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Research Article

Diagnosis of temporomandibular joint disorder using one-dimensional convolutional neural networks: A comparative study

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ABSTRACT

Temporomandibular Joint (TMJ) is a joint located on both sides of the cranium that connects the mandible to the cranium. Temporomandibular Joint Disorder (TMD) is generally defined as pathological conditions resulting from abnormal movement of the TMJ. Symptoms of TMD usually occur in the form of pain in the mandible and the muscles that control mandibular movement. One of the clinical diagnostic methods is the auscultation of sounds coming from the joint during the opening and closing of the mandible. In this study, previously recorded TMJ sounds were analyzed for TMD diagnosis using one-dimensional (1-D) convolutional neural networks (CNN), a sub-branch of deep learning algorithms. The obtained results were compared with the results of previous outcomes of studies which were using deep learning algorithms such as two-dimensional CNN, which is generally used for image processing, and LSTM network, which is widely used for time series analysis. Comparison results indicate that 1-D CNNs are less effective than image-based CNN algorithms. Results show that 1-D CNN classification of Type-1 algorithm and Type 2 algorithm are 75% and 65% accuracy respectively. These figures are significantly lower than the 94% accuracy achieved by the 2-D image-based algorithm. When compared to LSTM networks, which have an accuracy of 70%, 1-D CNNs yield comparable results. For a more comprehensive analysis, precision, recall, specificity, and F1-Score metrics were evaluated, and the findings were interpreted accordingly.

1. Introduction

Temporomandibular Joint (TMJ) is the joint between the skull and the jaw. Between the temporal bone of the skull and the mandible hence name comes from, there are two bilateral synovial articulations at each side of the face. These joints give the jaw capability of many different movements and allow mouth movements like chewing, biting, speaking etc. Temporomandibular Joint Disorder (TMD) is any health problems arising from TMJ capabilities and dysfunctions hence sometimes identified as Temporomandibular Joint Dysfunction. Graphical explanation of TMD and the localization of TMJ can be seen in Figure 1. TMD is a very common problem with a frequency in general population can be as high as 75%. But generally, frequency of patients who have one or more symptoms of TMD is accepted as around 33% [1]. According to Özan at al., these figures are even higher in Türkiye [2]. Symptoms usually emerge as referred pains that can be facial pains, external ear pains, facial muscle pains, migraine-type pains, even strains in the eyes, etc. Therefore, although TMD is often caused by tooth deformities, patients often seek help outside of the field of dentistry. These problems generally result in limited movement of jaw, jaw, skull and related muscle pain, sounding and pain during opening and closing of jaw even in extreme cases blocking of jaw movements.

TMD cases are generally diagnosed by health care professionals clinically by different diagnostic techniques. One of the most used methods is listening to the TMJ sounds during the opening and closing of the jaw. The dentists, then, form their opinion on the based on these sounds. Since jaw sounds are one of the main diagnostic elements of the disorder, the focus of many academic studies is on sound categorization. The importance of voice-based diagnosis systems comes from their simplicity. Furthermore, it is easier and cheaper than sending the patient for MRI, which is both costly and may not be available immediately. The sounds associated with TMD are often referred to by the dental

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community as crepitation, clicking, popping, popping clicking, etc.

Early and well-known studies were conducted by Wildmalm and his several colleagues. In their work, they defined five different classes by using Reduced Interference Distribution (RID) [3], and they also studied sound waveforms [4]. Subsequent works of Sano at al. [5], Djurdjanovic at al. [6], Zheng at al. [7] which were also contributed by Wildmalm centered on the amplitude-wave spectrum of TMJ sounds, pattern recognition-based classification.

