświadczenia lekarza stomatologa, użytych narzędzi pomiarowych, najlepiej ustandaryzowanych sond periodontologicznych kalibrowanych co 1 milimetr [74]. Do najczęściej stosowanych badań dodatkowych należą zdjęcia pantomograficzne na podstawie których można ocenić stopień utraty kości powstały w wyniku zapalenia przyzębia. Sieci neuronowe mogą być użyte do oceny zdjęć radiologicznych i do procentowego oszacowania utraty kości. Zapalenie przyzębia jest przewlekłą wieloczynnikową chorobą zapalną związaną z dysbiotycznym biofilmem płytki. Charakteryzuje się ona postępującą utratą kości i w rezultacie może doprowadzić do przedwczesnej utraty zębów i dysfunkcji narządu żucia. Najnowsza klasyfikacja chorób przyzębia wyróżnia cztery stadia zapalenia przyzębia, które określają ciężkość i złożoność choroby w chwili zgłoszenia się pacjenta do lekarza dentysty oraz stopnie, które określają tempo progresji zapalenia przyzębia. Oba te parametry są od siebie niezależne i poszczególne stadium zaawansowania może występować z każdym stopniem w zależności od tempa progresji zapalenia przyzębia. Stopień uzależniony jest od pośrednich i bezpośrednich dowodów progresji zapalenia przyzębia oraz od dodatkowych czynników, jak palenie i uregulowanie cukrzycy. Stopień może być zmieniony w czasie w zależności od czynników ryzyka, obciążenia stanem zapalnym oraz pośrednich oznak progresji [41-44].

5. Założenia pracy

1. Ocena zaawansowania zapalenia przyzębia z wykorzystaniem sieci neuronowych ze szczególnym uwzględnieniem parametrów badania klinicznego oraz czynników ryzyka.

2. Ocena wpływu wybranych parametrów w odniesieniu do pacjentów z różnym stopniem zaawansowania zapalenia przyzębia oraz zidentyfikowanie wzorców profili klinicznych pacjentów związanych z konkretnym parametrem.

3. Ocenę jakości sieci w podziale na stopnie zapalenia przyzębia, jak i globalną analizę wrażliwości, która pozwalała określić jak ważny jest każdy parametr wejściowy.

Na przeprowadzenie badań uzyskano zgodę Niezależnej Komisji Bioetycznej ds. Badań Naukowych przy Gdańskim Uniwersytecie Medycznym (uchwała nr NKBBN/347-8/2022).

6. Materiały i metody

6.1. Grupa badana i kontrolna

Według najnowszej klasyfikacji chorób przyzębia z 2017 roku, pacjentów można podzielić na tych ze zdrowym przyzębiem i dziąsłami, zapaleniem dziąseł oraz zapaleniem przyzębia. Zapalenie przyzębia może przebiegać z różnym nasileniem i złożonością co determinuje zakwalifikowanie pacjenta do jednego z czterech stadiów Tabela 1. Szacowanie tempa rozwoju choroby oraz szacowanie potencjalnego wpływu chorób ogólnoustrojowych na zapalenie przyzębia wpływa na określenie jednego z trzech stopni zapalenia przyzębia [70] Tabela 2.

Zapalenie przyzębia w I stadium to najłagodniejsza postać zapalenia przyzębia, która rozwija się tuż po zapaleniu dziąseł. Kluczowe jest wczesne rozpoznanie tego stadium i wdrożenie prawidłowego leczenia. Zapalenie przyzębia II stadium jest umiarkowanym zapaleniem przyzębia z charakterystycznymi zmianami w przyzębiu. Profesjonalne postępowanie może zatrzymać postęp choroby. Stadium III zapalenia przyzębia występuje, gdy kliniczna utrata przyczepu jest bardziej zaawansowana i istnieje ryzyko dodatkowej utraty zębów. Zapalenie przyzębia w stadium IV jest etapem podobnym do stadium III, ale istnieje tu konieczność kompleksowej rehabilitacji stomatologicznej z powodu utraty punktów podparcia, upośledzenia funkcji narządu żucia i ryzyka utraty uzębienia [70].

Tabela 1. Stadia zapalenia przyzębia

Stadium zapalenia przyzębia		Stadium I	Stadium II	Stadium III	Stadium IV
Ciężkość	Maksymalne interproksymalne CAL	1-2mm	3-4mm	≥5mm	≥5mm
	Radiologiczna utrata kości	<15%	15-33%	Powyżej 1/3 dokoronowej	Powyżej 1/3 dokoronowej
	Utrata zębów z powodu choroby przyzębia	Brak utraty	Brak utraty	4 zęby lub mniej	5 zębów lub więcej
Złożoność	Maksymalna PD	≤4mm	≤5mm	≥6mm	Kryteria jak w stadium III plus: Potrzeba złożonej rehabilitacji ze względu na: - dysfunkcję żucia -wtórny uraz zgryzowy -ruchomość 2 stopnia lub wyższa -ciężki stopień zaniku wyrostka -obniżenie zwarcie -przesunięcia zębów -mniej niż po 10 antagonistów
	Utrata kości	Głównie pozioma	Głównie pozioma	Pionowa utrata kości 3mm lub więcej	
				Zajęcie furkacji II lub III stopnia	
				Ubytek wyrostka średniego stopnia	
Zasięg	Zlokalizowany (do 30% zębów), uogólniony lub ograniczony do siekaczy i trzonowców				

Stopnie pozwalają ocenić tempo progresji choroby przyzębia i nie są one zależne od stadiów. Każdy pacjent może mieć inne tempo progresji zapalenia przyzębia. Według nowej klasyfikacji istnieją bezpośrednie i pośrednie dowody na progresję zapalenia przyzębia. Dowody bezpośrednie wymagają radiogramów z przeszłości, a pośrednie dowody wymagają oceny ubytku kostnego i uwzględnienia wieku pacjenta [72,74-76]. Nowa klasyfikacja rozróżnia 3 stopnie zapalenia przyzębia:

A, B i C. Mogą one być modyfikowane przez niektóre czynniki ryzyka, takie jak palenie tytoniu czy słabo kontrolowana cukrzyca. Wyróżnić też możemy grupę pacjentów mniej reagującą na standardowe leczenie periodontologiczne ze względu na inne czynniki ryzyka, na przykład czynniki genetyczne [77-78]. Celem określenia stopnia zapalenia przyzębia jest znalezienie najlepszej metody leczenia dla indywidualnego pacjenta z uwzględnieniem czynników ryzyka.

Tabela 2. Stopnie zapalenia przyzębia

Stopnie zapalenia przyzębia			**Stopień A: wolne tempo progresji**	**Stopień B: Umiarkowane tempo progresji**	**Stopień C: Szybkie tempo progresji**
Kryteria podstawowe	Bezpośrednie oznaki progresji	Dane z obserwacji długoterminowych	Udokumentowany brak utraty tkanek na przestrzeni 5 lat	<2mm w ciągu 5 lat	≥2mm w ciągu 5 lat
	Pośrednie oznaki prograsji	% utraty kości/wiek	<0.25	0.25 to 1.0	>1.0
		Fenotyp pacjenta	Obfite złogi biofilmu z niskim stopniem destrukcji	Destrukcja proporcjonalna do złogów	Destrukcja szybsza niż należałoby oczekiwać
Czynniki modyfikujące stopień choroby	Czynniki ryzyka	Palenie	Pacjent niepalący	<10 papierosów/dobę	≥10 papierosów/ dobę
		Cukrzyca	Pacjent normoglikemiczny	Cukrzyca HbA1c <7.0%	Cukrzyca HbA1c ≥7.0%

Badaniem objęto 110 pacjentów, w wieku od 30 do 60 lat. Badania przeprowadzono w 2022 roku w Poradni Chorób Przyzębia i Błony Śluzowej Jamy Ustnej USC GUMed. Dane pozyskano z historii choroby pacjentów. Do analizy została włączona dokumentacja pacjentów z pełnymi danymi dotyczącymi badania klinicznego oraz stadiów i stopni zapalenia przyzębia wg nowej klasyfikacji z 2017 roku. Grupę kontrolną stanowiło 10 osób ze zdrowym przyzębiem lub zapaleniem dziąseł, 12 osób zakwalifikowano do stadium pierwszego zapalenia przyzębia, 19 do stadium drugiego, 42 do stadium trzeciego, 27 do stadium czwartego. Pacjenci zostali losowo podzieleni na 2 grupy, pierwszą, do której włączono 90 osób, gdzie sieci neuronowe uczyły się, oraz drugą testową, która stanowiła 20 osób. Celem grupy testowej było sprawdzenie dokładności wcześniej nauczonej sieci neuronowej.

6.2. Dane kliniczne

Dane dotyczące badania klinicznego obejmowały: liczbę zębów zachowanych oraz liczbę zębów utraconych z powody choroby przyzębia, aproksymalny wskaźnik płytki (API), krwawienie przy zgłębnikowaniu (BoP), głębokość kieszonek (PD), utratę przyczepu klinicznego (CAL), ruchomość zębów oraz obecność furkacji w badaniu klinicznym. Pomiary zostały przeprowadzone z użyciem 15 – milimetrowej sondy wyskalowanej co 1mm, o zbieżności stożka 1,75^{o} i średnicą zakończenia sondy 0,5mm.

Z powyższych pomiarów zostały wykluczone zęby z recesjami o pochodzeniu urazowym, zęby z próchnicą w okolicy przyszyjkowej, drugie trzonowce z recesjami spowodowanymi ich niewłaściwą pozycją w łuku oraz trzecie zęby trzonowe, zęby ze zmianami w przyzębiu brzeżnym spowodowanymi zapaleniem miazgi oraz zęby z pionowym złamaniem korzenia [69].

6.3 Sieci neuronowe

Matematyczne modele, które naśladują działania ludzkiego mózgu analizują dane wejściowe po to by uzyskać jak najwłaściwsze odpowiedzi. Użyte w badaniach sieci neuronowe - sieci Kohonena oraz wielowarstwowe sieci neuronowe typu Multilayer Perceptron – zostały one stworzone przy użyciu programu Statistica Automated Neural Networks, TIBCO Software (Palo Alto, CA, USA, 2017).

6.3.1 Sieci neuronowe typu Multilayer Perceptron

Sztuczne sieci neuronowe użyły danych zebranych od przebadanych pacjentów z uwzględnieniem wieku, palenia tytoniu, higieny jamy ustnej, głębokości kieszonek, utraty przyczepu łącznotkankowego. W przypadku badania z użyciem sieci typu Multilayer Perceptron zebrano 543 danych wejściowych dla każdego pacjenta. Sieć zbudowana była z warstwy wejściowej, ukrytej i wyjściowej. Warstwa ukryta składała się z 19 neuronów, a warstwa wyjściowa z 4 neuronów. Sieci uczyły się pod nadzorem, a ich zadaniem było zakwalifikowanie każdego z pacjentów do jednego z trzech stopni zapalenia przyzębia lub do grupy pacjentów zdrowych. Stworzono 100 sieci neuronowych typu Multilayer Perceptron aby uzyskać jak najdokładniejsze wyniki. Spośród wszystkich sieci neuronowych wybrano tę, która charakteryzowała się największą jakością. Podczas procesu uczenia z nauczycielem wagi połączeń między neuronami były modyfikowane przez algorytm BFGS [79,80]. Współczynnik uczenia się wynosił 0,01, a liczbę epok ustalono na 1000, gdzie kolejność prezentowanych przypadków dla sieci neuronowej była różna w każdej epoce.

Aby określić jakość klasyfikacji sztucznej sieci neuronowej, wszyscy pacjenci zostali losowo podzieleni na dwie grupy: uczącą i testującą. Grupa ucząca składała się z 90 pacjentów, a grupa testowa z 20 pacjentów.

6.3.2 Sieci neuronowe Kohonena (SOM)

Celem sieci neuronowych Kohonena było stworzenie algorytmów działających bez nadzoru nauczyciela i na podstawie podanych danych zakwalifikowania poszczególnych pacjentów do jednego z trzech stopni zapaleń przyzębia i jednego z czterech stadiów zapaleń przyzębia. Do badań użyto komputera Intel® Core™ i7–9850H CPU© 2.60 GHz, 16 GB RAM, and 512GB HDD. Algorytm opisany przez Haykina [5] został stworzony przy pomocy programu Statistica Automated Neural Networks, TIBCO Software Inc. 2017 [22]. W powyżej pracy został użyty prosty model sieci Kohonena, który składał się tylko z warstwy wejściowej oraz wyjściowej, bez warstwy ukrytej. Każdy pacjent był reprezentowany przez wektor o liczbie współrzędnych i czynników, które go reprezentują. Aby wygenerować SOM wzięto pod uwagę - płeć, wiek, palenie tytoniu, higienę jamy ustnej, głębokość kieszonek i utratę przyczepu łącznotkankowego w przestrzeniach międzyzębowych.

6.4 Analiza statystyczna

Analizy statystyczne zostały przeprowadzone przy użyciu pakietu statystycznego TIBCO Software Inc. (2017). Statistica (data analysis software system), version 13. http://statistica.io. Wszystkie parametry ilościowe zostały wyrażone za pomocą średniej arytmetycznej i odchylenia standardowego wraz z 95%CI (przedział ufności). Parametry jakościowe przedstawiono za pomocą liczności i odsetka. Testem W Shapiro-Wilka sprawdzono zgodność z rozkładem normalnym, a Levena jednorodność wariancji. Różnice między dwoma grupami zbadano testami istotności różnic: t-Studenta lub test U Manna-Whitneya. Natomiast różnice pomiędzy więcej niż dwoma grupami sprawdzono testem F (ANOVA) lub Kruskala-Wallisa, stosując w przypadku otrzymania istotnych statystycznie różnic testy post hoc (dla F test Tukeya, dla Kruskala-Wallisa test Dunna).Testy niezależności Chi-kwadrat wykorzystano dla zmiennych jakościowych. W wszystkich analizach statystycznych za poziom istotności przyjęto $\alpha=0.05$.

