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MULTICLASS MOTOR IMAGERY DATA CLASSIFICATION USING DEEP LEARNING METHOD FOR BCI APPLICATION

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ABSTRACT

The Brain Computer Interface (BCI) systems have incredible applications both in clinical and non-clinical areas. Electroencephalography (EEG) is one of the most used neuroimaging techniques to acquire brain activity in BCI Systems. However, EEG signals are usually very complex and require extensive processing to analyse them. This paper explores the implementation of motor imagery (MI) paradigm based BCI system based on the on deep learning. A typical deep learning model includes the stages of pre-processing, feature extraction and classification in single model. However, such model requires lot of data for training purpose. In order to compensate this data requirement, this paper implements a deep learning model based on CNN with extracted features as an input. The implemented model consists of three CNN layers followed by fully connected layers. The model performed with 80% of classification accuracy on average in offline analysis. In real-time analysis, the approximate accuracy was 66.9 % across the subjects.

Keywords: BCI, deep learning, motor imagery, multiclass classification, EEG.

INTRODUCTION

Electroencephalography (EEG) is a neuroimaging technique which captures the brain activity by measuring the electrical fields resulted from the brain activity. For studies related to sleep patterns [1] and to detect epilepsy [2], EEG has been widely used. In addition, the EEG has also been majorly used in the area of Brain-Computer Interface (BCI) due to its relatively low cost and high temporal resolution [3].

Even though EEG is very useful to capture brain activity and required easy setup and provide good mobility, it also suffers from some shortcomings which hamper processing and analysing process [4]. One of the major limitations of EEG signal is poor Signal to noise ratio (SNR) [5]. Due to this, the signal pertaining the actual brain activity often overshadowed by the other signals from various sources such as environmental, biological and signals generated by user's physical activity. To increase the SNR and remove the unwanted components from the EEG signals, a multitude of various methods used by the researchers in recent years [6]. While these methods have been successful and highly beneficial in improvising signal quality and in the extraction of useful features, they are observed to reduce the generalization capabilities and flexibility of EEG based systems [7].

The Deep learning methods can be used to improvise the processing of EEG signals due to process the signal in single process which includes the stages or pre-processing, 6feature extraction and classification. The Deep Learning architectures have been very successful in recent years especially in the processing of Text, Sound signals and Images [8]. Recently, deep learning-based approaches using Convolution Neural Networks (CNN), Recurrent Neural Networks (RNN), Stacked Auto Encoders (SAE), and Deep Belief Networks (DBN) have been used in various BCI applications. [9-11].

While the Deep Learning methods can solve variety of problems but they are also not without limitations. One of the major limitations of the Deep Learning methods is the high requirement of data to train the network. Consequently, large amount of data required large number of computations also, so, the models are costly to train in terms of computational power. However, the computations required to classify new instance of data required very low amount of computations relatively.

In this paper, a CNN based Deep Learning model is implemented to classify four types of imagery motor activities.

EXPERIMENT DESIGN AND DATA COLLECTION

In this paper, the EEG machine used for data collection was supplied by the NCC medical corps. It is a portable EEG unit. The EEG data will be recorded from 24 channels arranged in 10-20 system standards. The signals were filtered 0.1 Hz−40 Hz using a band pass filter. The raw data was stored in system native in NED format which was subsequently converted to a.txt file for further processing using software supplied by the NCC medical. EEG system controls the data acquisition process and psychophysics toolbox controls experimental design. Data processing was done using Matlab. The EEG machine used for data collection is Type D EEG/ERP/PSG System (Fiber optical transmission) with ERP/PSG function, Model No: Nation 7128W-D. This system is useful for research purpose and is used by several laboratories. It has good features like a) provides good signal quality with optical fiber isolation. Only signal is transmitted. The data transmission bandwidth is better when compared to ordinary cable providing high speed data transmission. b) 24 bits analog to digital converter is used. c) Provision for in built impedance testing and automatic calibration (both sine wave and square wave). c) It is fully battery operated device.