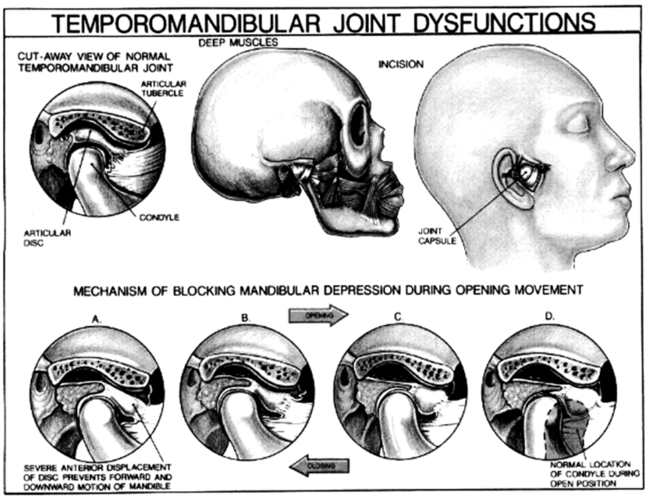

Figure 1. Temporomandibular Joint (TMJ) and explanation of some Temporomandibular Joint Dysfunctionalities

There are many different studies concentrated on TMJ sound classification. The author of this article Taskiran and his colleagues have studied classification of TMJ sounds. Their studies include classification based on frequency-based feature extraction and ANN classification [8] and statistical features-based feature extraction and ANN classification [9], a Convolutional Neural Network based Deep Learning image classification technique [10], [11] and an LSTM based deep learning method [12]. Akan at al. [13], [14] and Ghodsi at al. [15] studied categorization of TMJ sounds using classification techniques like spectrum-based techniques, time-frequency analysis, discrete evolutionary transform. A similar technique is used by Kim at al. diagnosing of knee joint problems [16].

Sound and signal classification by using deep learning techniques is gaining popularity in recent years. Along with author's own studies [10],[11],[12], there are many different works in the literature. In one of the studies, Malek at al. [17] use One Dimensional Convolutional Neural Networks (1-D CNN) for spectroscopic signal regression. In another study, Li at al. [18] reported highly successful classification results of heart sounds by using an improved 1-D CNN. A similar study of Electrocardiogram (ECG) based on CNN classification to catch cardiac anomalies is reported by Singstad and Tronstad [19]. Mattioli at al. is also reported similar study on Electroencephalogram (EEG) signals by using high accuracy 1-D CNN [20]. In the literature, there are many studies which use 1-D CNN for signal classification and processing like Kiranyaz at al. 2019 [21], Peng at al. 2019 [22], Wu at al. 2022 [23] etc.

In this study, previously recorded TMJ sounds [11] are used to classify the state of the patient by using 1-D CNN. Results, then, will be compared to previously used deep learning methods to evaluate the success of the 1-D CNN methods and conclusion will be given.

2. Material and Method

Voice-based diagnosis is one of the inexpensive methods to use in many application areas, especially in medicine and dentistry. In the many fields of medicine, physicians widely use stethoscopes to listen to the patient's body sounds for diagnosis. Unfortunately, identifying by listening requires practiced ears for correct diagnosis. At this point it would be very helpful to assist the physicians with a diagnostic tool.

In this study we tried to classify previously recorded TMJ sounds by using 1-D CNN techniques. Used audio data were recorded using specially developed tools and software under the supervision of experienced dentists in a real clinical environment. The data used in this study are the same data used in reference [11] and [12].

The data collection process is detailed and explained in reference [11].

Deep Learning Networks have been developed firstly for image classification. They were basically neural networks hence they are sometimes called deep neural networks. One of the main parts of the networks is known as convolutional neural network which is some kind of convolutional process operating on digital data. Images are generally represented as two-dimensional digital data consequently 2-D convolutional neural networks operate on picture data. 1-D convolutional neural networks usually are not exact but have similar structures with 2-D neural networks. They commonly are used to operate on one dimensional data like time series, voice data etc.