7. Omówienie publikacji wchodzących w skład rozprawy

Publikacja 1

Artificial intelligence in dentistry - narrative review, Int. J. Environ. Res. Public Health, vol. 19, 2022

Celem pracy był przegląd piśmiennictwa dotyczącego użycia sztucznej inteligencji w poszczególnych dziedzinach stomatologii. Na podstawie zebranej literatury stwierdzono, że sztuczna inteligencja jest coraz bardziej powszechna we wszystkich specjalizacjach stomatologicznych.

W stomatologii zachowawczej sztuczna inteligencja najczęściej jest używana w diagnostyce obrazowej w celu wczesnego wykrycia zmian próchnicowych, określenia rodzaju wypełnień czy zaplanowania kształtu opracowania ubytku. W endodoncji nowe technologie mogą zostać użyte w celu wykrycia zmian okołowierzchołkowych, złamań korzeni, oceny systemu kanałów korzeniowych, oceny długości roboczej, oceny położenia otworu anatomicznego oraz przewidywania potencjalnego sukcesu ponownego leczenia kanałowego. W ortodoncji sztuczne sieci neuronowe mogą pomóc lekarzowi ortodoncie w podjęciu decyzji o leczeniu ekstrakcyjnym lub bezekstrakcyjnym, mogą też wspomóc lekarza w diagnostyce schorzeń stawu skroniowo-żuchwowego, w przeprowadzeniu analizy cefalometrycznej, a nawet w pewnym stopniu przewidzieć rezultaty wybranego planu leczenia. W leczeniu ortognatycznym można przeprowadzić symulacje efektów leczenia, co w znacznym stopniu może ułatwić komunikację między lekarzem a pacjentem. W chirurgii stomatologicznej sztuczna inteligencja może być wykorzystana do określenia możliwych powikłań po ekstrakcji trzeciego zęba trzonowego i przewidzenia ewentualnych parestezji. W implantologii sieci neuronowe mogą wspomóc planowanie leczenia i precyzyjniejsze umieszczanie implantów. Mogą również służyć do oceny osteointegracji implantu oraz do oceny stopnia utraty kości w przypadku wystąpienia periimplantitis. W periodontologii sztuczna inteligencja może wspomóc ocenę zdjęć pantomograficznych i określenie stopnia utraty kości. Dodatkowo sieci neuronowe mogą przyczynić się do szybszego określenia stadiów i stopni zgodnie z najnowszą klasyfikacją chorób przyzębia.

Publikacja 2

Evaluation of the Progression of Periodontitis with the Use of Neural Networks, J.Clin.Med.,2022

Celem pracy była ocena dokładności sieci neuronowych typu Mulilayer Perceptron, których zadaniem było określenie stopnia progresji zapalenia przyzębia wśród pacjentów Poradni Chorób Przyzębia i Błony Śluzowej Jamy Ustnej Gdańskiego Uniwersytetu Medycznego.

W pracy wykorzystano dane z kart medycznych 110 pacjentów obu płci, w wieku od 30 do 60 lat. Do oceny stopnia progresji zapalenia przyzębia wzięto pod uwagę następujące parametry: liczbę zębów, aproksymalny wskaźnik płytki (API), krwawienie przy zgłębnikowaniu (BoP), głębokość kieszonek (PD) oraz utratę przyczepu klinicznego (CAL), ruchomość zębów oraz obecność furkacji. Pacjentów podzielono na dwie grupy: grupę uczącą się, do której włączono losowo 90 osób oraz grupę testową, do której włączono 20 osób. Grupą uczącą była grupa, w której sieci neuronowe nauczyły się klasyfikować pacjentów, a grupa testowa służyła do oceny jakości sieci. Pomiary przeprowadzono przy użyciu sondy periodontologicznej UNC 15 o kształcie cylindrycznym, skali 15 mm, stożkowatości 1,75˚ i średnicy końcówki sondy 0,5mm. Do badania włączono wyłącznie pacjentów, u których wykonano wszystkie niezbędne pomiary. Pacjentów zakwalifikowano następująco: 12 pacjentów z zapaleniem przyzębia w stadium I, 19 pacjentów z zapaleniem przyzębia w stadium II, 42 pacjentów z zapaleniem przyzębia w stadium III, 27 pacjentów z zapaleniem przyzębia w stadium IV oraz 10 pacjentów z zapaleniem dziąseł. We wszystkich grupach uczestniczyli pacjenci ogólnie zdrowi lub chorzy na cukrzycę i/lub palacze papierosów. Pacjenci z innymi chorobami ogólnoustrojowymi oraz pacjenci z implantami stomatologicznymi zostali wykluczeni. Według nowej klasyfikacji Chorób

Przyzębia z 2017 roku pacjent z zapaleniem przyzębia ma więcej niż 2 międzyzębowe CAL w zębach niesąsiadujących lub więcej 2 zęby z policzkowym/ustnym CAL powyżej 3 mm i kieszonkami > 3 mm. Z powyższych kryteriów powinny zostać wykluczone: zęby z recesjami dziąseł pochodzenia urazowego, zęby z próchnicą w okolicy szyjki zęba, drugi trzonowiec z kliniczną utratą przyczepu na powierzchni dystalnej z powodu nieprawidłowego położenia, zęby ze zmianami endodontycznymi w przyzębiu brzeżnym, zęby z pionowym złamaniem korzenia.

W celu uzyskania najlepszej jakości, zbudowano sto wielowarstwowych modeli sieci neuronowych (MLP). Zadaniem sieci neuronowych było przyporządkowanie pacjentów do jednego z trzech stopni zapalenia przyzębia lub ocena pacjentów jako zdrowych. Sieć neuronowa składała się z trzech warstw: wejściowej, ukrytej i wyjściowej.

W badanej grupie 110 pacjentów znalazło się 9,1% osób zdrowych, bez zapalenia przyzębia, 13,6% pacjentów ze stopniem A, 39,1% ze stopniem B i 38,2% ze stopniem C. W grupie badanej 10,9% stanowili pacjenci w I stadium zapalenia przyzębia, 17,3% z II stadium, 38,2% ze stadium III i 24,5% ze stadium IV. W stopniu C odsetek osób palących papierosy wynosił 50,0%. W pozostałych grupach odsetek palaczy nie przekracza 10%. Średni wiek zdrowych ochotników wynosił 33,1 (95% CI: 29,8–36,4), pacjenci ze stopniem A mieli średnio 43,1 lat (95% CI: 40,1–46,0), ze stopniem B 48,1 lat (95% CI: 46,0–50,2) i ze stopniem C 45,8 lat (95% CI: 43,8–47,9). Dokładność sieci neuronowej definiowana jako procent poprawnie sklasyfikowanych sieci pacjentów według stopnia zapalenia przyzębia wyniosła 84,2% dla zbioru uczącego się. Procent pacjentów błędnie sklasyfikowanych ze względu na stopień zapalenia przyzębia wyniósł 15,8%. Sztuczne sieci neuronowe mogą być przydatnym narzędziem w codziennej praktyce stomatologicznej do oceny ryzyka rozwoju zapalenia przyzębia. Ocena tempa postępu zapalenia przyzębia, zwłaszcza u młodych ludzi i w początkowej fazie choroby może być czasami trudna do ocenienia, a dodatkowe narzędzia, takie jak sztuczne sieci neuronowe, mogą ułatwić diagnozę i wybór planu leczenia. Konieczne są dalsze badania w celu udoskonalenia tej metody diagnostycznej.

Publikacja 3

Progression of selected parameters of the clinical profile of patients with periodontitis using Kohonen's self-organizing maps, J. Pers. Med., 2023

Zapalenie przyzębia to stan zapalny, który atakuje tkanki otaczające ząb i powoduje kliniczną utratę przyczepu (CAL). Zgodnie z najnowszą klasyfikacją zapaleń przyzębia możemy wyróżnić cztery stadia zapalenia różniące się między sobą zaawansowaniem. Zapalenie przyzębia może się rozwijać u poszczególnych osób w innym tempie, które może być wyrażone z pośrednictwem trzech stopni. Głównymi determinantami są wiek, płeć oraz czynnik genetyczny, a głównymi czynnikami ryzyka są nikotynizm i źle kontrolowana cukrzyca. Sztuczna inteligencja zyskuje coraz większe znaczenia w wielu dziedzinach medycyny oraz stomatologii. W powyższym badaniu użyto sieci neuronowych Kohonena (SOM) w celu określenia stadium i stopnia zapalenia przyzębia. Do badania użyto danych retrospektywnych zebranych od 110 pacjentów, gdzie 90 osób stanowiło grupę na której sieć się uczyła, a 20 osób stanowiło grupę na której została sprawdzona dokładność sieci. Grupa pacjentów obejmowała osoby obu płci w wieku od 30 do 60 lat, ogólnie zdrowe lub z cukrzycą typu I lub II i/lub palące papierosy. W celu zebrania danych periodontologicznych użyto sondy periodontologicznej UNC 15 wyskalowanej co 1mm, o kształcie cylindrycznym, stożkowatości 1,75˚ i średnicy końcówki sondy 0,5mm. Z badania zostały wykluczone zęby z recesjami dziąseł pochodzenia urazowego, zęby z próchnicą w okolicy szyjki zęba, drugi trzonowiec z kliniczną utratą przyczepu na powierzchni dystalnej z powodu nieprawidłowego położenia, zęby ze zmianami endodontycznymi w przyzębiu brzeżnym, zęby z pionowym złamaniem korzenia. Ocenianymi parametrami były liczba zębów, aproksymalny wskaźnik płytki (API), krwawienie przy zgłębnikowaniu (BoP), głębokość kieszonek (PD), utrata przyczepu klinicznego (CAL), ruchomość zębów oraz obecność furkacji.

Sieci neuronowe Kohonena są przykładem sieci samouczącej się zbudowanej z warstwy wejściowej oraz wyjściowej, bez warstw ukrytych. Jest to przykład prostej sieci neuronowej w porównaniu z innymi sieciami neuronowymi. Do badań użyto komputera Intel® Core™i7 –9850H CPU© 2.60 GHz, 16 GB RAM, and 512GB HDD. Użyto algorytmu Haykina przy użyciu programu Statistica, TIBCO Software Inc. (2017) W badaniu użyto następujących wektorów wejściowych: wiek, płeć, palenie papierosów, higiena jamy ustnej, głębokość kieszonek przyzębnych, maksymalna utrata przyczepu klinicznego w przestrzeniach międzyzębowych. Spośród 110 pacjentów 65,5% stanowiły kobiety, 9,1% zdrowych osób, 13,6% ze stopniem A, 39,1% ze stopniem B, 38,2% ze stopniem C. 10,9% pacjentów miało stadium I zapalenia przyzębia, 17,3% stadium II, 38,2% stadium III i 24,5% stadium IV. Średnia wieku pacjentów wynosiła 45,2 lata, średnia wartość wskaźnika API 77,9%, wskaźnika BoP 60,0%, średnia wartość utraty przyczepu klinicznego w przestrzeniach międzyzębowych miała wartość 3,63 mm, a średni pomiar kieszonek (PD) wynosił 2,90 mm.

Zastosowanie sieci Kohonena pozwoliło odkryć schemat pacjentów według stopnia i stadium zapalenia przyzębia. Pogrupowane neurony utworzyły trzy skupienia: pierwsze, które reprezentowało odsetek wolnego tempa progresji zapalenia przyzębia wynoszący prawie 75%, drugie, w której odsetek umiarkowanego tempa progresji wynosił prawie 65% oraz trzecie reprezentowane odsetek szybkiego tempa progresji wynoszący prawie 60%. Więcej węzłów mapy jest wspólnych dla pacjentów z dwóch ostatnich skupień niż w przypadku węższego pierwszego wolnego tempa progresji.

Z użyciem sieci neuronowych określono stadium oraz stopień zapalenia przyzębia. Na podstawie powyższego badania można stwierdzić, że sieci neuronowe mogą być przydatnym narzędziem w celu określenia zaawansowania zapalenia przyzębia.

8. Wnioski

1. Na podstawie powyższych badań można stwierdzić, że dokładność oceny zaawansowania zapalenia przyzębia z użyciem sieci neuronowych może być porównywalna z oceną doświadczonego lekarza periodontologa.

2. Ocena stopni zapalenia przyzębia przez sieci neuronowe z wykorzystaniem dużej liczby danych jest znacznie szybsza niż ocena przeprowadzana przez klinicystów.

3. Szybkie i dokładne określenie stopni zapalenia przyzębia pozwoli na wdrożenie odpowiednio dobranego leczenia dla poszczególnych pacjentów.

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Review

Artificial Intelligence in Dentistry—Narrative Review

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Abstract: Nowadays, artificial intelligence (AI) is becoming more important in medicine and in dentistry. It can be helpful in many fields where the human may be assisted and helped by new technologies. Neural networks are a part of artificial intelligence, and are similar to the human brain in their work and can solve given problems and make fast decisions. This review shows that artificial intelligence and the use of neural networks has developed very rapidly in recent years, and it may be an ordinary tool in modern dentistry in the near future. The advantages of this process are better efficiency, accuracy, and time saving during the diagnosis and treatment planning. More research and improvements are needed in the use of neural networks in dentistry to put them into daily practice and to facilitate the work of the dentist.

