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ORIGINAL RESEARCH

Maintaining patient oral health by using a xeno-genetic spiking neural network

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Abstract
Many people are affected by dental problems that have serious long-term effects. Thus, oral hygiene maintenance is necessary to prevent dry mouth tooth decay, bad breath, and cold sores, which adversely affect oral health. In this paper, we investigated patients' oral health by applying optimized machine learning techniques to successfully identify potential pathologies present in the oral cavity. During the oral health analysis process, dental X-ray images are collected from a patient and examined by using the xeno-genetic spiking neural network. This method effectively examines tooth structure, gaps between teeth, and positioning of teeth such as molars, premolars, and incisors. The resulting information facilitates oral health maintenance. Finally, we evaluated the efficiency of the system with the help of computerized dental applications.

Keywords Dental problems · Oral health · Machine learning techniques · Dental X-ray images · Molar

1 Introduction

Currently, people need to maintain their oral health, regardless of their age, because the mouth is an "open window" for the entire human body (Harris et al. 2014). Because of the importance of oral health, Americans exercise great care in their oral health, in order to maintain their natural teeth throughout their life (Aas et al. 2005). However, if they fail to manage their teeth successfully, cavities result in more chronic diseases; characterization of this relationship is in the early stage (Twetman and Fontana 2009). Surveys have been conducted to determine daily activities that influence oral hygiene (Horowitz and Kleiman 2012). This survey process (ADA 2018) includes multiple questions, such as name, identification number, age, location, number of remaining natural teeth, oral pain or infection in the last 12 months, whether they wear removable dentures, the status of their oral cavity, the time spent on oral hygiene, the oral hygiene instruments used (e.g., tooth brush, wooden toothpicks, plastic toothpicks, and/or charcoal), time spent visiting the dentist, reasons for visiting the dentist, and typical foods consumed (Wilson et al. 2016). According to the results of the survey, most people fail to maintain oral hygiene due to their lifestyles, which creates problems in their mouths, including disease, infection, and pain (Declerck et al. 2008).

Figure 1 depicts sample dental disease, decay related dental images. The dental images depict the problems which affect the people oral hygiene, in addition to this; it clearly shows that maintenance of oral health (Aleksejuniene et al. 2009) is crucial. Thus, it is important to manage oral hygiene to avoid future lifestyle difficulties. To overcome these challenges, a variety of multimedia techniques and machine learning techniques have been used to predict human oral health (Said et al. 2006) (Nomir and Abdel-Mottaleb 2007). Although the techniques are effective (e.g., support vector machine, neural networks, and other optimizing techniques), it is difficult to maintain their efficiency (Li et al. 2007). Herein, we introduce a Xeno-genetic spiking neural network-based oral health prediction system to improve the predictive efficiency. A detailed description of the system

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Fig. 1 Examples of dental disease and decay

is included. The rest of the paper is organized as follows: Sect. 2, describes the various authors' opinions regarding oral health, infection, and detection methodologies. Section 3 evaluates the overall Xeno-genetic spiking neural network system-based oral health prediction system and Sect. 4 analyzes the efficiency of the Xeno-genetic spiking neural network-based oral health prediction system. A conclusion is given in Sect. 5.

2 Related works

This section discusses the various researchers' opinions regarding oral health maintenance and detection with multimedia techniques. Huang and Lin (2017) assessed oral health maintenance by monitoring daily tooth brushing activities. During this process, a wrist watch was placed on the hand; different motions, complex hand structure, and brushing time were monitored continuously. The collected information was fed into an effective machine learning technique, known as a neural network, that predicted oral health based on magnetometer, accelerometer, and gyroscope-based sensor data. This neural network system successfully predicted oral health with approximately 91.2% accuracy, compared with traditional methods. (Mohamed Shakeel et al. 2018) monitored patient oral health in hearing-impaired and mute children in Jaipur Rajasthan. They collected information from 315 students who were divided into three different groups, each consisting of 105 children. Each group was monitored while brushing their teeth for up to 3 weeks. The results indicated that tooth brushing activities help to maintain oral health in an effective manner.