An outline of the method is given further down. Under the supervision of an orthodontist, 5 seconds of TMJ audio data are recorded as patients and subjects open and close their mouths in a real clinical environment. Audio data is sampled with a sampling rate of 51200 Hz at 24-bit resolution. The value of sampling rate is chosen according to Nyquist Theorem which states that sampling rate should be at least twice the maximum frequency of data. The maximum frequency is sound generally accepted is 22KHz consequently minimum sampling frequency should be 44KHz which is far less than the chosen 51.2KHz. Each audio data is recorded with 3 different sounds belonging to right TMJ, left TMJ and ambient. Each sound set has a total of 3 different, 24-bit 256000 sample data. Also, each recorded data has its own data and timestamps and associated tags, regardless of whether the recording belongs to a healthy or TMD patient.

When the spectra of the audio data were examined, it was seen that there were almost no prominent high-frequency components. Thus, the 51.2 kHz sample rate data is filtered by the BPF with crossover frequency limits of 100 Hz to 10 kHz at 51.2 kHz. Low frequency components are sacrificed due to 50 Hz power line noise. After filtering, all data is sampled down to 20 kHz because all data above 10KHz is filtered down, resulting in reduced data size without losing the quality of the records. Classification procedure in the study ignores the records of ambient sounds and only uses chosen right TMJ and/or left TMJ sounds. All resulting signals then have 100 thousand samples per sound data per recording.

Main data set has total of 150 data. 96 of the data belongs to unhealthy patients and 54 of the data belongs to healthy test subjects. By simply choosing one or two recorded healthy joints sounds, the healthy set increased to have 73 signal data. To make a balanced set of data, unhealthy data set reduced to 73 signal data by omitting the data belonging to patients who have other than clicking sound. The data set is also consistent with previously used data sets of references [11] and [12] which have reported only using clicking sound data.

After processing the data as explained above, MATLAB's Deep Learning tools for 1-D classifications are used for classification. Two types of 1-D algorithms are used. Type 1 program is based on multidimensional time series 1-D CNN classifier in which only one dimension is used. Type 2 program based on image classification algorithm which uses 1-D feature vectors. Chosen 40 of the chosen 73 voice data is used for training of both networks and the rest are used as validation data. Classification algorithms run 50 times with randomly chosen training and validation data.

Type 1 Deep Learning Network Layers consist of in following order: sequence Input Layer, convolution 1D Layer, relu Layer, layer Normalization Layer, convolution 1D Layer, relu Layer, layer Normalization Layer, global Average Pooling 1D Layer, fully Connected Layer, softmax Layer, classification Layer. Block diagram is given in Figure 2.

Type 2 Deep Learning Network Layers consist of in following order: one image 1-D Input Layer, modified Convolution 2D Layer, relu Layer, 1st fully Connected Layer, 2nd fully Connected Layer, 3rd fully Connected Layer, softmax Layer, classification Layer. Block diagram is given in Figure 3.

Obtained results are compared with previously obtained results. More classification methods are planned to be tested in the future, and hopefully a more robust real-time diagnostic machine.

3. Results

As previously mentioned, a total of 146 data sets are divided into two groups. One of the groups consisting of 73 data is chosen from healthy subjects' voice data and the other 73 data is chosen from the patients having click sound TMJ movements. The first group labeled as 0 has healthy subject data, and the second group labeled as 1 has unhealthy data. A simplified success rate is Accuracy which is used as a comparison metric calculated by using Equation (1).

$$A = 100 \times \frac{NTP + NTN}{NTP + NTN + NFP + NFN} \% \quad (1)$$

Where A is accuracy, NTP is the Number of True Positives, NTN is the Number of True Negatives, NFP is the Number of False Positives, and NFN is the Number of False Negatives.