Keywords: artificial intelligence; neural networks; dentistry

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1. Introduction

Nowadays, artificial intelligence (AI) is becoming more important in medicine and in dentistry. It can be helpful in many fields where the human may be assisted and helped by new technologies. The developments in AI started in 1943 but the term "artificial intelligence" was created in 1956 at a conference in Dartmouth by John McCarthy. Machine learning, neural networks, and deep learning are subsets of artificial intelligence. Machines can learn through data to build algorithms and in this way, they can solve the prediction problems without human help. Neural networks (NNs) use artificial neurons that are similar to human neural networks and mimic the human brain in a mathematical non-linear model. NNs are able to simulate human cognitive skills such as problem solving and human thinking abilities, which includes learning and decision making. Neural networks in a simple form have three layers: input layer (where the information enters the system), the hidden layer (where the data are processed), and the output layer (where the system decides what to do). Given a set of mathematical models, NNs are able to outline any input to an output. If an adequately large amount of data are available, such NNs can be trained to represent the intrinsic statistical figures of the provided data. The topology of the simple artificial neural network is shown in Figure 3 in Swietlik D et al. (2004). There are also more complex artificial neural networks where there are more hidden layers and these are called multilayer perception (MLP) neural networks. The most commonly used types of neural networks are artificial neural networks (ANN), convolutional neural networks (CNN), and recurrent neural networks. Deep learning is a part of neural networks where the computer learns on its own how to process the data. Deep learning neural networks have between a few thousand and a few million neurons in the hidden layer [1–5]. Artificial intelligence (AI) may be used in planning more effective therapies, prophylaxis, and the reduction in treatment costs [2,4]. We can benefit from AI in medicine, mostly in the fields such as radiology, pathomorphology, and oncology (by using "Thermalitics" technique in breast cancer detection), in cardiology (to help in ECG analysis), in psychiatry (to diagnose, prevent and treat mental illnesses), nuclear medicine, and many others [6–10]. The computer models of neural networks are also one of the methods to understand the functioning of the nervous system, which we cannot study in natural conditions due to the limitations of modern research methods [11–15].

Artificial intelligence is also spreading in dentistry due to the technological advancements and digitization of dentistry. Dental second opinions can now be made by computers in many dental fields. NNs in dentistry can be used to make the process of diagnosis more accurate, rapid, and efficient. Fast development and new studies related to neural networks in dentistry were the reason to provide this narrative review. The aim of this study was to outline the overall picture of the possibilities of using neural networks in modern dentistry.

2. Neural Networks in Restorative Dentistry

Dental caries is the most common dental disease and that is why its disclosure in the early stage is crucial. For the screening and diagnosis of dental caries, dentists mostly use dental probes, and through the observation of the texture and discoloration, they can determine whether the tooth is sound or not. This method is very subjective and is based on the dentist's experience. In particular, the approximal surfaces may be problematic in dental examination [16,17]. Additional tests such as radiographs are essential in modern dentistry and can enhance the detection of caries. The most common types of radiological images used in caries screening are bitewings, periapical X-rays, and panoramic X-rays. CBCT is used less frequently in tooth decay detection [18,19]. Dental caries detection on radiological images might be assisted by neural networks, which makes the examination faster and more precise. Neural network use in conservative dentistry has developed quickly, but is not very widespread yet [20]. Algorithms can be used to locate the edges of anatomical and pathological structures, which might be very similar to each other due to the image noise and low contrast [21]. In the work by Geetha et al., an artificial neural network was used to determine whether there were caries or not in the 105 radiograph images. They extracted sixteen feature vectors from the segmented image and these were the input nodes. There were two output nodes that consisted of caries or sound tooth. The accuracy of caries detection was 97.1%, and the false positive rate was 2.8%. This study indicates that neural networks may be much more precise in tooth decay detection than traditional dental examination [22]. Moreover, dental restorations may be revealed by the use of artificial intelligence. In restorative dentistry, AI can be used to detect and classify dental restorations such as in Abdalla-Aslan R et al.'s research from 2020. The algorithms used in their work detected 93.6% of dental restorations on 83 panoramic images. Additionally, restorations were classified into 11 categories by using the shape and distribution of grey values [23]. Neural networks might be helpful in planning the selection of the dental treatment and cavity preparation technique. Artificial neural networks were used in Javed et al.'s study to predict the post-Streptococcus mutans prior to dental caries excavation based on pre- Streptococcus mutans using an iOS App developed on an artificial neural network (ANN). For the research, 45 primary molars with occlusal caries were used. The colony forming units for pre- and post-Streptococcus mutans were recorded. The study demonstrates that ANN can predict which excavation method is the best for an individual patient. The accuracy of ANN was 99.03% and it was microbiologically checked (Table 1). The prediction of post-Streptococcus mutans avoids the examination of post-Streptococcus mutans, re-excavation, and re-examination, and pulpal trauma with the excavated cavity [3].

Table 1. Baseline characteristics of the studies included in the review by studying neural networks in restorative dentistry.

Study [Ref.]	Year of Publication	Type of Data	Type of Neural Network	Number of Database	Accuracy of Neural Network
Javed [3]	2019	Primary molars	Artificial neural network (ANN)	45 teeth	99.03%
Geetha [22]	2020	Periapical radiographs	Back -propagation neural network	105 images	97.7%
Abdalla-Aslan [23]	2020	Panoramic radiographs	Cubic support vector machine algorithm with error-correcting output codes	83 images	93.6%

Neural networks in restorative dentistry may be used in a few clinical purposes. Frequently performed diagnosis and the choice of treatment method can now be assisted by artificial intelligence. The most common way to engage new technologies is the analysis of dental X-rays and caries or restoration detection, but also in other fields such as microbiology, which can be assisted by neural networks to make the best treatment decisions. More studies need to be performed to introduce new technologies to daily practice but other fields of restorative dentistry might also be helped by neural networks in decision-making.

3. Neural Networks in Endodontics

Artificial intelligence has an increasing relevance in endodontics. It can be useful in detecting periapical lesions and root fractures, root canal system anatomy evaluation, predicting the viability of dental pulp stem cells, determining working length measurements, and predicting the success of retreatment procedures [24]. Artificial neural networks may be used as a decision-making system for locating the minor apical foramen on radiographs. In Saghiri et al.'s research, endodontic files were used to determine the length of the canals on the radiology images with the use of artificial neural networks and without. The measurements were taken before the extraction of the teeth and after the extraction with the use of stereomicroscopy. The correct assessment made by the endodontics was strict in 76% and by the artificial neural network in 96% (Table 2). This shows that artificial neural networks may be used to assess the localization of apical foramen more precisely than humans [25]. Apical periodontitis is an inflammatory process mainly caused by the bacterial infection of the root canal system. It may be detected through radiographic diagnostics and manifest as periapical translucencies that are also named periapical lesions. To reveal periapical translucencies, most are taken as periapical or panoramic radiographs and cone-beam computed tomographic images [26,27]. Setzer et al. in their research used deep learning to detect periapical lesions on cone-beam computed tomographic (CBCT) images. The accuracy of finding the lesions was 93% [25,27]. CNN was also used in Orhan et al.'s work to detect periapical lesions on CBCT images. The convolutional neural network detected 142 of 153 periapical lesions (92.8% accuracy). The results obtained by CNN were similar to those obtained by an experienced dental practitioner [28]. Convolutional neural network (CNN) is a specialized kind of artificial neural network that is very useful when extracting features from the image by engaging convolutional operations. These convolutional neural networks were used in Pauwels et al.'s work. The periapical radiographs were evaluated to find periapical lesions made in bovine ribs. The results were compared with three oral radiologists and the CNN showed a perfect accuracy of 87% [26,29]. Ekert et al. assessed panoramic images for the presence of periapical lesions with the help of CNN. They concluded that different tooth types are difficult to assess on panoramic image in different ways because of the radiographic image generation process. This is why the diagnostic may be uncertain and the sensitivity needs to be improved, although the results of periapical lesion detection by neural network have been satisfactory. In molars, the CNN's sensitivity was higher (87%) than on other teeth, whereas the specificity was lower [26]. Artificial neural networks may not only be used in dental radiology, but also in genetics as it comes to endodontics [30]. In the study of Poswar et al., artificial intelligence was used to analyze the gene expression for radicular cysts (RCs) and periapical granulomas (PGs). The results showed that not only the inflammation, but also other biological processes may individuate the RCs and PGs because of their different gene expression [31].

Table 2. Baseline characteristics of the studies included in the review by studying neural networks in endodontics.

Study [Ref.]	Year of Publication	Type of Data	Type of Neural Network	Number of Database	Accuracy of Neural Network
Saghiri [25]	2012	Teeth	ANN	50 teeth	96%
Ekhert [26]	2019	Panoramic radiographs	CNN	-	87% (molars)
Setzer [27]	2020	CBCT images	Deep Learning	20 images	93%
Orhan [28]	2020	CBCT images	CNN	153 images	92.8%
Pauwels [29]	2021	Periapical radiographs	CNN	-	87%

Neural networks in endodontics may be useful in X-ray analysis and mostly in the detection of periapical lesions. This detection process can still be improved to obtain good accuracy for all teeth. Artificial intelligence might also be used in non-radiological areas such as genetics or others to ease the diagnosis.

4. Neural Networks in Orthodontics

Artificial intelligence is spreading widely in the field of orthodontics. The most often used types of algorithms in orthodontics are artificial neural networks (ANN), convolutional neural networks (CNN), support vector machine, and regression algorithms [32]. Peilini et al. used an ANN in their study to predict whether patients need extractions or not in their treatment plan. Moreover, they took the anchorage patterns into consideration. The accuracy of the artificial neural network in the success of the treatment plan was 94.0% for extractions and 92.8% in the prediction of the use of maximum anchorage. These results indicate that ANN can be used by orthodontists to make more precise treatment plans [33]. Auconi et al. developed a system based on artificial neural networks with the purpose to predict the treatment outcomes in class II and III patients. The analysis could anticipate the co-occurrence of auxological anomalies during individual craniofacial growth and possibly localize reactive sites for a therapeutic approach to malocclusion [34,35]. The research indicates that the deep learning neural networks might be the best for TMJ osteoarthritis detection. Temporomandibular joint (TMJ) disorders are the second most common musculoskeletal condition affecting 5 to 12% of the population, and chronic disability in TMJ osteoarthritis (OA) increases with age. The main goal is to diagnose the impairment of the TMJ before morphological degeneration occurs. To achieve this goal in Bianchi et al.'s research, TMJ CBCT scans, serum, and saliva tests were taken [36–38]. In the study by Muraev et al., ANN was used to place the cephalometric points on cephalometric radiography. The accuracy of CP placement was compared between the ANN and three groups of doctors: expert, regular, and inexperienced. The results showed that ANN had a similar accuracy in planning cephalometric points as an experienced dentist and in some cases, they can be even more precise than new doctors [39]. In addition, ANN may help in the determination of the growth and development periods. In the research by Kök et al., the cephalometric and hand-wrist radiographs were obtained from patients aged between eight and 17 years. The growth-development periods and gender were determined from the cervical vertebrae by using ANN and the accuracy value of the results was found to be 94.27% [40].

To resume, the most common fields of orthodontics where neural networks may be used are in diagnosis and treatment planning, automated anatomic analyses, assessment of growth and development, and the evaluation of treatment outcomes (Table 3) [32]. It seems that artificial intelligence in orthodontics may be widely used and its use for sure can be extended even further.

Table 3. Baseline characteristics of the studies included in the review by studying neural networks in orthodontics.

Study [Ref.]	Year of Publication	Type of Data	Type of Neural Network	Number of Database	Accuracy of Neural Network
Auconi [33]	2015	Cephalometric records	Fuzzy clustering repartition	54 cephalograms	83.3%
Peilini [34]	2019	Medical records	ANN	302 patients	94.0% (extraction pattens); 92.8 % (anchorage patterns)
Bianchi [36]	2020	CBCT blood serum saliva clinical investigation	Logistic Regression, Random Forest, LightGBM, XGBoost	52 patients	82.3%
Muraev [39]	2020	Cephalometric records	ANN	330 cephalograms	99.9%
Kök [40]	2021	Cephalometric and hand-wrist radiographs	ANN	419 patients	94.27%

5. Neural Networks in Dental Surgery

According to the found literature, neural networks may be widely used in dental surgery. The purpose of Chien-Hsun Lu et al.'s study was to evaluate and improve post-orthognathic surgery image predictions for the individual patient. Simulations made by neural networks may be helpful for surgeons, orthodontists, and for the patients to improve the treatment plans [41]. The research of Patcas et al. indicated that artificial intelligence may characterize the impact of orthognathic surgery on facial attractiveness and age appearance. Pre- and post-treatment photographs of orthognathic patients were collected and convolutional neural networks were trained on >0.5 million images for age estimation and with >17 million ratings for attractiveness. According to the algorithms, most patients' appearance improved with treatment (66.4%), resulting in a younger appearance of nearly one year. The same author used convolutional neural network to assess the attractiveness of patients who had undergone cleft surgeries [42,43]. In Byung Su Kim et al.'s work, convolutional neural networks were used to predict whether third molar extraction may lead to paresthesia of the inferior alveolar nerve. Extraction of the lower third molar is one of the most popular dental surgery procedure. The paresthesia of the nerve after mandible wisdom tooth extraction is quite a common complication. The panoramic images were used before the extraction and the anatomical relationship between the nerve canal and dental roots was used by the CNN to predict the occurrence of nerve paresthesia. However, the authors concluded that two dimensioned images as panoramic radiographs may lead to more false positive and false negative results, therefore, future research is needed [44]. Deep learning can be beneficial in odontogenic lesion detection. Two common diseases that might occur in jaws, and especially in the posterior ramus and body of the mandible, are ameloblastoma (AB) and odontogenic keratocyst (OK). In Liu et al.'s research, panoramic radiographs were used to detect these two tumors due to the lower cost and better accessibility than CT or MR images. Since it is difficult for human eyes to identify AB and OK in panoramic radiographs, a convolutional neuron network based on the transfer learning algorithm was used. The radiographs were especially prepared to obtain better contrast in the region of interest. All of the lesions were confirmed by the histopathological examination. The accuracy of the convolutional neural network was 90.36%, which was a better result than the accuracy of three other neural networks used in the same research. The above study indicates that neural networks may be useful to oral maxillofacial specialists before surgery [45].