Chuang et al. (2011) detected oral cancer by applying a support vector machine, because oral cancer affects oral health. For the oral cancer examination process, data were collected from a single nucleotide polymorphism dataset, which consisted of 238 samples, and were examined in terms of X-ray repair and DNA gene repair. During computation, the support vector machine uses 10-fold cross-validation to detect oral cancer with higher accuracy. The efficiency of the system was compared with several traditional methods, revealing that the 10-fold cross validation method attains 64.2% accuracy. (Crowe et al. 2017) introduced a classification tree analysis method for predicting dental problems in Irish preschool-aged children. Their method examines parameters such as body-mass index, dietary intake, sociodemographics, and health behaviors, to predict oral health problems. Within the collected data, different weights were assigned to effectively predict dental problems based on foods and risk factors.

Dima et al. (2018) determined dental-related problems in children and their parents by applying the decision tree approach. During the examination process, different dental-related problems, such as the presence of periodontopathic and cariogenic bacteria, were measured. During the examination, data were collected and Kendall ranks were assigned to the data, in order to derive oral information by applying the C4.5 algorithm. Further examinations included identification of missing data, filled permanent teeth, and a periodontopathic test, which helps to detect oral problems with up to 93.33% accuracy, compared with other methods. Machuca et al. (2017) examined dentin hypersensitivity

(DH) by using a classification regression tree method; notably, dentin hypersensitivity affects the overall quality of life. Initially, data were collected by using the Dentin Hypersensitivity Experience Questionnaire (DHEQ), where information is ranked according to importance. From the collected data, various DH aspects are predicted effectively. Taken together, these machine learning techniques all work to detect oral health problems, in order to improve quality of life. Due to the importance of the oral health, in this paper, we develop an oral health maintenance system by applying a machine learning technique, Xeno-genetic spiking neural network, to improve oral health. Detailed discussions of the Xeno-genetic spiking neural network-based oral health maintenance system are in the following section.

3 Xeno-genetic spiking neural network based oral health detection

This section discusses the Xeno-genetic spiking neural network-based oral health detection and maintenance system. Initially, dental X-ray images are taken for the purpose of collecting oral information, such as tooth structure, gaps between teeth, and positioning of teeth (e.g., molars, premolars, and incisors), which helps to effectively predict oral health status. Before obtaining detailed oral information, noise present in the X-ray images is eliminated by applying an adaptive median filter that improves the overall oral health prediction system. The overall processing structure of dental X-ray images is shown in Fig. 2.

Figure 2 depicts the overall Xeno-genetic spiking neural network-based oral health prediction system, which utilizes different stages, such as X-ray image preprocessing, feature extraction, and oral health prediction, as explained in the following section.