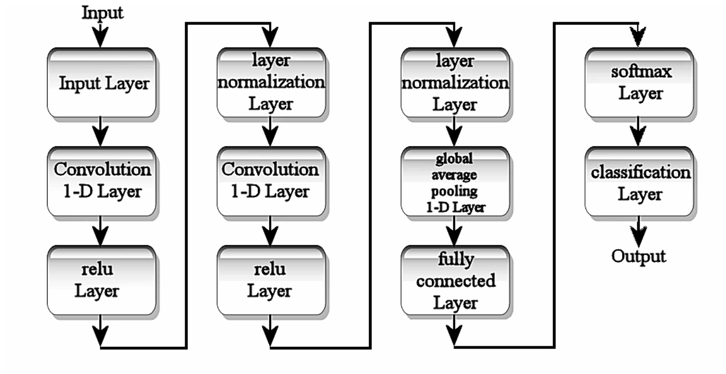

Figure 2. Type 1 Deep Learning Network Block Diagram.

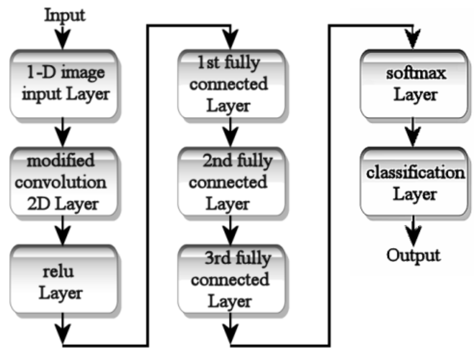

Figure 3. Type 2 Deep Learning Network Block Diagram.

Two different MATLAB classification programs prepared for this specific data set run 50 times with randomly chosen training and validation sets. Type 1 program is based on multidimensional time series 1-D CNN classifier in which only one dimension is used. Type 2 program based on image classification algorithm which uses 1-D feature vectors.

It has been observed that the success rate of the Type 1 algorithm varies from a minimum of 60% to a maximum of 86%. Mean success rate is around %74.79. Best and typical confusion matrix are given in Figure 4 and Figure 5, respectively. The best outcome's run-time training result is also given in Figure 8.

It has been observed that the success rate of the Type 2 algorithm varies from a minimum of 50% to a maximum of 74%. Mean success rate is around %64.38. Best and typical confusion matrix are given in Figure 6 and Figure 7, respectively. The best outcome's run time training result is also given in Figure 9.

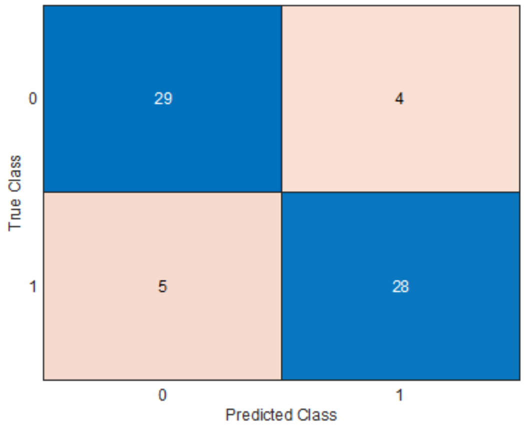

Figure 4. Confusion Matrix of the Classification Algorithm Type 1 for best results.

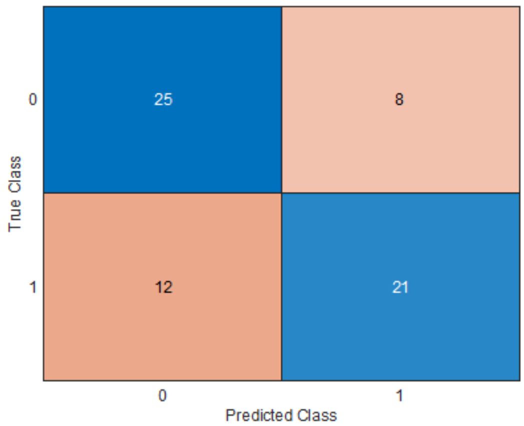

Figure 5. Confusion Matrix of the Classification Algorithm Type 1 for typical results.