According to previous studies, neural networks may be used in implantology. Dental implant treatment planning with the usage of three-dimensional cone-beam computed tomography (CBCT) images can be facilitate by AI systems [46]. Moreover, convolutional neural networks can be used to identify dental implant brands on panoramic radiographs and to identify the stage of treatment [47]. The quality of the osteointegration can be assessed by using convolutional neural networks (Table 4). The difficulties in osteointegration might occur due to the presence of a soft tissue layer (non-mineralized bone tissue) around the bone–implant interface, which can be exposed upon ultrasound examination [48]. Finally, artificial intelligence has been used in studies to measure the peri-implant bone loss [49].

Table 4. Baseline characteristics of the studies included in review by studying neural networks in dental surgery.

Study [Ref.]	Year of Publication	Type of Data	Type of Neural Network	Number of Database	Accuracy of Neural Network
Chien-Hsun Lu [41]	2009	Profile photographs	ANN	30 patients	84.5%
Patcas [42]	2018	Photographs	CNN	146 patients	-
Patcas [43]	2019	Frontal and profile images	CNN	20 patients	-
Byung Su [44]	2021	Panoramic radiographs	CNN	300 images	82.7%
Liu [45]	2021	Panoramic radiographs	CNN	420 images	90.36%
Bayrakdar [46]	2021	CBCT	CNN (Diagnocat)	75 images	72.2% for canals detection; 66.4% for sinuses/fossae and 95.3% for missing tooth regions
Sukegawa [47]	2021	Panoramic radiographs	CNN	9767 images	81.83%

Neural networks in dental surgery might be widely used in many areas starting with the orthognathic surgeries, changes in the bones or post extraction complications, and ending with implantology treatment. In particular, implantology is an area that is developing very rapidly and the use of neural networks might be very helpful in daily practice because of the need for high precision and meticulous planning. Neural networks may also help to predict some complications that may occur during surgical treatment and therefore avoid some of them.

6. Neural Networks in Periodontology

Periodontitis is a wide spread disease that concerns billions of people worldwide and if untreated, leads to tooth mobility and in severe cases, to tooth loss. To prevent this from happening, early disease detection and effective therapy needs to be carried out. To obtain reliable diagnosis, a meticulous physical examination needs to be performed. For this reason, dental probing to measure pocket depth and clinical attachment loss is performed. Periodontal probing has limited accuracy because of the individual examiner's assessment. Commonly used additional examinations are dental radiographs, whose evaluation also depends on the examiner's experience. To minimize errors in diagnosis, some authors have used neural networks. Krois et al. evaluated panoramic radiographs with the help of convolutional neural networks to detect periodontal bone loss in percentage of the tooth root length. The results were compared with the measures made by six experienced dentists. The CNN had higher accuracy (83%) and reliability than the dentists (80%) in detecting periodontal bone loss [50]. Peri-implant bone loss can be detected on dental periapical radiographs, but the difficulty is that the margins of bone around the implants are usually unclear or the margins can overlap. For this reason, convolutional neural networks can assess the marginal bone level, top, and apex of implants on dental periapical radiographs. In the study by Jun-Young Cha et al., the bone loss percentage was calculated and classified by the automated system. This method can be used to assess the severity of peri-implantitis [51]. In the research of Lee et al., a deep convolutional neural network was used to analyze the radiographs and measure the radiographic bone loss (RBL) for each tooth. RBL percentage, staging, and presumptive diagnosis according to the new periodontitis classification made by CNN were compared with the measurements made by independent examiners. The accuracy for the neural network was 85%. Thus, neural networks may be useful tools to assess radiographic bone loss and to obtain image-based periodontal diagnosis [49]. Other authors have also used neural networks to evaluate radiographic bone loss, and in this way, developed an automatic method for staging periodontitis according to the new criteria proposed at the 2017 World Workshop on the Classification of Periodontal and Peri-implant Diseases and Conditions. Chang et al.

used panoramic images and convolutional neural networks to detect the periodontal bone level (PBL), the cementoenamel junction level (CEJL), and the teeth, and in this way, made a diagnosis of periodontitis stage [52]. Vadzyuk et al. took into consideration the psychological features to predict the development of periodontal disease. They concluded that patients' level of anxiety and stress hormone levels had an impact on periodontitis (Table 5). Assessment of the condition of teeth hard tissues, the level of oral hygiene, and the evaluation of psychophysiological features with the use of neural networks can effectively predict the risk of periodontal disease development in young people [53].

Table 5. Baseline characteristics of the studies included in review by studying neural networks in periodontology.

Study [Ref.]	Year of Publication	Type of Data	Type of Neural Network	Number of Database	Accuracy of Neural Network
Lee [49]	2018	Periapical radiographs	CNN	1044 images	81.0% for premolars 76.7% for molars
Krois [50]	2019	Panoramic radiographs	CNN	353 images	81%
Chang [52]	2020	Panoramic radiographs	CNN	340 images	93%
Vadzyuk [53]	2021	Survey (oral hygiene and nutrition) dental examination, psychological testing	ANN	156 students	-
Jun-Young Cha [51]	2021	Periapical radiographs	CNN	708 images	88.89%

The use of neural networks in periodontology can be a helpful tool for clinicians in daily practice as well as for scientists. The precise assessment of bone loss can be crucial in making periodontal diagnosis and treatment planning. More research and improvements are needed to introduce this tool into everyday periodontal use.

7. Conclusions

Dentistry is a field of medicine where new technologies are developing very quickly. Nowadays, artificial intelligence and neural networks are mostly used in dental radiology to facilitate diagnosis, treatment planning, and prediction of the treatment results. Other areas of dentistry where neural networks are used are genetics, psychology, microbiology, and many others. The most frequently used types of neural networks are artificial neural networks and convolutional neural networks. In restorative dentistry, neural networks can detect tooth decay or restorations, moreover, they can facilitate the choice of caries excavation method [3,22,23]. In endodontics, neural networks can be useful in detecting periapical lesions and root fractures, root canal system anatomy evaluation, predicting the viability of dental pulp stem cells, determining working length measurements, and predicting the success of retreatment procedures [25–29]. In orthodontics, they can facilitate the diagnosis and treatment planning, cephalometric points marking, anatomic analyses, assessment of growth and development, and the evaluation of treatment outcomes [33,34,36,39,40]. In dental surgery, neural networks may be helpful in orthognathic surgery planning, prediction of post-extraction complications, bone lesion detection, and differentiation and implantological treatment planning [41–47]. Furthermore, artificial intelligence is spreading into periodontology and in the above-mentioned studies, it was used to evaluate the periodontal bone loss, peri-implant bone loss, and to predict the development of periodontitis due to the psychological features [49–54]. This review shows that artificial intelligence has developed very fast in recent years and it may become an ordinary tool in modern dentistry in the near future. The advantages of this process are better efficiency, accuracy and precision, better monitoring, and time saving [55]. More research is needed with the use of neural networks in dentistry to put them into daily practice and to facilitate the work of dentist.

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Evaluation of the Progression of Periodontitis with the Use of Neural Networks

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Abstract: Periodontitis is an inflammatory disease of the tissues surrounding the tooth that results in loss of periodontal attachment detected as clinical attachment loss (CAL). The mildest form of periodontal disease is gingivitis, which is a necessary condition for periodontitis development. We can distinguish also some modifying factors which have an influence on the rate of development of periodontitis from which the most important are smoking and poorly controlled diabetes. According to the new classification from 2017, we can identify four stages of periodontitis and three grades of periodontitis. Grades tell us about the periodontitis progression risk and may be helpful in treatment planning and motivating the patients. Artificial neural networks (ANN) are widely used in medicine and in dentistry as an additional tool to support clinicians in their work. In this paper, ANN was used to assess grades of periodontitis in the group of patients. Gender, age, nicotinism approximal plaque index (API), bleeding on probing (BoP), clinical attachment loss (CAL), and pocket depth (PD) were taken into consideration. There were no statistically significant differences in the clinical periodontal assessment in relation to the neural network assessment. Based on the definition of the sensitivity and specificity in medicine we obtained 85.7% and 80.0% as a correctly diagnosed and excluded disease, respectively. The quality of the neural network, defined as the percentage of correctly classified patients according to the grade of periodontitis was 84.2% for the training set. The percentage of incorrectly classified patients according to the grade of periodontitis was 15.8%. Artificial neural networks may be useful tool in everyday dental practice to assess the risk of periodontitis development however more studies are needed.

Keywords: periodontist; periodontal diseases; diagnosis; computer simulation; artificial neural networks

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1. Introduction

Periodontitis is an inflammatory disease of the tissues surrounding the tooth that results in loss of periodontal attachment detected as clinical attachment loss (CAL). The supportive apparatus of the tooth (periodontium) consists of gingival tissue, alveolar bone, cementum, and periodontal ligaments. The mildest and most common form of periodontal disease is gingivitis which is the inflammation of the gingiva mostly caused by dental plaque. If the microbial biofilm is not removed properly within days or weeks, the changes in the gingiva start. The patient usually may notice bleeding, swelling, redness of the gingiva, and furthermore halitosis [1–4]. The common clinical signs of plaque-induced gingivitis include erythema, edema, bleeding, tenderness, and enlargement [5]. Potential modifying factors of plaque-induced gingivitis are hormonal changes, hyperglycemia, leukemia, smoking, malnutrition, prominent subgingival restorations margins, and hyposalivation [6–8]. Gingivitis is regarded as a necessary condition for subsequent periodontitis and progressive attachment loss. This process is highly connected with patient's immune-inflammatory response which is why not all people with gingivitis will develop periodontitis [9,10].

The progression of periodontal disease depends on many factors and some patients will develop severe periodontitis in a short time whereas others can have a mild stadium for a whole life. Moreover, in some patients, periodontitis progression is less predictable than in others and involves different treatment plans. Well-known risk factors accelerating bone loss are nicotinism and poorly controlled diabetes, in addition to obesity, genetics physical activity, or nutrition. The clinician assesses the stadium of periodontitis taking into account the age of the patient which is an indirect way to evaluate the individual susceptibility to periodontitis. A common tool in assessing bone loss in daily practice is the measurement of the bone loss on radiograms expressed as a percentage of tooth length and divided by the age of the patient. In recent years, dentists compared clinical attachment loss (CAL) with the age of the patient to assess the standard clinical attachment loss for the age. This measurement can be completed by using the standardized probe UNC 15 [11,12].

Nowadays, artificial intelligence (AI) is becoming more important in medicine and in dentistry. It can be helpful in many fields where the human may be assisted and helped by new technologies. Machines are able to create algorithms through data learning, which allows them to handle prediction issues without human assistance. In a mathematical nonlinear model, neural networks (NNs) imitate the human brain by using artificial neurons that are similar to human neural networks. NNs can mimic human cognitive abilities including problem-solving and human thinking, which involves learning and making decisions. Simple neural networks contain three layers: input, hidden, and output. The input layer is where information enters the system, and the hidden layer is where the data are processed (where the system decides what to do). NNs may outline any input to output given a set of mathematical models if there is enough data, a lot of data [13].

2. Materials and Methods

2.1. Patients' Population

This was a retrospective study, and the database consists of 110 patients, both genders aged 30 to 60 were included. The selection of the patients was performed in 2022 in the Department of Periodontology and Oral Mucosa Diseases, Medical University of Gdańsk. Only the patients with all necessary measurements were included into the study. There were 12 patients with stadium I periodontitis, 19 patients with stadium II periodontitis, 42 patients with stadium III periodontitis, 27 patients with stadium IV periodontitis and 10 patients with gingivitis. All groups included patients generally healthy or with diabetes or/and smokers. Patients with other systemic diseases and patients with dental implants were excluded. Dental assessment of the patients was performed, and the following indicators were included: gender, age, active nicotinism, the number of preserved teeth, approximal plaque index (API), bleeding on probing (BoP), pocket depth (PD), and clinical attachment loss (CAL). Patients were divided into 2 groups, the training group (90 persons) and test group (20 persons). Training group was the group in which neural networks learned how to classify patients and test group was a group in which the quality of neural networks was checked.

2.2. Clinical Periodontal Measurements

Dental assessment of the patients was performed, and the following indicators were included: the number of teeth preserved, approximal plaque index (API), bleeding on probing (BoP), pocket depth (PD), and clinical attachment loss (CAL). The measurements were performed with the use of periodontal probe UNC 15 with a cylindrical shape, 15 mm scale, 1.75° cone taper, and 0.5 mm probe tip diameter [12].