Experimental Procedure

The subject is seated in a comfortable chair wearing an EEG cap as shown in the figures. We have two types of subjects, normal healthy adults and patients with cognitive disability. The subject is shown a stimulus on the LCD monitor placed approximately 2 feet in front of him/her. The stimulus consists of images of hands and legs which appear in four boxes.

The images of hands will appear in the top row of boxes and images of legs will appear in the bottom row of the boxes. Only one image will appear at a time. When image of a hand appears in the left box (Top row), the subject has to imagine the movement of the left and when image of the leg appears on the left box (Bottom row), the subject has to imagine the movement of the left leg. The subject has to imagine movement of hand and leg of right side when stimuli appear on the right side of the boxes. Each of this imagery activity is called a trial and there are total 50 trials for each of the hand and leg movement making a total of 200 trials. Each trial is about the duration of three seconds, followed by three seconds of rest or relaxation period. Figures 1 & 2 shows visual presentations of the experimental setup for ALS patient and healthy control respectively.

Figure-1. Experimental setup for ALS patient.

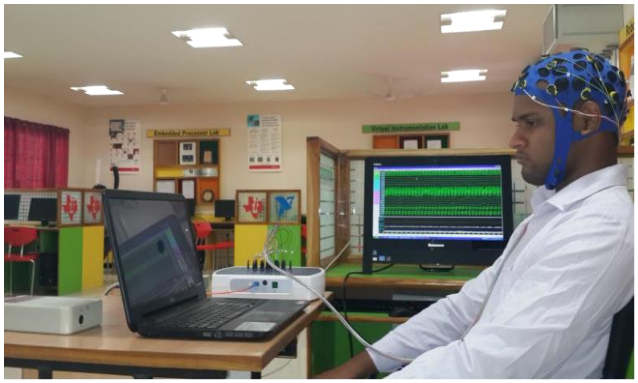

Figure-2. Experimental setup for healthy controls.

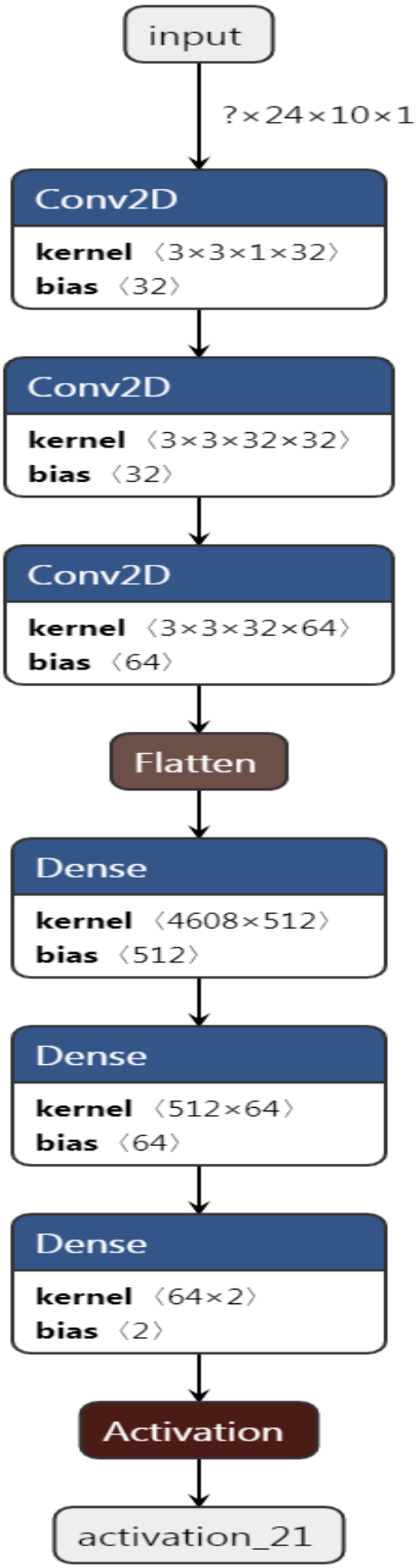

Figure-3. DNN architecture.