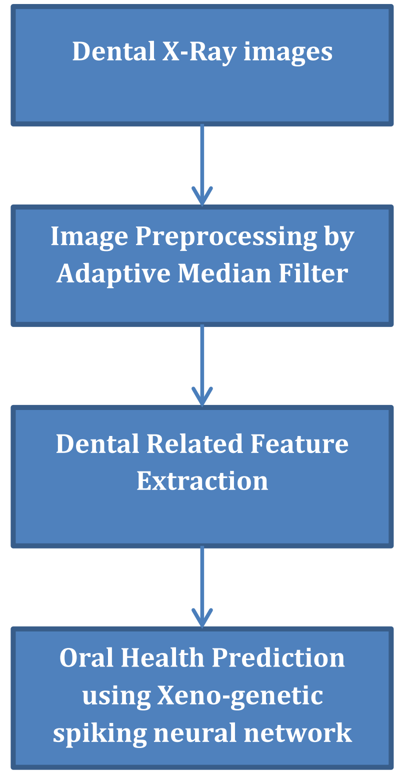


Fig. 2 Overall processing of dental X-ray images

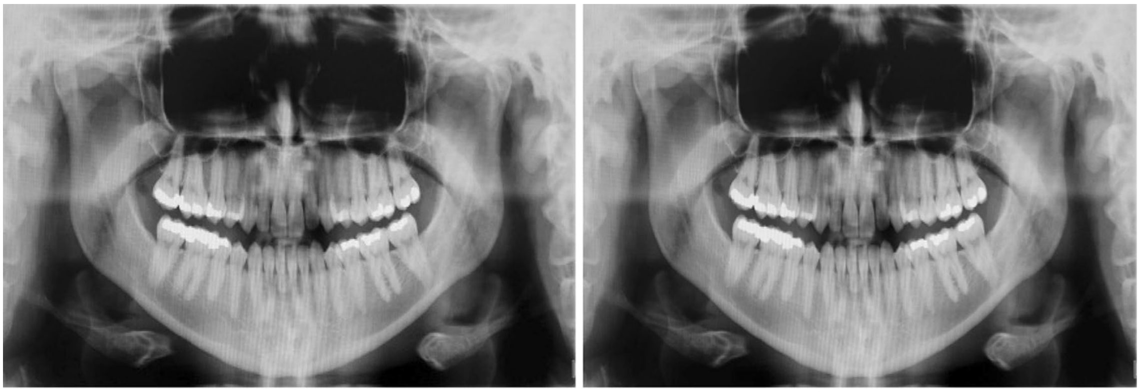
3.1 Dental X-ray image preprocessing

The first step of this oral health prediction system is image preprocessing, which removes noise from X-ray images, in order to increase overall oral health prediction and efficiency of the system (Shrestha 2014). Initially, raw X-ray images are collected, which consist of noise, data, and other irrelevant pixel information that must be eliminated from the image without affecting the overall quality of the oral health prediction system. The effectiveness of the system is improved by applying an adaptive median filter to remove noise from the image without compromising information regarding image edges (Rajeshwari and Sharmila 2013). The adaptive median filter examines the captured X-ray image pixels in an iterative manner until it has eliminated noise from the image. If a scanned image pixel is affected by any noise, the window size is increased and pixels are arranged according to intensity and brightness values. Based on these image characteristics, the pixels are ranked and sorted to determine the median value. If a pixel exhibits any noise relative to a neighboring pixel value, it is replaced with the median pixel value because the pixel values are nearer to each other, so the missing value must be average or median value of the neighboring pixels. This process is repeated continuously to reach the maximum threshold of intensity and brightness values. After following the above process, noise is removed; the noise-eliminated X-ray image is shown in Fig. 3.

Figure 3 shows that the adaptive median filter effectively eliminates noise from an X-ray image without damaging the quality of the oral image. From the preprocessed images, effective oral health information is extracted, as explained in the following section.

3.2 Tooth feature extraction

The next step is to feature extraction, in which tooth structure, gap between teeth, and tooth position are extracted to determine oral health (Raju and Modi 2011). From the preprocessed dental X-ray image, a gap valley is detected by computing the sum of the intensity values in the x-axis of a given preprocessed image. Generally, the teeth have high intensity values in a grey image, compared with the



(a) **Original Oral X-ray Image** **(b)** **Preprocessed Oral X-ray Image**

Fig. 3 Preprocessed oral X-ray image

jaw; this creates a gap valley in the y-axis. This gap valley is different from the normal gap, which must be detected through a user-assisted initialization process. Considering the user initialization position, the gap between lower and upper jaws is denoted as $\hat{y}$. From this position, the valleys are represented in the histogram projection D_i with respective depth v_i, where i = 1,2,3……n. The projected tooth structure histogram is shown in Fig. 4.