According to the new classification in the context of the 2017 World Workshop on the Classification of Periodontal and Peri-Implant Diseases and Conditions, a patient with periodontitis has more than 2 interdental CAL in non-adjacent teeth or more than 2 teeth with buccal/oral CAL $\geq$ 3 mm and pocketing > 3 mm. From above criteria should be excluded:

- Teeth with gingival recession of traumatic origin;
- Dental caries near cervical area of the tooth;
- The presence of CAL at the distal surface of second molar due to the malposition
- Extraction of third molar;
- An endodontic lesion in the marginal periodontium;
- Vertical root fracture [11].

We can qualify patients with periodontitis into four stages to classify the severity and extent of the disease and to assess its complexity. Moreover, we can distinguish three grades to assess risk of progression and potential risk of systemic impact of the patient's periodontitis [11].

Stage I periodontitis is the mildest form of periodontitis which develop just after the gingivitis. It is crucial to capture this stadium and implement the correct intervention and monitoring. Stage II periodontitis is moderate periodontitis with characteristic lesions in the periodontium. Professional management can arrest the disease's progression. Stage III periodontitis is when the clinical attachment loss is more advanced and there is a risk for additional tooth loss. Stage IV periodontitis is a stage similar to stage III but also there is a need to complex dental rehabilitation due to the teeth loss, disabled masticatory function, and risk of loss the dentition Table 1.

Table 1. Periodontitis stage.

Periodontitis Stage		Stage I	Stage II	Stage III	Stage IV
Severity	Interdental CAL [1] at site of greatest loss	1–2 mm	3–4 mm	$\geq$5 mm	$\geq$5 mm
	Radiographic bone loss	<15%	15–33%	Extending to mid-third of the root or beyond	Extending to mid-third of the root or beyond
	Tooth loss	No tooths loss due to the periodontitis	No tooths loss due to the periodontitis	Tooth loss due to the periodontitis $\leq$ 4	Tooth loss due to the periodontitis $\geq$ 5
Complexity	Local	Probing depth $\leq$ 4 mm	Probing depth $\leq$ 5 mm	Probing depth $\geq$ 6 mm	Criteria as in III stage plus:
		Horizontal bone loss	Horizontal bone loss	Vertical bone loss $\geq$ 3 mm	Need for complex rehabilitation due to:
				Furcation II or III class	-masticatory dysfunction -secondary occlusal trauma
				Moderate ridge defect	-severe occlusal defect -less than 10 opposing pairs of teeth
Extent and distribution	Localized (<30% teeth involved), generalized, molar/incisor pattern				

[1] clinical attachment loss.

The classification to the stage is mostly carried out on the basis of CAL and radiographic bone loss (RBL). If a stage shifting complexity factor(s) were eliminated by treatment, the stage should not be changed to a lower since the original stage complexity factor should always be taken into consideration [11].

Grading allows us to assess the progression of periodontitis and it is not dependent on staging. Each patient can have a different rate of progression of periodontitis. Due to the new classification, there is direct and indirect evidence of periodontitis progression Table 2. Direct evidence requires diagnostic radiographs from the past, and indirect evidence requires the assessment of the bone loss and taking into account the age of patient [14–16]. The new classification distinguishes 3 periodontitis grades A, B, and C. They can be modified by some risk factors such as smoking or the presence of poorly controlled diabetes. There is also a group of patients who is less responsive to the standard periodontal treatment due to some other risk factors for example genetics [17]. The aim of the grading assessment is to find the best treatment for periodontitis by taking into consideration the rate of progression. Bone loss in percentage divided by the age of the patient was used in the periodontal risk assessment (PRA) system [18].

Table 2. Periodontitis grade.

Periodontitis Grade			Grade A: Slow Progression	Grade B: Moderate Progression	Grade C: Rapid Progression
Primary criteria	Direct evidence of progression	Longitudinal data	Evidence of no loss over 5 years	<2 mm over 5 years	≥2 mm over 5 years
	Indirect evidence of progression	% Bone loss/age	<0.25	0.25 to 1.0	>1.0
		Phenotype	Heavy biofilm deposits and slow progression	Progression corresponding with biofilm deposits	Rapid progression which exceeds amount of biofilm, early onset of disease
Grade modifiers	Risk factors	Smoking	Non-smoker	<10 cigarettes/day	≥10 cigarettes/day
		Diabetes	Normoglycemic	Diabetes HbA1c < 7.0%	Diabetes HbA1c ≥ 7.0%

Artificial intelligence (AI) is gaining importance in the fields of medicine and dentistry nowadays [13]. It can be useful in a variety of situations where new technologies might benefit and help people. AI can help us in the medical profession, particularly in areas such as radiology, pathomorphology, oncology, cardiology, psychiatry, nuclear medicine, and many more [19–23]. One way to comprehend the working of the nervous system, which we are unable to examine under natural conditions due to the limits of contemporary research techniques, is through the use of computer models of neural networks [24–28]. In silico methods have been widely used recently in a variety of contexts, including cancer, autoimmune, and neurodegeneration, to identify potential innovative pharmaceutical treatments [29–31].

2.3. *Artificial Neural Network*

The mathematical models that simulate how the brain works are called neural networks. It is a computing system made up of numerous processing components that are intricately integrated. It analyzes the data from outside sources and produces dynamic state responses. The ANN was created using a software network simulation program (Statistica Automated Neural Networks, TIBCO Software Inc. (Palo Alto, CA, USA, 2017). Statistica (data analysis software system), version 13. http://statistica.io, accessed on 1 September 2021). In order to obtain the best efficiency, one hundred multi-layer perception neural network models (MPL) were built. Neural network models were classified as classification networks, their task was to assign patients to one of the three classes related to the grading of periodontitis or to assess patients as healthy. In created models, the methods of "teacher projects" were used. The number of hidden neurons, the error function as a sum of squares or mutual entropy, and activation functions of hidden and output neurons from the available: linear, logistic, hyperbolic tangent, exponential, or sine were selected automatically.

2.3.1. ANN Construction

Finally, the model of neural networks which was characterized by the lowest error and the highest quality of testing was selected. The neural network consisted of three layers: input, hidden, and output. The corresponding numbers of neurons in the individual layers were 543, 19, and 4 Figure 1. The activation and rejection levels for the neuron outputs were selected automatically by an artificial neural network simulator in order to minimize losses. During the learning process with the teacher, the weight connections between the neurons were modified by the BFGS algorithm [32]. The logistic activation function and Softmax were used for the neurons in the hidden layer and the output layer, respectively.

The learning coefficient was 0.01 and the number of epochs was set to 1000, where the order of the presented cases for the neural network was different in each epoch. The initialization of weights for the neural network was performed randomly using Gaussian method. To calculate the classification quality of the artificial neural network, all patients were randomly divided into two groups: teaching and testing. The training group consisted of 90 patients and the testing group of 20 patients.

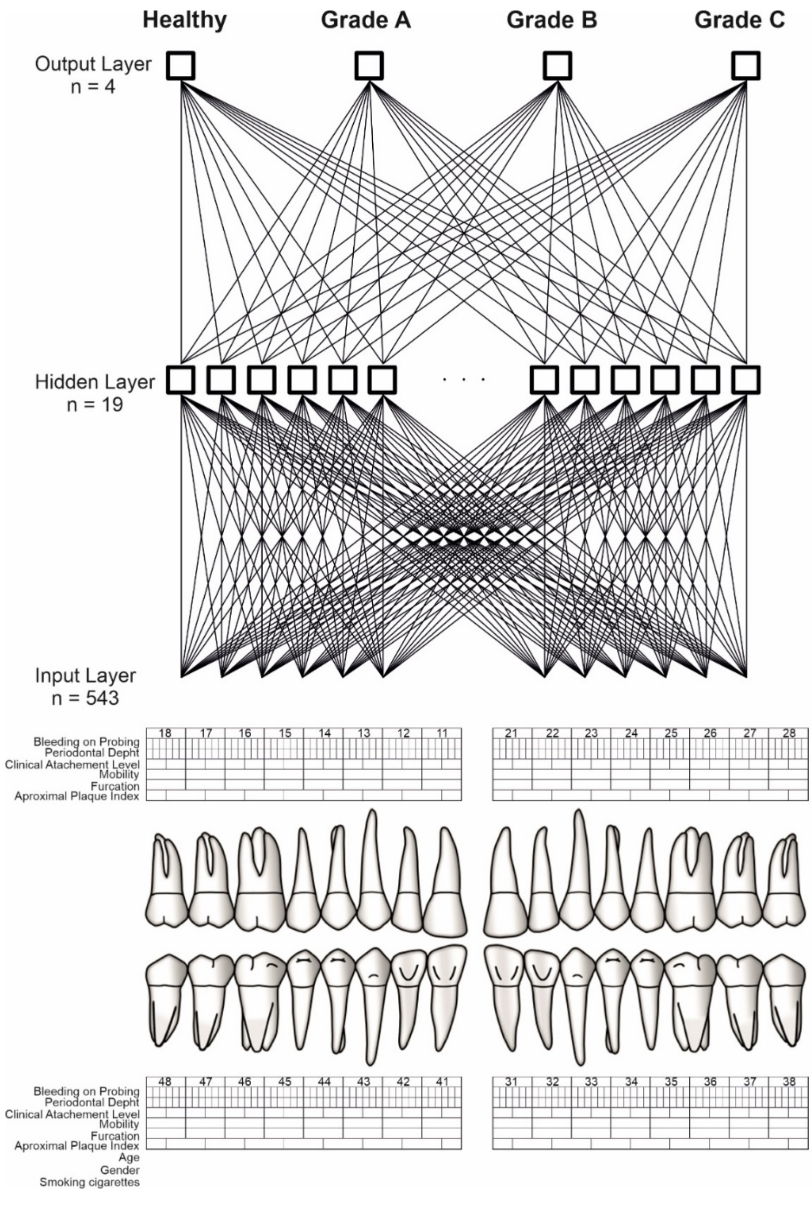

Figure 1. ANN construction. Source: https://www.periodontalchart-online.com/uk/ (accessed on 1 May 2020). Periodontal chart with input layer (n = 543), hidden layer (n = 19) and output layer (n = 4) which refers to periodontitis grading. Sex, age, smoking, approximal plaque index, bleeding on probing, periodontal pocket depth, and maximal interproximal loss of connective tissue attachment were all taken into account by the artificial neural network. For each patient, a set of 543 inputs was produced. By the use of the Statistica Automated Neural Networks, TIBCO Software Inc. (2017). Statistica (data analysis software system), version 13. http://statistica.io (accessed on 1 September 2021) the output layer has been received. The output layer consists of three grades (A,B,C) and a group of healthy patients.

2.3.2. Input Signals for Artificial Neural Network

The artificial neural network used information from patients' records regarding sex, age, smoking, oral hygiene, periodontal pocket depth, and maximum interproximal loss of connective tissue attachment. A set of 543 inputs was prepared for each patient.

2.4. Software Simulation of ANN and the Statistical Analysis

All calculations were performed in the Statistica Automated Neural Networks, TIBCO Software Inc. (Palo Alto, CA, USA, 2017). Statistica (data analysis software system), version 13. http://statistica.io (accessed on 1 September 2021).

3. Results

3.1. Basic Characteristics

The study group of 110 patients included 9.1% of healthy subjects without periodontitis, 13.6% of patients with grade A, 39.1% with grade B, and 38.2% with grade C. Regarding the stages of periodontitis, in the study group 10.9% were patients with stage I, 17.3% with stage II, 38.2% with stage III and 24.5% with stage IV. The highest percentage of cigarette smokers was in the group of patients with stage C periodontitis at 50.0%. In the remaining groups, the percentage of smokers does not exceed 10% (Table 3). The average age of healthy volunteers was 33.1 (95% CI: 29.8–36.4), patients with grade A was 43.1 years (95% CI: 40.1–46.0), with grade B 48.1 years old (95% CI: 46.0–50.2) and with grade C 45.8 years (95% CI: 43.8–47.9). There were statistically significant age differences in relation to the grading of periodontitis ($p < 0.0001$). Healthy volunteers were significantly younger than patients with periodontitis ($p < 0.05$). The mean approximal plaque index (API) in the control group was 55.1% (95% CI: 35.8–74.5), in patients with grade A it was 64.7% (95% CI: 49.7–79.8), with grade B it was 78.5% (95% CI: 72.0–85.1) and with grade C it was 87.3% (95% CI: 81.6–93.0). There were statistically significant differences in the API oral hygiene status in relation to the groups ($p = 0.0004$). Patients with grade C had a significantly higher API index compared to healthy subjects ($p = 0.0043$) and patients with grade A ($p = 0.0200$). Average bleeding on probing index (BOP) in the control group was 40.3% (95% CI: 15.4–65.3), in patients with grade A it was 47.2% (95% CI: 33.2–61.1), with grade B it was 62.5 % (95% CI: 52.4–72.7) and with grade C it was 66.7 % (95% CI: 55.4–78.0). There were no significant statistical differences between groups ($p = 0.0511$). Average interproximal clinical attachment loss (CAL) in patients with grade A was 1.7 mm (95% CI: 1.0–2.4), with grade B 3.4 mm (95% CI: 2.8–3.9) and with grade C 4.6 mm (95% CI: 3.8–5.3). There were statistically significant differences in maximum CAL between groups ($p = 0.0001$). Patients with grade A had significantly lower scores than patients with grade B ($p = 0.0143$) and grade C ($p < 0.0001$).

The comparison of the demographic data of the training and test sets of the neural network is presented in Table 4. There were no statistically significant differences between the demographic factors in relation to the two sets of neural networks ($p > 0.05$).

On the other hand, the comparison of the periodontal assessment in the groups of the training and test sets of the neural network is shown in Table 5. There were no statistically significant differences in the periodontal assessment in relation to the two sets of the neural network ($p > 0.05$).