Subjects

Ten neurotypical subjects aged from 20 to 30 years (6 Male, 4 Female) and Four neurologically disordered (2 ALS, 1 Quadriplegic, 1 Diplegic patient) subjects were used to the MI paradigm. Among the two ALS patients, one was 58 years old, Female, in the advanced stages of the disease. The other patient was of age 22, Male in the beginning phase of the illness. The quadriplegic patient was of age 35, Male, while the diplegic patient is of age 40, Male. The participants had no previous exposure to BCI or psychological experiments. The study was done after getting approval from the local ethics committee.

METHODOLOGY

Convolution neural networks (CNN) can learn powerful representations which are invariant against partial spatial translation or deformation made them leading the deep learning architectures. The proposed method was aimed to implement the CNN architecture for BCI system. In general, CNN architecture entails multiple convolution layers followed by dense or fully connected layers. CNN usually takes raw data as input for training the network. The data required for training CNN are much more than the traditional machine learning approaches. The amount of available was not sufficient to train a CNN based model, So, it was decided to reduce convolution layers in the architecture and use features as an input so as to train the network.

24 channel EEG data was used in this study. For each channel, the features were calculated using cross correlation method [12].

The cross correlation (CC) method was used to extract features. The features used in this method are total 10 features. They arei) mean, ii) median, iii) variance, iv) first quartile, v) third quartile, vi) inter-quartile range, vii) minimum, viii) maximum, ix) mode and x) RMS value of the signal. As there are twenty-four channels in the EEG data used, the feature matrix consists of size 24x10. The extracted features are of similarity-based type features, so a single architecture will not be able to perform classification for more than two classes.

For multiclass classification, the problem needs to be simplified into multiple binary classifications. The one verses rest approach is designed for such scenarios and hence implemented in this work. Figure-1 shows the architecture of neural networks. One dimensional discrete convolution is given by the equation

$$\mathrm{H[i]} = \sum_{\mathrm{u=-k}}^{\mathrm{k}} \mathrm{F[u].G[i-u]}$$

Where H is result of convolving F and G, i points to discrete value.

The modified convolution with filter size k is

$$H[i] = \sum_{u=-k}^{k} F[u].G[i-u] \quad \forall i \in \{1,2 \ldots\ldots n\}$$

Where n is number of elements in G.

Neural network has multiple parameters which are updated or trained to match the patterns of the data. The parameters of the proposed neural network architecture are shown in Table-1.

The Neural Network architecture has more than 2.4 million parameters which are updated or trained. Thus, this neural network architecture has high requirements of both data and in terms of training time. However, when it comes to classifying the data, the classification time can be considered as reasonably low, which makes these types of architectures good choice for real-time classification problems. Figure-2 illustrates the overall flow of the processes followed.

Table-1. DNN parameters.

Layer	Output Shape	Parameters
(Conv2D)	(None, 22,8,8)	80
(Conv2D)	(None, 20,6,16)	1,168
(Conv2D)	(None, 18,4,32)	4,640
(Flatten)	(None, 2304)	0
(Dense)	(None, 512)	11,80,160
(Dense)	(None, 64)	32,832
(Dense)	(None, 2)	130
(Activation)	(None, 2)	0
Total parameters:	12,19,010	