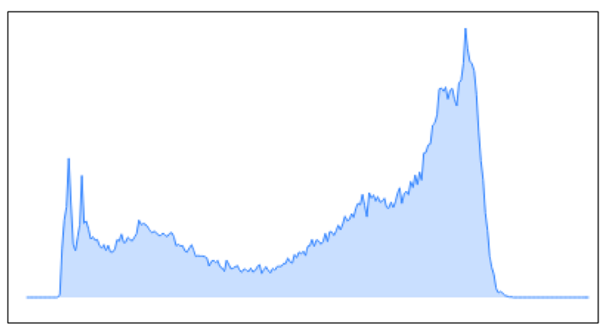
In the projected histogram, various valleys are detected; only one is treated as the gap valley. The gap valley is computed with the help of the probability values of D_i and y_i, which are estimated as follows,

$$p_{v_i}(D_i, y_i) = p_{v_i}(D_i)p_{v_i}(y_i). \tag{1}$$

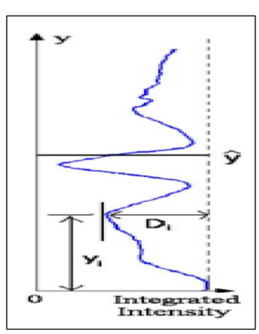
In Eq. (1), each value is computed as follows,

$$p_{v_i}(D_i) = c\left(1 - \frac{D_i}{\max_k D_k}\right) \tag{2}$$

(a) **Preprocessed Oral X-ray Image**



(b) **Histogram of Oral X-ray Image**



(c) **Intensity Histogram Projection of Oral X-ray Image**

Fig. 4 Histogram projection of oral X-ray Images

$$p_{v_i}(y_i) = \frac{1}{\sqrt{2\pi\sigma}} e^{-(y_i-\hat{y})^2/\sigma^2}. \quad (3)$$

From the above Eq. (2), c is defined as the normalizing constant that satisfies the $p_{v_i}(D_i)$ probability mass function, the values of which are added obtain to 1. $p_{v_i}(D_i)$ is the gap valley-based likelihood pixel intensity of D_i. If the computed likelihood value is very low, then the gap is regarded as the gap valley. The computed likelihood value is compared each other, from the value low value is chosen that is named as gap valley. $p_{v_i}(y_i)$ is denoted as the likelihood value of y_i, which is denoted as the normal distribution of distance between the computed gap valley position and true position of the teeth; σ is designated as the user assistant error occurrence due to patient carelessness. After computing the gap between the jaws, the gap valley is defined as follows,

$$p_{v^*}(D^*, y^*) = \max p_{v_i}(D_i, y_i). \quad (4)$$

Based on the gap valley, strips of teeth are derived in the image based on the gap valley position; the divided strips of teeth are shown in Fig. 5.

The divided strips of teeth are used to divide the upper and lower teeth; then, in each row that has been examined, different statistical features such as entropy, correlation, contrast, variance, mean, inertia, skewness and kurtosis features are extracted, which are used to determine the oral health of a particular patient (Robert and Adam 2016). The features are extracted from teeth in both rows, which are fed into the Xeno-genetic spiking neural network for effectively predicting oral health, as explained in the following section.

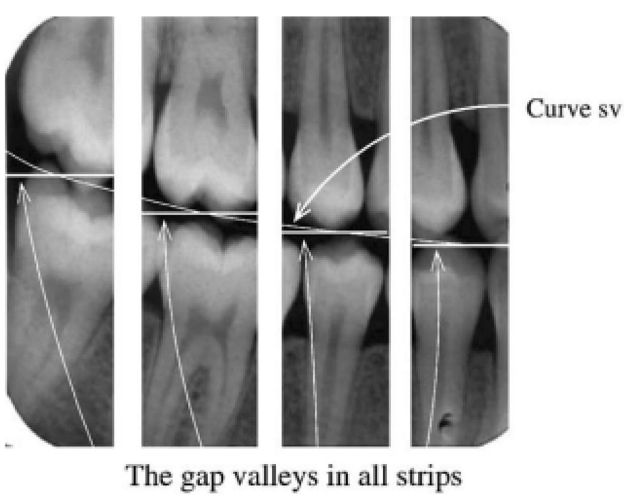


Fig. 5 Strips of teeth

3.3 Oral health prediction with the xeno-genetic spiking neural network

The last step is oral health prediction which is conducted by applying the Xeno-genetic spiking neural network. The spiking neural network (SNN) (Jin et al. 2008) is an effective neural network that works according to the neural function of the brain, which means that it does not require any propagation model for processing the extracted features. The SNN model works automatically; when the extracted features reach the network, it is further improved by applying the Xeno-genetic approach, which works according to chromosome activities. The block diagram of the Xeno-genetic approach is shown in Fig. 6, consisting of different operators such as selection, crossover, and mutation operator. First, the extracted features are arranged in the SNN and the numbers of neurons and weights are selected. The selected neurons are trained by applying the trainlm and trainscg functions. This neural network improves feature training and avoids the kernel-based design to select parameters.