Table 3. Demographic characteristics.

	Healthy (n = 10)	A (n = 15)	B (n = 43)	C (n = 42)
Gender				
Female	6 (60.0%)	12 (80.0%)	30 (69.8%)	24 (57.1%)
Male	4 (40.0%)	3 (20.0%)	13 (30.2%)	18 (42.9%)
Grade				
gingivitis	10 (100.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)
1	0 (0.0%)	12 (80.0%)	0 (0.0%)	0 (0.0%)
2	0 (0.0%)	3 (20.0%)	12 (27.9%)	4 (9.5%)
3	0 (0.0%)	0 (0.0%)	28 (65.1%)	14 (33.3%)
Nicotinism	1 (10.0%)	1 (6.7%)	2 (4.7%)	21 (50.0%)
Age	33.1 (4.7)	43.1 (5.4)	48.1 (6.8)	45.8 (6.5)
API [1] (%)	55.1 (27.1)	64.7 (27.1)	78.5 (21.3)	87.3 (18.4)
BoP [2] (%)	40.3 (34.9)	47.2 (25.2)	62.5 (33.1)	66.7 (36.2)
PPD [3] (mm)	2.1 (0.1)	2.3 (0.1)	2.8 (0.5)	3.4 (0.9)
CAL [4] (mm)	-	1.7 (1.3)	3.4 (1.8)	4.6 (2.4)

[1] approximal plaque index, [2] bleed-ing on probing, [3] pocket depth, [4] clinical attachment loss.

Table 4. Demographic factors for the training and the test groups.

	Training Group (n = 90)	Test Group (n = 20)	*p*-Value
Gender			0.5706
Female	60 (66.7%)	12 (60.0%)	
Male	30 (33.3%)	8 (40.0%)	
Age mean (SD)	45.5 (7.2)	43.9 (8.9)	0.3849

Table 5. Periodontal assessments for the training and the test groups.

	Training Group (n = 90)	Test Group (n = 20)	*p*-Value
API [1]	79.8 (23.0)	69.2 (25.7)	0.0713
BoP [2]	60.2 (35.0)	59.2 (31.6)	0.9051
PPD [3]	2.9 (0.8)	2.7 (0.7)	0.1313
CAL [4]	3.6 (2.2)	4.1 (2.2)	0.3952

[1] approximal plaque index, [2] bleed-ing on probing, [3] pocket depth, [4] clinical attachment loss.

3.2. Classification Assessment of the ANN

The quality of the neural network, defined as the percentage of correctly classified patients according to the grade of periodontitis was 84.2% for the training set. The percentage of incorrectly classified patients according to the grade of periodontitis was 15.8%. Detailed classification results of the neural network in the healthy group and in the groups of patients according to the grade of periodontitis from A to C are, respectively: 80.0%, 100.0%, 80.0%, and 80.0%. The corresponding percentages of incorrect classifications were, respectively: 20.0%, 0.0%, 20.0%, and 20.0%. The quality of the neural network for the women was: 90.9% and for the men 75.0%. On the other hand, the quality of the neural networks according to the grading and smoking was from 83.3% up to 100.0% (Table 6). Based on the definition of sensitivity and specificity in medicine we obtained 85.7% and 80.0% as correctly diagnosed and excluded diseases, respectively.

Table 6. The quality of the neural network according to the grades.

		Correctly%
All		84.2%
	healthy	80.0%
	A	100.0%
	B	80.0%
	C	80.0%
Gender		
	Female	90.9%
	Male	75.0%
Age (years)		
	20–30	100.0%
	30–40	80.0%
	40–50	83.3%
	50–60	85.7%
Cigarettes		
	smoking	100.0%
	no smoking	83.3%

3.3. Sensitivity Analysis

Global sensitivity analysis gives us an idea of how important each network input field is. The values of the quotients for individual parameters range from 0.990 to 1.417 (Table 7).

Table 7. Global sensitivity analysis.

Parameter	Correctly%
Cigarettes	1.417
API [1]	1.052
PPD [2]	1.048
Age	1.038
CAL [3]	1.015
Gender	1.0
BoP [4]	0.994

[1] approximal plaque index, [2] pocket depth, [3] clinical attachment loss, [4] bleed-ing on probing.

3.4. Implementation of the Model into Clinical Practice

To use a previously saved neural network for new data, you need to open database. The active data file must contain the same fields as the input fields used to build the ANN model. During implementation, we are dealing with the new data, not those that were used to teach the ANN.

4. Discussion

Evaluation of the progression of periodontitis is an important step for a dentist while preparing a treatment plan, but also it might be helpful in motivating patients to participate actively in treatment. The above study takes also into consideration grades of periodontitis of the new classification of periodontitis from 2017. The parameters which were taken into consideration in the above study were age, gender, API, BoP, PPD, CAL, and smoking. The link between plaque (API) and periodontitis development is well known and the first works which take into consideration dental plaque as a causative factor of gingivitis and periodontitis are dated 1965. Due to not brushing, gingivitis will develop in all patients but periodontitis development is more complex, more diverse, and dependent on many factors [33–35]. According to Kornman et al. and Page et al. there has to be an interaction between the immune-inflammatory response of the host which depends on genetic polymorphism [36,37]. These polymorphisms together with environmental factors determine the development of disease [10,38–40]. The main parameter of gingivitis and periodontitis is bleeding on probing (BoP) which also differentiates both conditions into localized and generalized and tells us about the severity of inflammation. The high percentage of pockets depth of more than 6 mm also indicates higher severity [41]. Clinical attachment loss (CAL) to age ratio is the main parameter in grading and is the main indicator of the rate of progression. CAL higher than 6 mm means severe periodontitis but we should also take into consideration teeth that were already extracted and that will change our evaluation. Higher CAL at a younger age can be a predictor of fast-developing periodontitis [11]. Well-known unmodified risk factors for periodontitis are age, gender, and genetics, modified factors are bacteria, nicotinism, general diseases, malnutrition, socio-economic status, and stress [42]. Aging is a risk factor for periodontitis due to many causes from which we can highlight immunoaging which leads to increased susceptibility to infections because of the lower reactivity of lymphocytes. What is more, with the age the number of systemic diseases increases which may be an additional risk factor [41]. When it comes to gender men are at a greater risk for developing destructive periodontal disease than women because of sex-specific differences in immune function. Sex steroids, innate and acquired immunity, and higher levels of inflammatory cytokines, including interleukin-1β and tumor necrosis factor-α in men, makes them more susceptible to destructive periodontal disease [43]. The most important bacteria in periodontitis in dental plaque are Porphyromonas gingivalis, Tannerella forsythia, Treponema denticola, Aggregatibacter actinomycetemcomitans, and F. nucleatum [35–37]. One of the most important modified factors is nicotinism which increases the risk of periodontitis from 85% to 282%. According to the work by Dietrich et al., cigarette smoking is associated with a higher risk of tooth loss. The association between smoking and the incidence of tooth loss is stronger in men than women and stronger in younger than older individuals. Heavy smoking ($\geq$15 cigarettes/d) was associated with >3 times higher risk of tooth loss in men [40,43,44]. The third major risk factor in periodontitis is poorly controlled diabetes which can increase the risk of periodontitis by 86%. Vascular changes caused by hyperglycemia are associated with the development of periodontal pathogens species. Moreover, diabetics show an exacerbated host response with hyperproduction of inflammatory mediators and polymorphonuclear dysfunction [45]. There are also some other risk factors of periodontitis that were not taken into consideration in the above. The artificial neural network may help clinicians to evaluate the risk of periodontitis development when taking into consideration modified and non-modified periodontitis risk factors. The overall accuracy of our ANN achieved 84.2% which is a similar result to other works where artificial neural networks were used. Thanathornwong et al. used a convolutional neural network (CNN) in their work to identify periodontally compromised teeth on digital panoramic radiographs. The average precision of these networks was 81% [46]. Lee et al. measured the radiographic alveolar bone level and assessed alveolar bone loss by using CNN. They made the diagnosis according to the new periodontitis classification from 2017. The accuracy of the case diagnosis was 85% [47]. Additionally, other authors used an artificial neural network to assess radiographic bone loss. Chang et al. used a deep learning hybrid method for staging periodontitis on panoramic radiographs. Deep learning was used to detect radiographic bone level or CEJ level and was used for periodontitis staging. The above method demonstrated high accuracy [48]. Krois et al. measured the percentage of periodontal bone loss using CNN. Neural networks showed at least a similar discrimination ability as dentists for assessing PBL on panoramic radiographs [49]. Özden et al. used three kinds of tools to classify periodontal disease. They used artificial neural networks, a supportive vector machine, and decision tree. The two last had better results than artificial neural networks [50]. In the study of Jun-Young Cha et al., the bone loss percentage was calculated and classified by convolutional neural networks on periapical radiographs and its accuracy was 88.89%. This method can be used to assess the severity of peri-implantitis [50–52].

In the work of Vadzyuk et al. two neural networks were designed with the dental examination, psychological testing, parameters of higher nervous activity, and heart rate variability analysis. The diagnostic sensitivity of the first prognostic model was 83.33% and the specificity was 92.31%. They concluded that assessment of the condition of teeth hard tissues, the level of oral hygiene, and the evaluation of psychophysiological features can effectively predict the risk of periodontal disease development in young people aged 18–23 [51].

According to the above study and the works of other authors, we can take into consideration artificial neural networks as a useful tool in daily practice. As it comes to periodontology ANN may be helpful in periodontitis grading assessment and periodontal treatment planning. The use of artificial neural networks may be helpful not only for periodontists but also for general dentists in evaluating the grades according to the new classification and it may facilitate communication between dentists of all specializations.

This work is limited by the relatively small number of patients. Further studies on a larger group of patients, taking into account risk factors are necessary.

5. Conclusions

Artificial neural networks may be a useful tool in everyday dental practice to assess the risk of periodontitis development. The accuracy of artificial intelligence is comparable to a dentist or even higher so it can be taken into consideration in clinical work as well as scientific work. Assessing the rate of progression of the periodontitis, especially in young people and at the initial stage of the disease might be sometimes difficult for the clinician, and additional tools such as artificial neural networks can ease the diagnosis and the treatment plan choice. Further studies are needed to improve this diagnostic method.

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Article

Progression of Selected Parameters of the Clinical Profile of Patients with Periodontitis Using Kohonen's Self-Organizing Maps

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Abstract: (1) Background: Periodontitis is an inflammatory condition that affects the tissues surrounding the tooth and causes clinical attachment loss, which is the loss of periodontal attachment (CAL). Periodontitis can advance in various ways, with some patients experiencing severe periodontitis in a short period of time while others may experience mild periodontitis for the rest of their lives. In this study, we have used an alternative methodology to conventional statistics, self-organizing maps (SOM), to group the clinical profiles of patients with periodontitis. (2) Methods: To predict the periodontitis progression and to choose the best treatment plan, we can use artificial intelligence, more precisely Kohonen's self-organizing maps (SOM). In this study, 110 patients, both genders, between the ages of 30 and 60, were included in this retrospective analysis. (3) Results: To discover the pattern of patients according to the periodontitis grade and stage, we grouped the neurons together to form three clusters: Group 1 was made up of neurons 12 and 16 that represented a percentage of slow progression of almost 75%; Group 2 was made up of neurons 3, 4, 6, 7, 11, and 14 in which the percentage of moderate progression was almost 65%; and Group 3 was made up of neurons 1, 2, 5, 8, 9, 10, 13, and 15 that represented a percentage of rapid progression of almost 60%. There were statistically significant differences in the approximate plaque index (API), and bleeding on probing (BoP) versus groups ($p < 0.0001$). The post-hoc tests showed that API, BoP, pocket depth (PD), and CAL values were significantly lower in Group 1 relative to Group 2 ($p < 0.05$) and Group 3 ($p < 0.05$). A detailed statistical analysis showed that the PD value was significantly lower in Group 1 relative to Group 2 ($p = 0.0001$). Furthermore, the PD was significantly higher in Group 3 relative to Group 2 ($p = 0.0068$). There was a statistically significant CAL difference between Group 1 relative to Group 2 ($p = 0.0370$). (4) Conclusions: Self-organizing maps, in contrast to conventional statistics, allow us to view the issue of periodontitis advancement by illuminating how the variables are organized in one or the other of the various suppositions.

Keywords: periodontitis; diagnosis; computer simulation; artificial neural networks; self-organizing maps

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1. Introduction

Periodontitis is an inflammatory condition that affects the tissues surrounding the tooth and causes clinical attachment loss, which is the loss of periodontal attachment (CAL). Gingival tissue, alveolar bone, cementum, and periodontal ligaments make up the tooth's supporting structure (periodontium). Gingivitis, an infection of the gingiva mainly carried on by tooth plaque, is the most common and mildest form of periodontitis. The gingiva alterations begin if the microbial biofilm is not properly removed within a few days or weeks. The patient frequently experiences halitosis, hemorrhage, edema, and redness of the gingiva [1–4]. Apart from bleeding, pain, and enlargement, erythema, edema, and bleeding are typical clinical symptoms of plaque-induced gingivitis [5,6]. Biological changes, diabetes, leukemia, smoking, malnutrition, and hormonal changes are all potential factors that can influence plaque-induced gingivitis. Hormonal alterations, hyperglycemia, leukemia, smoking, malnutrition, prominent subgingival restoration margins, and hyposalivation are potential modifying variables of plaque-induced gingivitis [7–9]. Periodontitis and increasing attachment loss are thought to require gingivitis as a prerequisite. Not everyone who has gingivitis will progress to periodontitis because this process is significantly correlated with the patient's immune-inflammatory response [10,11].