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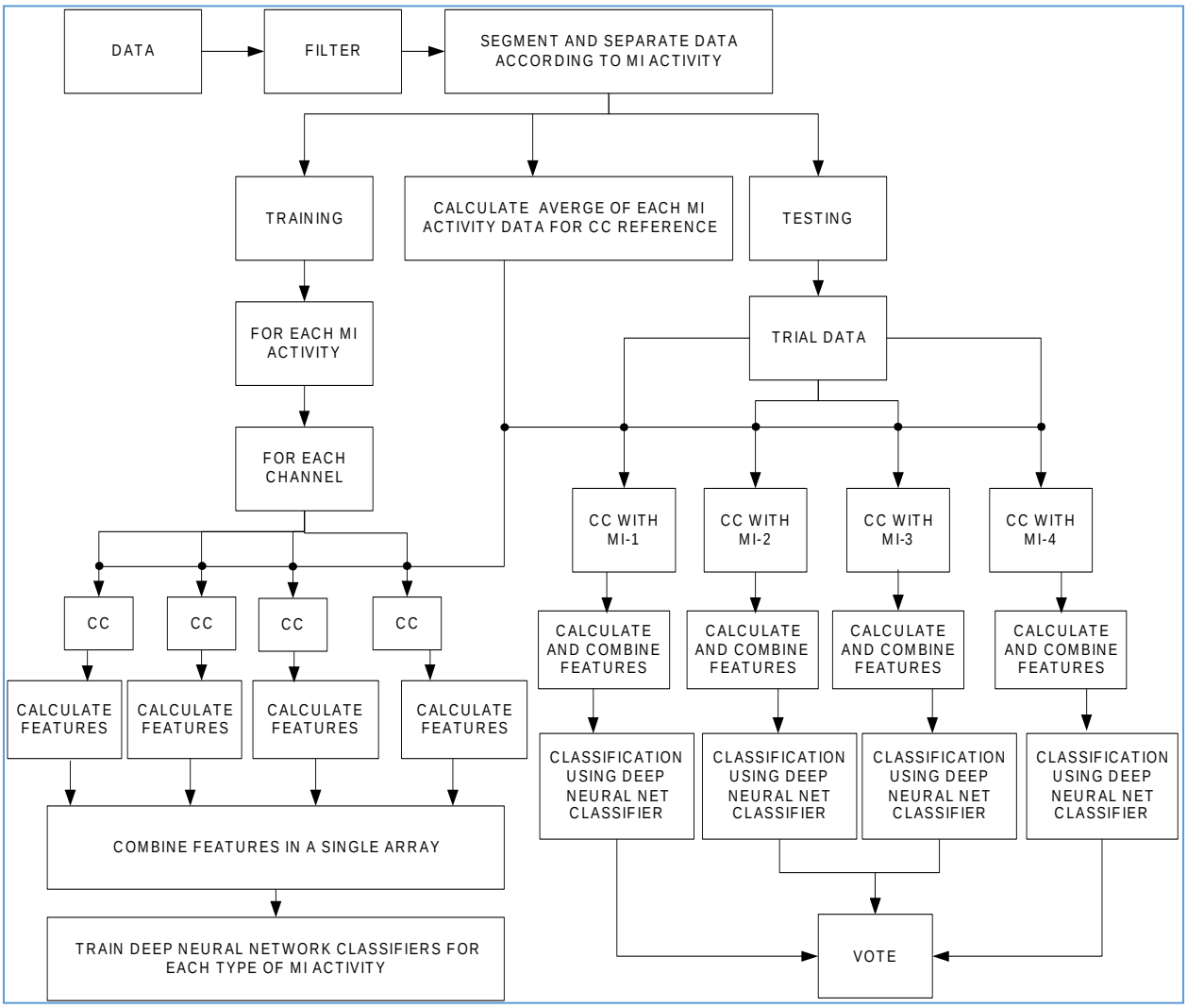

Figure-4. Deep neural network-based classification.

Importance of Various Layers in Neural Networks

The traditional machine learning algorithm takes features as input data and provides a classification label as an output. However, in case of DNN model, the neural network itself takes care of extraction part. This approach requires multiple convolution layers which serve as a feature extraction process. In this approach, though features are provided as inputs, because the available data deemed to be not sufficient to fully train the deep neural network, the proposed architecture basically extracts features from the set of features. This can be assumed as transformation process or as a feature selection. The fully connected or dense layers followed by convolution layers do the classification process. Ten features are calculated in this method. They are Mean, Median, Mode, SD, Maximum, Minimum, Q1, Q3, IQR and RMS value.