During the oral health prediction process, the system utilizes the selection, crossover, and mutation operators (Wulfram 2001) for updating and optimizing network weights and bias values, which are then used to create the effective neural network structure. The selected features are predicted by using the sigmoid-based activation function, which is obtained with the following Eq. 5.

$$\boldsymbol{G}(\boldsymbol{a}_i, \boldsymbol{x}_j, \boldsymbol{b}_i) = \frac{1}{1 + \boldsymbol{e}^{-(-\boldsymbol{a}_i \boldsymbol{x}_j + \boldsymbol{b}_i)}}. \quad (5)$$

The final prediction output is computed by applying the inverse operation to the output of the hidden layer. The

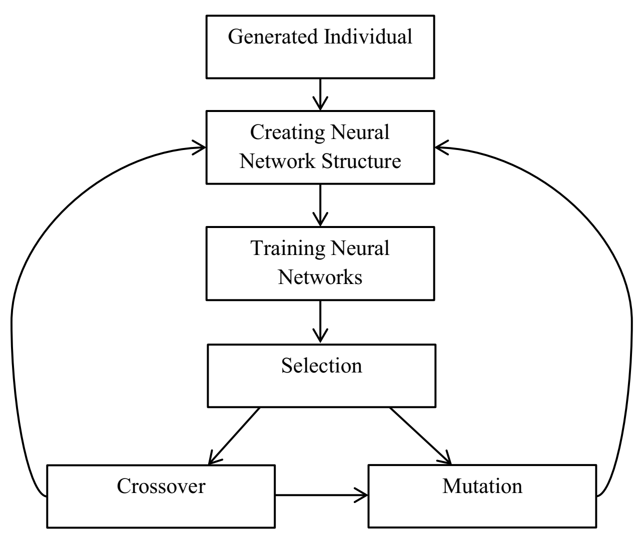


Fig. 6 Block diagram for bio-inspired xeno-genetic spiking neural networks

Table 1 Algorithm for oral health prediction

Algorithm for Xeno-genetic Spiking Neural Network
Step 1: Collect the set of the oral health features from the feature extraction process Step 2: Generate the individuals for each feature Step 3: Create the network according to the number of input features Step 4: Train the network by applying the selection, crossover, and mutation operators to improve network performance Step 5: Repeat step 4 until the network is trained successfully Step 6: During the training process, trainlm and trainscg training functions are applied to enhance the network performance which is predefined in the neural network process. Step 7: The incoming test input features are analyzed by applying the sigmoid activation function, defined as follows: $$G(a_i, x_j, b_i) = \frac{1}{1 + e^{-(-a_i.x_j + b_i)}}$$ Step 8: From step 7, outputs are compared with the trained features output and used to predict exact oral health features. Step 9: Repeat this process to detect exact oral health features.

Fig. 7 Sample oral X-ray images

Table 2 Error rate

Method	Error rate
Support vector machine (SVM)	0.13
Neural networks (NN)	0.021
Multilayer perceptron (MLP)	0.019
Xeno-genetic spiking neural network	0.017