Periodontitis can advance in various ways, with some patients experiencing severe periodontitis in a short period of time while others may experience mild periodontitis for the rest of their lives. Additionally, the evolution of periodontitis differs depending on the patient and is less predictable in certain cases than in others. In addition to weight, genetics, physical activity, or nutrition, well-known risk factors for accelerated bone loss include nicotine dependence and poorly managed diabetes. Furthermore, nicotinism is a major risk factor for the changes in oral mucosa such as leukoplakia [12]. The age of the patient is taken into consideration when the doctor evaluates the stage of periodontitis, which is an indirect technique to measure each patient's vulnerability to periodontitis. The measurement of bone loss on radiograms expressed as a percentage of tooth length and divided by the patient's age is a popular method of assessing bone loss in daily practice. In recent years, dentists assessed the typical clinical attachment loss for the patient's age by comparing clinical attachment loss (CAL) with age. The UNC 15 standard probe can be used to make this measurement [13,14].

Artificial intelligence (AI) is gaining importance in the fields of medicine and dentistry nowadays. It can be beneficial in a variety of areas where helping humans is possible. It can be useful in many situations where new technologies might benefit and help people. In the above study, Kohonen's self-organizing maps (SOM) were used. Artificially intelligent systems have the ability to remotely conduct quantitative calculations and can recognize aspects in clinical photographs that human specialists hardly ever discover. Deep learning algorithms are frequently utilized in picture prediction and diagnosis due to their advantages in terms of speed, accuracy, and reproducibility [15–17].

The aim of this study was to assess the progression and grade of periodontitis with the usage of given data and with the help of the self-organizing model. In this study, we have used an alternative methodology to conventional statistics, self-organizing maps (SOM), to group the clinical profiles of patients with periodontitis. Using this technique, we will be able to divide the study participants into a specific number of neurons. The value of each research variable relating to each of those neurons will be determined using the SOM algorithm. This allows for the simultaneous visualization of the values of each study variable in each group of patients contained in a neuron. With the use of this grouping technique, we can see how each variable affects the various patient groups and identify behavioral patterns that are related to a particular variable, in this case, the requirement to carry out a fenestration.

2. Materials and Methods

2.1. Patients' Population

This was a retrospective study, and the database consisted of 110 patients; both genders aged 30 to 60 were included. The selection of the patients was performed in 2022 in the Department of Periodontology and Oral Mucosa Diseases, Medical University of Gdansk. Only the patients with all necessary measurements were included in the study. All groups included patients generally healthy or with diabetes or/and smokers. Patients with other systemic diseases and patients with dental implants were excluded. A dental assessment of the patients was performed, and the following indicators were included: gender, age, active nicotinism, the number of preserved teeth, approximal plaque index, bleeding on probing, pocket depth, and clinical attachment loss. The measurements were performed by one dentist with the use of a standardized periodontal probe with 15 mm scaling. The study only included participants with all required measurements. Stadium I periodontitis affected 12, stadium II periodontitis affected 19, stadium III periodontitis affected 42, stadium IV periodontitis affected 27, and gingivitis affected 10. Patients who were usually healthy, had diabetes, or smoked were included in all categories. Patients having dental implants and those with other systemic disorders were not included.

2.2. Network and Programming

2.2.1. Basics of Kohonen Neural Networks

In 1982, in the article titled "Self-Organized Formation of Topologically Correct Feature Maps", T. Kohonen proposed a new algorithm of artificial neural networks, which was named Kohonen networks [18]. Those networks can be characterized as self-learning with built-in competition and a neighborhood mechanism. They are constructed from two layers: input and output. Self-learning is based on the fact that learning, also known as network training, takes place in the "unsupervised learning" (self-organizing) mode, which means that for the given input data for training there is no presented correct answer.

The network is not familiar with what output signals should correspond to the input signals. Competition is the mechanism by which neurons learn to recognize input signals by competing with each other. The neuron which reacts most strongly to a given input signal wins: the more the neurons' weights are similar to the input signals (input values), the stronger the reaction "wins" in the competition of recognizing specific input signals. Other neurons become winners in recognizing other input signals (values). Neighborhood is understood here as such teaching of the network that the neighbors of the neuron that are victorious in recognizing specific signals learn along with it, although less intensely. Such network training causes the neighboring neurons to respond to similar input signals (values). The training result of the network (output layer neurons) is plotted in a graph called a Kohonen map or topological map. The individual observations are called input or training cases.

2.2.2. Architecture and Training

The KNN architecture consists of a multi-dimensional input layer and a typically one-dimensional or two-dimensional output layer. The neurons fight with one another in the output layer, also known as the competitive layer, and only one is chosen as the winner, or put another way, as the class most appropriate for a certain input vector x. Each component of the input vector is connected to every component of the output layer in these networks. Weight w_{ij} between the input neurons j and the output layer's neurons i serves as a proxy for the strength of the connections.

The Euclidean distances D_i between the input vector and the weights connected to each of the output neurons are calculated during the training of the KNN model, as indicated by the following equation:

$$D_i = \sqrt{\sum_{j=1}^{K} \left(x_j - w_{ij}\right)^2},\ i = 1,\ 2,\ 3,\ \ldots,\ L, \quad (1)$$

where K is the input vector x's dimension, L is the total number of neurons in the output layer, and x_j is the input vector x's j-th component.

The winner neuron is the output neuron i with the least Euclidean distance relative to the input vector. The Kohonen rule [19] is then used to update the weights related to this neuron i and the neurons nearby V_{i^*}, as stated in the following equation:

$$w_{ij}(n) = w_{ij}(n-1) + \propto \left[x_j(n) - w_{ij}(n-1)\right],\ i \in V_{i^*},\ j = 1,2,\ \ldots,\ K \quad (2)$$

where n is an index that specifies the order in which samples are presented to the network, and α is the learning rate.

The Euclidean distance becomes lower as a result of the Kohonen rule, which drives the weights linked to the winner neuron and its neighbors to move in the direction of the input vector provided to the network. As a result, these neurons learn to identify related vectors. The full dataset can also be used to present input vectors to the network prior to any weight updates. Batch mode is the name given to this display style. In this scenario, each input vector is searched for the winning neuron, and the weight vector is then changed to a position determined by the average of the input vectors for which the winning neuron or its neighbor was present. After several iterations of the input dataset presentations, the weights typically stabilize.

2.2.3. Application of the KNN Model

In our study, the structure of the Kohonen network was not complicated compared to other types of neural networks. The Kohonen network consists of input and output layers, but it does not have any hidden layers, as with other types of networks. Technical data for network maintenance have been standardized. The data were normalized before scheduling so that the average would be 0 and the unit standard deviation would be 1. Each patient was represented by a vector of the number of coordinates and factors that need to be taken into account: in our case, 171 variables initially, in order to generate a SOM (sex, age, smoking, oral hygiene, periodontal pocket depth, and maximum interproximal loss of connective tissue attachment); see Table 1. The patients were divided into blocks called neurons using an iterative method with the goal that the patients making up each neuron have similar characteristics and distinct ones from those making up other neurons.

Table 1. Variables represented on the SOM.

Variable	Description	Valuation
Sex	Woman/man	0 = woman. 1 = man
Age	Initial age on beginning treatment	Decimal age (years)
Smoking	Smoking cigarettes	0 = no. 1 = yes
API [1]	Approximal plaque index	0 = no. 1 = yes
BoP [1]	Bleeding on probing	0 = no. 1 = yes
PD [1]	Pocket depth	Decimal (mm)
CAL [1]	Clinical attachment loss	Decimal (mm)
Mobility [1]	Tooth mobility	0 = normal (physiologic) tooth mobility; 1 = detectable mobility (up to 1 mm horizontally); 2 = detectable mobility (more than 1 mm horizontally); 3 = detectable vertical tooth mobility
Furcation [1]	Severity of furcation involvement	0 = furcation not detectable; 1 = furcation detectable, with a horizontal component of probing ≤3 mm; 2 = furcation detectable, with a horizontal component of probing >3 mm; 3 = furcation is opened through and through

[1] for each tooth (28).

In this study, the vectors of the input layer had 195 neurons representing information from the patients' records regarding sex, age, smoking, oral hygiene, periodontal pocket depth, and maximum interproximal loss of connective tissue attachment (Table 1). Each patient was represented by a vector of the number of coordinates and factors that need to be taken into account, in our case, 171 variables initially, in order to generate a SOM.

A popular method of mapping elements into layers was divided into its forms of a two-dimensional network, and shared with (rectangles, circles) in preparation from the software that corresponds to individual neurons.

At the start of the SOM, a decision must be made regarding the number of neurons and, consequently, the number of groups to form. Between a few dozen and several thousand neurons may exist. In our instance, the number of patients and variables to be researched led us to select a collection of 16 neurons which are related to the periodontitis grade (Healthy, A–C) and stage (I–IV). The distribution of the patients on the map after the SOM training process revealed that certain neurons had more patients than others or even had empty neurons. Not one of our patients had the pattern that corresponded to that neuron, as seen by empty neurons.

2.2.4. Computer Processing and Program

We used a computer Intel® Core™ i7–9850H CPU© 2.60 GHz, 16 GB RAM, and 512GB HDD. The algorithm described by Haykin [20] was applied to the neural network routine that was created, and Statistica Automated Neural Networks, TIBCO Software Inc. (2017). Statistica (data analysis software system), version 13. http://statistica.io (accessed on 13 January 2023) was used to process the results.

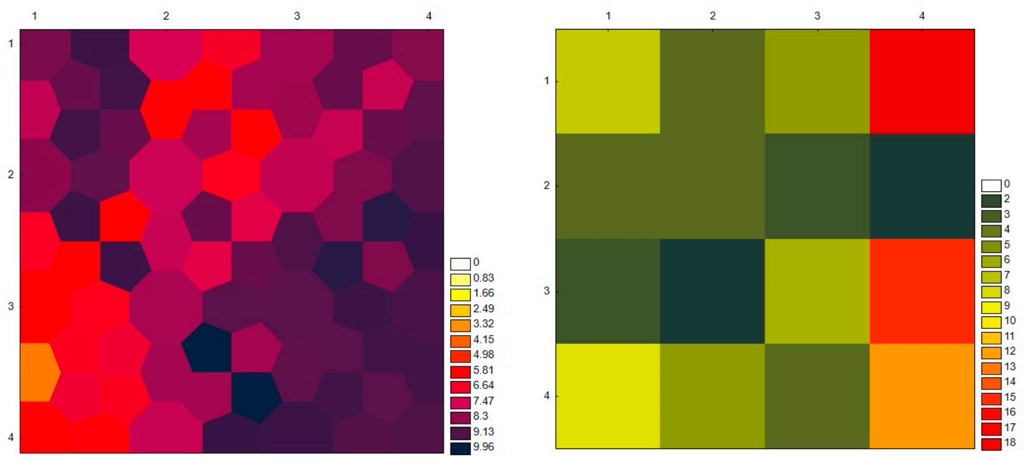
3. Results

3.1. Basic Characteristics

Of the 110 patients, 65.5% were female, and the study group included 9.1% of healthy individuals free of periodontitis, 13.6% of patients with grade A, 39.1% of patients with grade B, and 38.2% of patients with grace C. In total, 10.9% of the study group's patients had stage I periodontitis, followed by stage II patients 17.3%, stage III patients 38.2%, and stage IV patients 24.5%. The average age was 45.2 (95% CI: 43.8–46.6). The mean approximal plaque index (API) was 77.9% (95% CI: 73.4–82.4), bleeding on probing index (BOP) was 60.0% (95% CI: 53.5–66.5), interproximal clinical attachment loss (CAL) was 3.63 mm (95% CI: 3.19–4.08), and pocket depth was 2.90 mm (95% CI: 2.75–3.05). Most of the patients (about two-thirds) had non-physiologic tooth mobility. Over 68% of the study group had furcation that could not be detected.

3.2. SOM Analysis

Each patient was represented by a vector made up of as many components and variables as there were in the study, or initially 171 variables, as described in the preceding section. When the patients had comparable traits, we could classify them into neurons by analyzing the minimal distances between those vectors. Our study used a map of 171 neurons because there were so many instances involved, and the 110 patients were dispersed among them as indicated in Figure 1a,b.



(a) (b)

Figure 1. Distribution of SOM: (**a**) distances between neurons of a KNN model for the determination of the neighborhood; (**b**) distribution of the study participants among each neuron while accounting for the 171 study-related variables.

Using the criteria outlined in the Material and Methods section, where a higher percentage of a neuron's filling denotes a greater number of patients with that pattern and an empty neuron denotes the absence of any cases exhibiting the characteristics associated with that neuron, we can see that neuron 13 had the most patients with 19 and that neurons 1, 4, 15, and 16 each had 8–16 patients. Between one and seven patients were present in the other neurons. As a result, each neuron displayed the many patient patterns that were discovered during our study (Figure 1b).

The distribution of each of these magnitudes in the pattern corresponding to each neuron is shown in Figure 2 for the clinical attachment loss of the 28 variables included in the study on a color scale. Because the procedure projected the value of the variable that would correspond to that neuron, it can be seen in this situation that every neuron, including the empty ones, had a value assigned for the variable specified. The pattern associated with those vacant neurons is unimportant to our investigation because no patients were allocated to them during the course of it.