1. Mean (μ)of cross correlated signal is

$$\mu = \frac{\sum_{i=1}^{m} \check{R}[i]}{m}$$

2. Median: The first step in calculation of median is arranging the data in ascending or descending order. This is followed by conversion of simple frequencies into cumulative frequencies. Hence another column for cumulative frequency needs to be constructed, wherein the last value is labelled as the value of N (i.e. ∑f). Next, we need to find the value of (N+1)/2. Lastly, the value corresponding to the cumulative frequency just greater than (N+1)/2 is termed as the median for the data.

   Median = value of $\left(\frac{N+1}{2}\right)^{th}$ item

   Where N is number of observations
3. Mode: Most frequent value in a data set
4. Standard deviation (σ)of cross correlated signal is

$$\sigma = \sqrt{\frac{\Sigma(\check{R}_i - \mu)^2}{N}}$$

5. Minimum value = $\min_{1 \le n \le m} (\check{R}_m)$
6. Maximum value = $\max_{1 \le n \le m} (\check{R}_m)$

7. 1st quartile is given by
   Q1=value of $\left(\frac{n+1}{4}\right)^{th}$ item ($n = \sum f$)
8. 3rd quartile is given by
   Q3=value of 3 $\left(\frac{n+1}{4}\right)^{th}$ item
9. IQR= Q3-Q1
10. $\text{RMS} = \sqrt{\frac{\sum_{n=0}^{N-1} u^2\ (n)}{N}}$

Where N is number of samples
And u(n) is sampled instance of u(t)

Performance Evaluation

The functionality of the algorithm can be calculated in several parameters. The most frequently used parameter used to measure performance in classification tasks is classification accuracy. Another parameter which can be counted as equally important in real-time classification tasks is the time taken to classify a sample. There are several other parameters which are also used to evaluate a classifier model such as accuracy, Error, sensitivity, specificity, Precision, FP Rate, F1_score, MCC and Kappa value. The values of the given performance parameters are given by

1. Accuracy (A) is calculated using equation
$$\text{Accuracy(A)} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$
2. Error (E) =1-A
3. Sensitivity: It is also called as true positive rate (TPR) and an indication of samples that are genuinely positive.
$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}} \times 100$$
4. Specificity: Also called as true negative rate (TNR). It is an indication of samples that are genuinely negative.
$$Specificity = \frac{TN}{TN + FP} \times 100$$
5. Precision: Ratio of correct positive values to total positive values
$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$
6. Recall and sensitivity are same
$$Recall = \frac{TP}{TP + FN}$$
7. False Positive Rate (FPR): It is the ratio between number of negative events classified as positive (FP) and total number of actual negatives (FP+FN)
$$FPR = \frac{FP}{FP + TN}$$
8. F1_score: is a measure of test accuracy. It is the harmonic mean of precision and recall. Its highest value is 1 which indicates perfect precision and recall whereas lowest value is 0 if either precision or recall is 0.
$$F1\ Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$
9. Matthews Correlation Coefficient (MCC): It has range from -1 to +1, where -1 indicates complete wrong classification whereas +1 indicates correct classification
$$\text{MCC} = \frac{\text{TP X TN} - \text{FP X FN}}{\sqrt{(\text{TP} + \text{FP})(\text{TP} + \text{FN})(\text{TN} + \text{FP})(\text{TN} + \text{FN})}}$$
10. Kappa value is calculated using the equation
$$\text{K} = \frac{\text{P}_\text{o} - \text{P}_\text{e}}{1 - \text{P}_\text{e}} = 1 - \frac{1 - \text{P}_0}{1 - \text{P}_\text{e}}$$

Where:
Po = Observed Accuracy
Pe = Expected Accuracy (random chance)

The range of Kappa value is 0 to 1. Where the values of 0 signify that the classifier is performing worst while the values of >0.8 indicates almost perfect classification.

RESULTS AND DISCUSSIONS

Deep neural network classification results are represented in **Error! Reference source not found.**. From the table, it has been observed that the average classification accuracy is 80.56%. There are multiple parameters which can be used to evaluate a classification model. The results from a model are usually tallied into a table called confusion matrix which can be used to calculate different parameters to estimate the performance of the classifier. Table-3 represents confusion matrix for one of the subject's data. From the confusion matrix, multiple parameters can be calculated. The class-specific parameters are shown in Table-4. The parameter values in the Table-4 specifies that the class-wise performance of the given classification model is uniform across the classes. The overall performance measure for the given subject data is displayed in Table-5. The parameters in Table-5 indicate the classification model's performance. The Accuracy as well as Error of the model can be considered good. The other parameters show that the performance of the classifier model performed decently for this subject data.