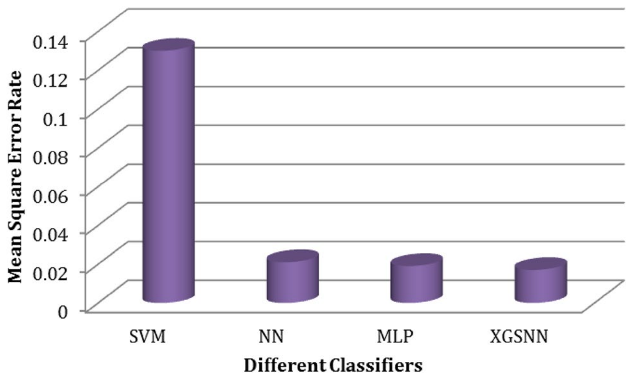


Fig. 8 Mean square error rate

Table 3 Precision and recall

Method	Precision	Recall
Support vector machine (SVM)	84.3	86.21
Neural networks (NN)	91.43	92.21
Multilayer perceptron (MLP)	92.98	93.34
Xeno-genetic spiking neural network	97.867	98.2

detailed algorithm of the Xeno-genetic spiking neural network is explained in Table 1.

Based on this algorithm, the proposed system effectively places the selected features into normal and abnormal oral health results. The accuracy of the system is experimentally evaluated below.

4 Experimental evaluation

The efficiency of the Xeno-genetic spiking neural network-based oral health prediction process was examined by using X-ray images collected from the AM radiographic dataset (Papantonopoulos et al. 2014). The collected information was processed by applying the adaptive median filter to eliminate noise from the image. The above-described methods were applied to the preprocessed image to obtain the features that are used to predict the quality of oral health. Sample oral X-ray images are shown in Fig. 7.

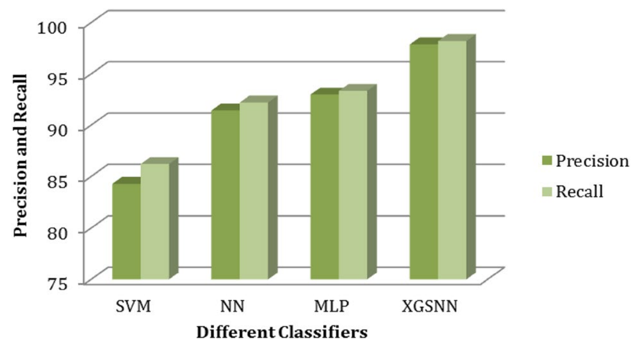


Fig. 9 Precision and recall

Table 4 Accuracy

Method	Accuracy
Support vector machine (SVM)	86.12
Neural networks (NN)	92.6
Multilayer perceptron (MLP)	93.1
Xeno-genetic spiking neural network	98.5

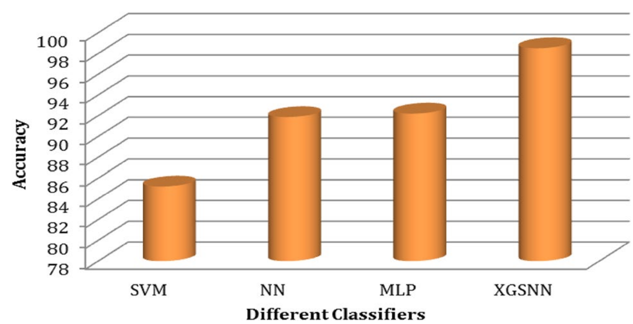


Fig. 10 Accuracy

The captured images were examined by the above methods and the efficiency of the system was evaluated by using different metrics such as precision, recall, accuracy, and prediction rate (Alarifi et al. 2018). By using the above metrics (Gu et al. 2009), the efficiency of the Xeno-genetic spiking neural network (XGSNN) was examined. The effective utilization of the chromosome operators and the training function reduces the system error rate relative to other methods, such as support vector machine (SVM) (Maity and Abdel-Mottaleb 2015), neural networks (NN) (Sridhar et al. 2018), and multilayer perceptron (MLP) (Yadav and Sengar 2014). The resulting error rate values are shown in Table 2.

Table 2 depicts the error rate of the Xeno-genetic spiking neural network-based oral health prediction system, which attains an error rate of 0.017. This is lower than SVM (0.13),

Table 5 Prediction rate

Model	Data set		Prediction Rate (%)		
	Training Images	Testing Images	Training Images	Testing Images	Overall Prediction Rate
Support vector Machine (SVM)	700	100	75.98	60.26	68.12
Neural networks (NN)	700	100	84.08	84.18	84.13
Multilayer perceptron (MLP)	700	100	95.23	93.97	94.69
Xeno-genetic spiking neural network	700	100	99.48	94.75	97.115

NN (0.021), and MLP (0.019). A graphical representation of the results is shown in Fig. 8.