In Table 1 results of previously used methods and two types of 1-D CNN classification results are given for comparison. Addition to accuracy results, precision, sensitivity, specificity, and F1-Score values of the methods. Mentioned metrics which provide some measurements of observational error are included for comparison. Following is the explanation used metrics for comparison.

Accuracy generally defined as closeness of the results are to their real values and given previously in Equation (1).

Precision defined in Equation (2). In cases where the cost of incorrect positives is important, the precision value becomes significant.

$$P = 100 \times \frac{NTP}{NTP + NFP}\% \tag{2}$$

Where P is precision, NTP is Number of True Positive Classifications and NFP is Number of False Positives.

Recall is defined in Equation (3). It is a metric that measures the rate of number of transactions predicted as to number of transactions should be predicted as positive.

$$R = 100 \times \frac{NTP}{NTP + NFN}\% \tag{3}$$

Where R is Recall, NTP is Number of True Positive Classifications and NFN is Number of False Negatives. Recall is sometimes called Sensitivity.

Specificity defined in Equation (4) is the conditional probability of negative results given them being truly negative.

$$S = 100 \times \frac{NTN}{NTN + NFP}\% \tag{4}$$

Where S is Specificity, NTN is Number of True Negative Classifications and NFP is Number of False Positives.

The F1 Score defined in Equation (5). The F1 Score is the harmonic average of Precision and Recall values. Using harmonic averages instead of simple average means extreme cases are not ignored.

$$F1 = 2 \times \frac{P \times R}{P + R}\% \tag{5}$$

Where $F1$ is F1 Score , P is Precision given in Equation (2) as percentages and R is Recall given in Equation (3) as percentages.

The numeric results belong to presented data, namely Accuracy, Precision, Recall, Specificity, and F-1 Tests are all summarized in Table 1.

From results obtained we could say that 1-D CNN Type 1 have an acceptable success rate of 75% and but not successful as 2-D image-based classification algorithm. The rest of the metrics except Recall value shows 2-D image-based classification has greater achievement values. 1-D classification algorithms are not as successful as 2-D image based and comparable success values against LSTM network. Especially Type 2 1-D algorithm has low Recall values meaning that algorithm mistakenly classifies large number of positive results as negatives. On the other hand, Type 1 1-D algorithm is unsuccessful classifying negative results.

It is known that deep learning algorithms are greatly successful in image classification and results agree with the previous conclusions. But unfortunately, although the Type 2 method is based on image classification algorithms, it is not successful as 2-D image-based algorithms even worse than Type 1 algorithm. We can conclude that we need more improvement in success rates of the 1-D classification algorithms.

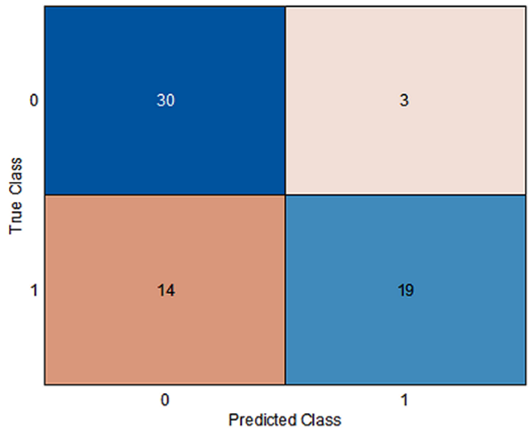

Figure 6. Confusion Matrix of the Classification Algorithm Type 2 for best results.

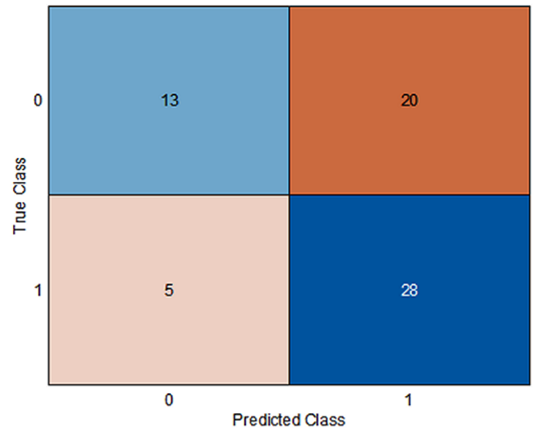

Figure 7. Confusion Matrix of the Classification Algorithm Type 2 for typical results.