Table-2. Classification accuracies.

Subject	Classification accuracy (%)
S1	80.21
S2	80.15
S3	79.83
S4	81.34
S5	78.38
S6	79.67
S7	81.29
S8	80.55
S9	78.28
S10	85.94

Average	**80.56**

Table-3. Confusion matrix - DNN method.

Actual / Predicted	Class1	Class2	Class3	Class4
Class1	43	4	1	0
Class2	5	38	3	0
Class3	3	3	39	2
Class4	1	2	3	40

Table-4. Classifier performance parameters.

	Sensitivity	Specificity	Precision	F1_score	Matthews Correlation Coefficient	Kappa
Class1	0.86	0.9404	0.82692	0.84314	0.7901	0.51817
Class2	0.76	0.9404	0.80851	0.78351	0.71533	0.54836
Class3	0.78	0.95364	0.84783	0.8125	0.75494	0.54868
Class4	0.8	0.98675	0.95238	0.86957	0.83655	0.55836

Table-5. Overall performance parameters.

Parameter	Value
Accuracy	0.801
Error	0.199
Sensitivity	0.84
Specificity	0.9512
Precision	0.7014
False Positive Rate	0.0488
F1_score	0.6884
Matthews Correlation Coefficient	0.6711
Kappa	0.3781

The Deep Neural Network did not yield classification accuracy as compared to other methods available in the literature. However, the time to classify new data in real-time scenario was observed to be least among all four real-time methods. For real-time, the average classification accuracy was estimated of approximately 66.9 % as shown in Table-6 based on the feedback received from the subjects.

Table-6. Real-Time results.

Subject	Approx. rate of MI Activity Detection (%)
1	75
2	67
3	68
4	60
5	71
6	63
7	67
8	63
9	64
10	71
Average	**66.9**

Finally, the proposed DNN method is compared with state of art methods in the literature. The Figure-5 depicts the comparison of the performance of the proposed DNN method with the other similar research work in terms of classification accuracy.

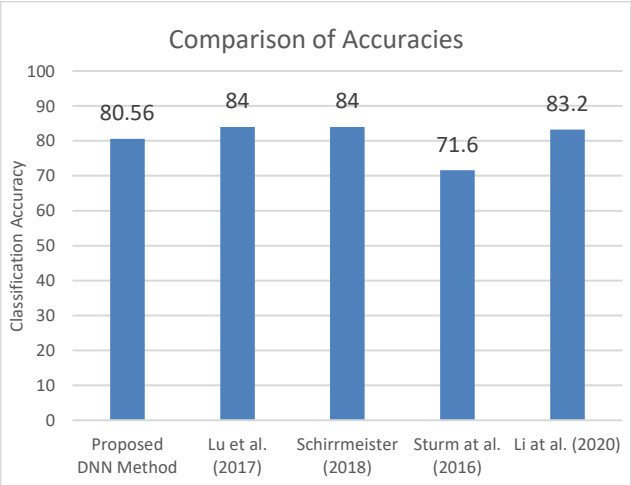

Figure-5. Comparison of DNN method with latest methods.

The classification accuracies reported by Lu e*t al.* [13] and Schirrmeister *et al*. [14] and Li *et al.* [15] are higher than the proposed DNN methods. The classification accuracies reported by the above studies was 3-4 % higher than the proposed DNN method. However, the abovementioned studies were implemented for classifying between two types of MI activities whereas the proposed method is aimed to classify between four types of MI activity. The method proposed by Sturm [16] was implemented to classify three types of MI activity but was reported classification accuracy of 71.6 % while the average classification accuracy of the proposed DNN method is 80.56 %.

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