Figure 8 shows that the Xeno-genetic spiking neural network attains a minimum error rate, compared with other methods; this is accomplished by the use of its weight and training functions, which improve oral health prediction. The reduced error rate improves the overall prediction rate, which is measured in terms of precision and recall. Table 3 depicts the precision and recall values of the Xeno-genetic spiking neural network.

Table 3 depicts the precision and recall values of the Xeno-genetic spiking neural network-based oral health prediction system, which attains 97.867% precision and 98.2% recall. These are higher than SVM (84.3% precision, 86.2% recall), NN (91.43% precision, 92.21% recall), and MLP (92.98% precision, 93.34% recall). A graphical representation of the results is shown in Fig. 9.

The reduced error rate enhances the oral health prediction rate, which is characterized by precision and recall. The collected oral features are processed; effective dental structures, gaps between teeth, and tooth positions are detected and used to detect oral health with higher accuracy. The resulting oral health prediction accuracy is shown in Table 4.

Table 4 depicts the accuracy of the Xeno-genetic spiking neural network-based oral health prediction system, which attains 98.5% accuracy. This is higher than SVM (86.12% accuracy), NN (92.6% accuracy) and MLP (93.1%). A graphical representation of the results is shown in Fig. 10.

Figure 10 demonstrates that the Xeno-genetic spiking neural network-based oral health prediction system provides a high oral health prediction rate (98.5%), compared with SVM (86.12%), NN (92.6%), and MLP (93.1%). This is because of its use of oral-related features. The overall oral health prediction rate is described in Table 5. The prediction rate is computed based on how the Xeno-genetic spiking neural network system collects patient oral health information and effectively selects features from the set of collected patient features. The prediction rate is further improved by continuous training of the collected patient oral health features. The resulting prediction rates are as follows.

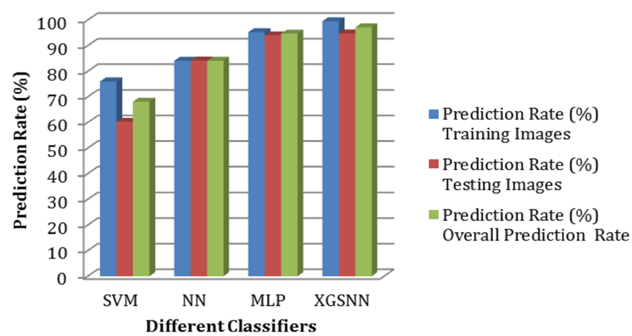


Fig. 11 Prediction rate

Table 5 shows that the Xeno-genetic spiking neural network method has an oral health prediction rate of 97.12% when compared to the other prediction methods. A graphical representation of the results is shown in Fig. 11.

The above metrics show that the Xeno-genetic spiking neural network effectively extracts oral features that can be used to predict oral health with high accuracy, superior to other classification methods. In this manner, the proposed technique effectively predicts oral health.

5 Conclusion

This paper described oral health prediction by the Xeno-genetic spiking neural network. Initially, dental X-ray images were collected from the AM radiography dataset. The collected images were analyzed on a pixel-by-pixel basis, using an adaptive median filter approach where noise in the images was replaced by median pixel values. Various oral structures, gap valleys, strips of teeth, and statistical features were extracted and used to detect oral health. The extracted features were processed by the Xeno-genetic spiking neural network, which works in a manner similar to brain function; thus, it is able to accurately detect oral features. During this process, weights and bias values were continuously updated according to the selection, crossover, and mutation operators, thereby reducing the error rate in an effective manner. This effective extraction of oral features helped to increase the oral health prediction rate. The efficiency of the system was experimentally evaluated; the Xeno-genetic spiking neural network method attained 97.115% accuracy, which was comparatively higher than other methods. In future the oral health prediction process is further improved by examining lot of teeth features using optimization techniques.

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