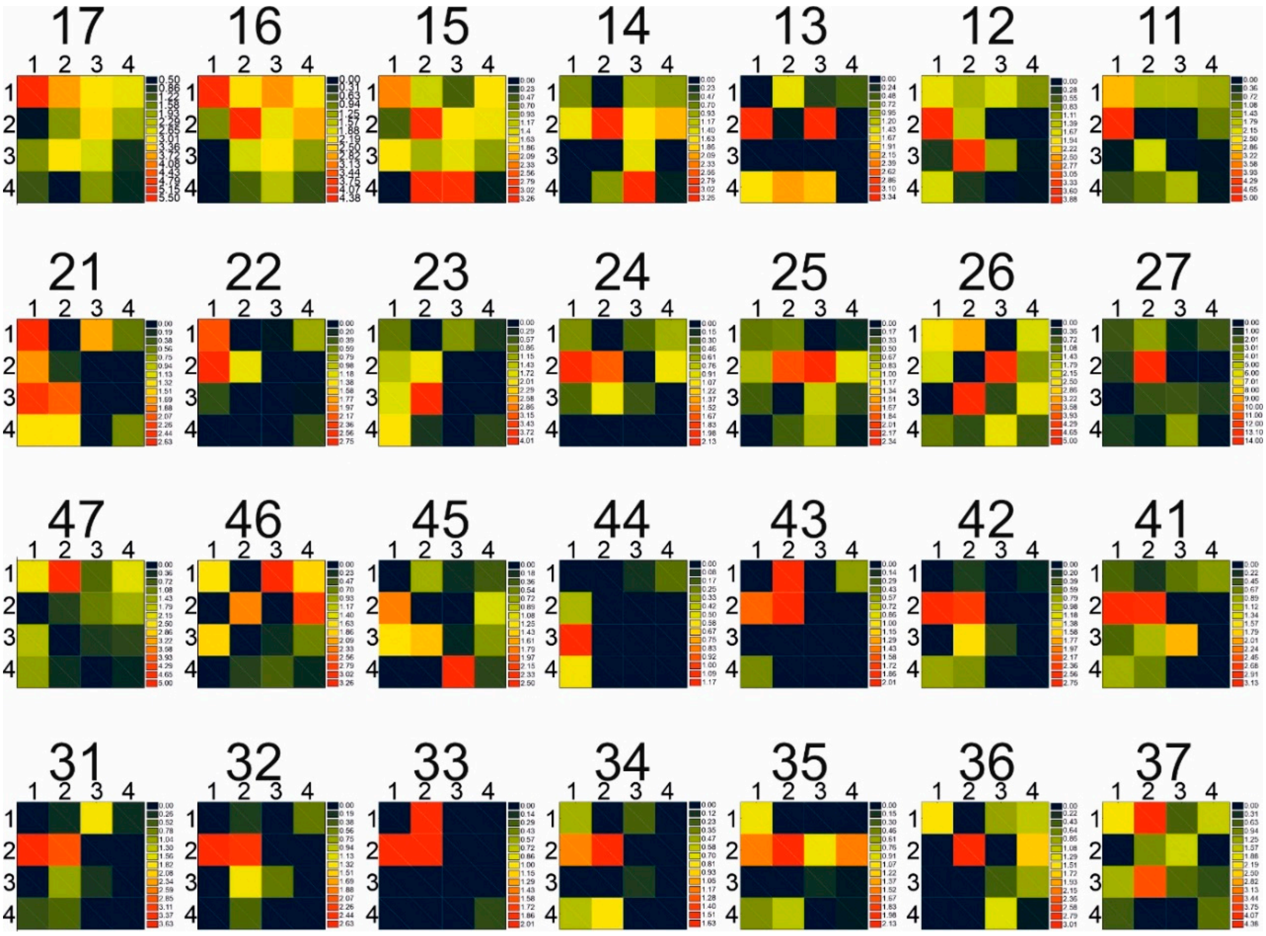


Figure 2. The distribution of study variable values in each neuron that contains a pattern of patients with a comparable minimum distance in accordance with the artificial neural network algorithm for the 28 variables (clinical attachment loss, all tooth) taken into consideration is referred to as the map component for each of the 16 variables. Over each map, the variable under analysis is shown.

It is clear that some variables' values greatly varied between the investigated neurons, whereas their values in other neurons were more or less the same (Table 2).

Table 2. Average values of the patient pattern corresponding to each neuron (N) considered.

Neuron	Sex	Age	Smoking	API	BoP	PD	CAL	Mobility	Furcation
1	0.3	46.5	0.3	0.91	0.93	4.26	6.12	0.65	0.17
2	0.8	42.3	0.5	1.00	0.89	3.34	4.37	0.37	0.09
3	0.5	47.0	0.2	0.94	1.00	3.02	4.59	0.20	0.03
4	0.4	43.9	0.1	0.91	0.96	2.91	3.75	0.09	0.02
5	0.5	45.5	0.8	0.87	1.00	3.26	4.04	0.42	0.08
6	0.3	46.3	0.3	0.73	0.76	3.26	3.79	0.39	0.07
7	0.7	47.0	0.0	0.79	0.67	2.75	4.56	0.30	0.01
8	1.0	39.0	0.5	0.68	0.76	2.99	2.48	0.02	0.01
9	0.3	52.3	0.3	0.86	1.00	2.76	3.21	0.35	0.02
10	0.0	46.0	0.5	0.66	0.38	3.32	4.56	0.28	0.02
11	0.0	50.3	0.3	0.69	0.44	2.68	2.95	0.21	0.01
12	0.3	42.2	0.1	0.54	0.41	2.40	2.88	0.01	0.01
13	0.6	52.0	0.3	0.97	0.32	3.29	3.21	0.34	0.10
14	0.0	51.7	0.3	0.65	0.38	2.59	3.17	0.35	0.01
15	0.0	43.8	0.0	0.78	0.46	2.96	3.91	0.02	0.01
16	0.4	38.3	0.3	0.57	0.20	2.18	1.92	0.03	0.01

To discover the pattern of patients according to the periodontitis grade and stage, we grouped the neurons together to form three clusters: Group 1 was made up of neurons 12 and 16 that represented a percentage of slow progression of almost 75%; Group 2 was made up of neurons 3, 4, 6, 7, 11, and 14 in which the percentage of moderate progression was almost 65%; and Group 3 was made up of neurons 1, 2, 5, 8, 9, 10, 13, and 15 that represented a percentage of rapid progression of almost 60%. Table 3 displays the pattern for each of the groups taken into consideration, and a variance analysis revealed the variables that were important for differentiating between these three patient groups. The significance values for each variable are shown in Table 3. There were no statistically significant differences in age, sex, and smoking on periodontitis progression. Mean values for API in the slow, moderate, and rapid progression groups were 59.71 vs. 82.27 vs. 89.56. There were statistically significant differences in API, BoP, PD, CAL, mobility, and furcation versus groups ($p < 0.0001$). The post-hoc tests showed that API values were significantly lower in Group 1 relative to Group 2 ($p = 0.0010$) and Group 3 ($p = 0.0001$). Furthermore, the BoP was significantly lower in Group 1 relative to Group 2 ($p = 0.0029$) and Group 3 ($p = 0.0002$). A detailed statistical analysis of PD showed that the PD value was significantly lower in Group 1 relative to Group 2 ($p = 0.0001$). Furthermore, the PD was significantly higher in Group 3 relative to Group 2 ($p = 0.0068$). There was a statistically significant CAL difference between Group 1 relative to Group 2 ($p = 0.0370$). The post-hoc tests showed that mobility was significantly lower in Group 1 relative to Group 2 ($p = 0.0121$) and Group 3 ($p = 0.0002$). A detailed statistical analysis of furcation showed that the furcation was significantly lower in Group 1 relative to Group 2 ($p = 0.0057$). Furthermore, the furcation was significantly higher in Group 3 relative to Group 2 ($p = 0.0015$) (Table 3).

Table 3. Periodontitis grade: probability of progression.

	Group 1	Group 2	Group 3	p-Value
Progression	Slow	Moderate	Rapid	
Sex	0.3	0.3	0.4	0.4827
Age	43.4	47.3	47.0	0.0638
Smoking	0.2	0.2	0.4	0.1028
API	0.60	0.82	0.90	<0.0001
BoP	0.34	0.65	0.74	<0.0001
PD	2.40	2.90	3.41	<0.0001
CAL	2.51	3.72	4.19	0.0212
Mobility	0.02	0.21	0.37	<0.0001
Furcation	0.02	0.04	0.16	0.0007

4. Discussion

Nowadays, the disciplines of medicine and dentistry are becoming more and more dependent on artificial intelligence (AI) [15,21]. It can be helpful in a range of circumstances when new technology could be advantageous and helpful to people. In the medical field, AI can be useful, especially in fields such as radiology, pathomorphology, oncology, cardiology, psychiatry, nuclear medicine, and many others [22–26]. The use of computer models of neural networks is one way to understand how the nervous system functions, which we are unable to study under natural conditions due to the limitations of current research techniques [27–31]. Recent years have seen a significant increase in the application of in silico approaches to find novel pharmaceutical treatments for conditions such as cancer, autoimmune disease, and neurodegeneration [32–34].

Periodontitis progression evaluation is a crucial phase in the treatment planning process for a dentist, and it may also be useful in encouraging patients to actively engage in their care. The study mentioned above also considers periodontitis staging and grading according to the classification from 2017 of periodontitis. The relationship between plaque (API) and the onset of periodontitis is widely understood. Gingivitis will occur in all individuals who do not brush their teeth properly; however, the development of periodontitis is more complicated, more varied, and depends on numerous circumstances. The immune-inflammatory response of the host, which is dependent on genetic polymorphism, must participate [35,36]. The development of a disease is determined by these polymorphisms as well as environmental factors [37–39]. The primary indicator of gingivitis and periodontitis is bleeding on probing (BoP), which also distinguishes between localized and generalized forms of each ailment and provides information on the degree of inflammation. Additionally, a significant percentage of pockets with a depth of more than 6 mm signal greater severity. There are already some studies in which radiographic bone loss is measured with the use of artificial neural networks. To improve the quality and efficiency, deep learning models with the use of panoramic radiographs or intraoral radiographs have been developed to assist clinicians in interpreting and measuring alveolar bone to reach a periodontal diagnosis with high accuracy and reliability [40,41]. Kohonen networks are used in other medical fields, for example, in detecting breast cancer. In the study of Ashokkumar et al. deep learning techniques have been proposed as a potential way to accurately predict breast cancer in its early stages. The Kohonen self-organizing algorithms, feed forward, and radial basis functions are examples of assessment techniques for artificial neural networks. The outcomes of the study indicate that the deep learning model can more accurately assess the final diagnosis of the axillary lymph node metastatic from US imaging of initial breast cancer [42]. Kohonen's artificial neural networks were also used to select new inhibitors of SARS-CoV-2 activator protein furin. In this research, it was found that 15 existing FDA antiviral drugs can have the potential to inhibit furin. Kohonen's self-organizing maps (SOM) are widely employed today in pharmaceutical research to establish the connection between structure and biological activity for medication discovery [43]. In the study of Zhao Y et al. an upgraded collaborative neural network model was suggested in order to address the self-organizing mapping network's Kohonen layer structure. The study investigated the relationship between branch retinal vein occlusion and arteriosclerosis by quantitatively measuring retinal vessel diameter and choroidal thickness with the use of Kohonen networks [44]. In addition, in psychiatry, neural networks can be successfully used, for example, in the study of Loula et al. where according to Brazilian statistics on mortality and the prevalence of major depressive disorder, a virtual population was created, and its five different types of inhabitants were clustered using Kohonen's self-organizing map (SOM) [45]. In another study, Kohonen networks were used to assess the nutrition quality with frailty syndrome among the elderly [46]. Self-organizing maps (SOMs) were used with the socio-demographic data such as age, gender, and race to perform the correct classification of asthma outcome. Kohonen self-organizing maps, especially when integrating multi-dimensional data, are effective classification models for studying asthma outcomes, according to the study's findings [47]. In the dermatologic study of Styła et al. the dermatoscopic images were used to train Kohonen neural networks to provide fully automatic diagnostic systems capable of determining the type of pigmented skin lesion [48]. Referring to the above and recent studies, it was shown that machine learning algorithms, particularly Kohonen networks, might be useful in medicine and can improve diagnosis and give clinicians more tools in treatment planning [42–52]. According to our study, we can recommend other specialists use Kohonen networks in their daily practice to ease the prediction of the progression of periodontitis with the usage of data: gender, age, active nicotinism, the number of teeth still present, the approximate plaque index (API), bleeding on probing (BoP), pocket depth (PD), and clinical attachment loss. After giving all of these input data, neural networks may predict the possibility of the progression of periodontitis that may be helpful for the clinicians, researchers, but also for the patients to outline the severity and probability of progression of the disease.

The methodology that we have employed allows us to notice some of variables which present statistically significant differences in terms of the probability of progression. The dependences of these magnitudes do not appear when a customary statistics method comparing the means between the several groups is undertaken [21].

5. Conclusions

We discovered the pattern of patients according to the periodontitis grade and stage, and grouped the neurons together to form three clusters: Group 1 represented a percentage of slow progression of almost 75%; Group 2 in which the percentage of moderate progression was almost 65%; and Group 3 represented a percentage of rapid progression of almost 60%. More map nodes are shared between patients from Groups 2 and 3 than the more narrowly focused Group 1. When examining the patterns of each of these groups, it becomes clear that Groups 2 and 3 are interconnected, since we identify neurons that contain examples from both of these groups. However, this circumstance is a reflection of reality, rather than a flaw in the network.

To conclude, we can say that self-organizing maps can be taken into consideration while assessing the risk of the progression of periodontitis. It can be helpful especially for clinicians, but also for scientists while defining the stage of periodontitis.

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