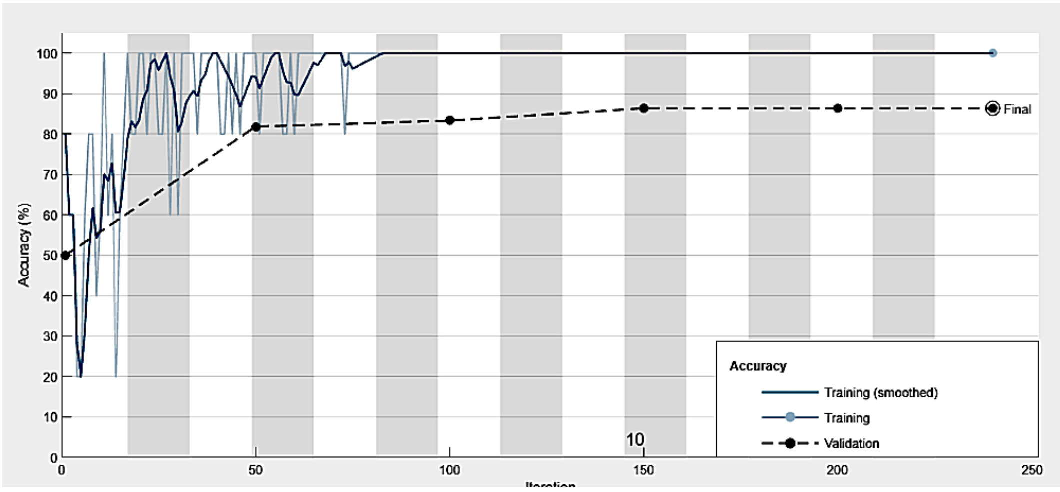

Figure 8. Run time process of the 1-D CNN algorithm Type 1.

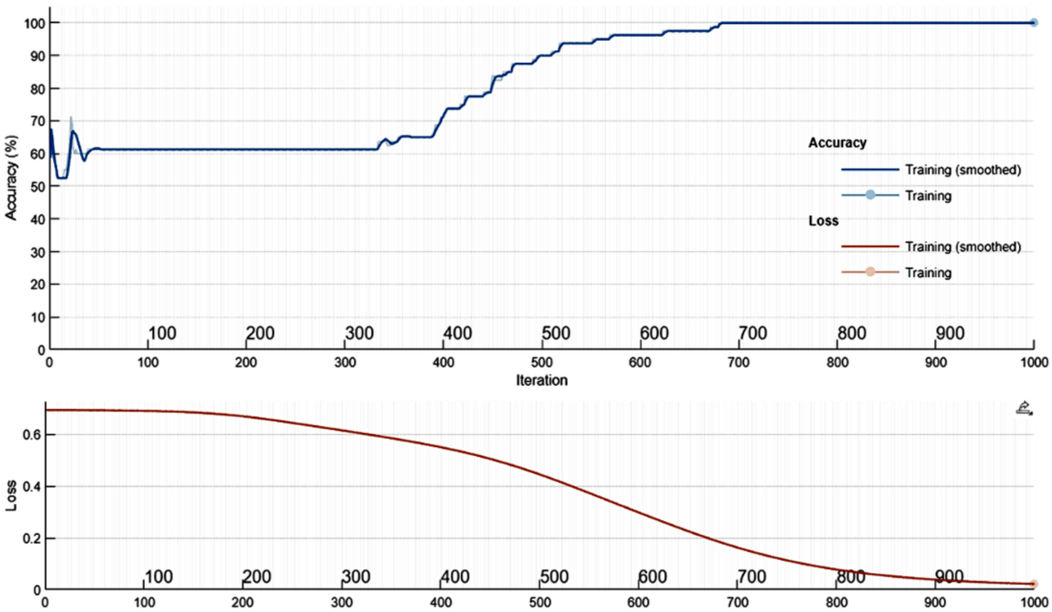

Figure 9. Run time process of the 1-D CNN algorithm Type 2.

Table 1. Ram position details of the motion segments (Times New Roman, 9)

Method	Deep Learning 2-D Image Based CNN (%)	Deep Learning Time Series LSTM (%)	Deep Learning 1-D CNN – Type 1 (%)	Deep Learning 1-D CNN – Type 2 (%)
Accuracy (A)	94	70	75	65
Precision (P)	100	79	68	68
Recall (R)	83	75	91	76
Specificity (S)	100	60	58	64
F1 Score (F1)	91	77	78	72

4. Conclusions

The aim of this study is to investigate TMJ audio data and to evaluate the classification capacity of 1-D Convolutional Neural Networks, two of the subsets of the most popular deep learning tools. For this purpose, previously obtained datasets by the author were used. The performance of the 1-D CNN networks is analyzed in detail.

Deep learning networks application of classification of 2-D data like images are well known and proved greatly successful in many image classification areas. In this study using two types of 1-D approach for classification of 1-D sequences like sound data is tested and reasonably acceptable results in accuracy for 1-D Type 1 CNN are obtained. Regrettably, the accuracy results for the 1-D Type 2 CNN are 65%. Precision, another critical metric, indicates that the 1-D algorithms perform the poorest among the evaluated models. Despite exhibiting satisfactory recall values, specificity values of the 1-D CNN algorithms are significantly inferior to those of the 2-D CNN algorithm.

As concluded in previous studies deep learning networks need a great number of different data sets for successful classification results. In here, we also observe that data sets which we had, do not have enough data for successful data classification.

MATLAB’s Deep Learning toolbox is used as the software development base. Two different approaches using 1-D CNN network are trained and tested using the preprocessed data. According to the results, the 1-D CNN networks trained very successfully, but did not perform as well as expected. As seen from the results, the test accuracy is around 75% and 65% for Type 1 and Type 2 algorithms respectively, although the accuracy of the training results is over 90% for both types of algorithms. The other metric values like precision, recall, specificity also show unsuccessful classification results compared to 2-D image-based classification method.

As previously mentioned, results indicate that during the training phase, the network memorizes the submitted training data. This is generally the result of insufficient data records or data likeness of collections. For more truthful results, more datasets from several subjects should be collected.

In summary, it was concluded that further enhancements in the success rates of the 1-D classification algorithms are necessary. The following paragraphs provide recommendations for improving the research outcomes.

As we continue research and development process, we are planning to gather more data from healthy and unhealthy subjects in the future. In addition, some data preprocessing on collection may be necessary to improve the training and validation success rate.

Our effort to extend the records of the TMJ sound classification continues. To improve to get better results, our research concentrates on sound data classification using larger collection and different sound types belonging to different class of TMD like crepitation, clicking, popping, and popping clicking.

Using additional deep learning methods and algorithms like Hidden Markov Models are planned and currently under study.

The proposed methods enable clinical diagnosis of individuals having TMD. This approach provides physicians with insights into the effectiveness of treatment modalities such as use of drugs and/or splint application during the management of the disorder. Additionally, it facilitates the detection of reductions in joint sounds. Consequently, we believe that this study will be beneficial to dentists in the diagnosis of TMJ disorder.

Notes

The data collection phases of this study were conducted at Selcuk University, Faculty of Dentistry, utilizing a setup developed by the author. Ethical approval was obtained from the Non-Invasive Clinical Research Evaluation Committee of Selcuk University, Faculty of Dentistry (Meeting number: 2011/05, Date: 05.05.2011).

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