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An Effective Cluster-Based Outlier Detection with Optimized Deep Neural Network for Epileptic Seizure Detection and Classification Model

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Abstract *- Epileptic seizure diagnosis using Electroencephalogram (EEG) signal is an essential process in the healthcare sector to detect the abnormal growth of brain activities. Since epileptic seizure detection by physicians requires more time, it is needed to design an automated epileptic detection model. Due to the advancements in the Deep Learning (DL) models, it can be employed in the diagnosis of epileptic seizures from EEG signals. This paper presents a new hierarchical clustering with adaptive momentum (ADAM) optimized Deep Neural Network (DNN), called the HC-DNN-ADAM model. The presented model involves HC-based outlier detection to remove the unwanted data from the input dataset; thereby, the classifier results can be improved. In addition, the HC-DNN-ADAM model utilizes DNN for the classification process where the hyperparameters of DNN are tuned by ADAM optimizer. For examining the effectual classifier results analysis of the HC-DNN-ADAM model, a benchmark Epileptic Seizure Recognition dataset is utilized. The application of HC and ADAM paves a way to achieve better classification outcomes. The performance of the HC-DNN-ADAM model has been validated using a benchmark dataset. The simulation outcomes signified that the HC-DNN-ADAMmodel has resulted in maximum detection performance with an accuracy of 99.74% on the classification of multiple classes of seizures.*

Keywords: *Data classification, Deep learning, Epileptic seizure, Outlier detection.*

I. Introduction

Epilepsy is a neurological brain infection caused due to the prominent existence of epileptic seizures, which is emerged from irregular brain activities. The features of seizures are loss of awareness, interrupted action, sensation, and alternate cognitive movements. The complete incidence of epilepsy is considered to be 23-100 per 100,000. Mostly, aged peoples are affected by epilepsy, and young individuals are affected rarely. Epilepsy is a highly dreadful disease where the massive number of peoples is infected globally. Around 70% of epileptic patients can be recovered by using Anti-Epileptic Drugs (AED), where some peoples exceed the normal stage, which results in a mortal rate.

Followed by, Electroencephalogram (EEG) is a digital device that records electrical signals of brain movements which are assumed as an effective diagnostic tool of epilepsy. Physicians categorize the brain functions of epileptic patients with the help of EEG details into 4 stages, namely, Preictal state, and it is a time period immediately before the seizure occurrence; Ictal state, it is period of seizure existence; then, Postictal state, which is allocated to the certain period after the seizure is caused and lastly, interictal state means the period among seizures when compared with traditional modules. Because of the irregular seizure times, epilepsy is impacted by psychological and social effects, which result in life-threatening disorders. As a result, earlier detection and diagnosis of epileptic seizures are highly essential for enhancing the lifetime of epileptic affected patients; some of the measures are invoking an alarm before the seizure occurrence so that enough time is given to take appropriate actions, making better treatments and novel strategies to know the principle of this disease.

Based on the above statement regarding the brain function of epileptic patients, seizure prediction can also view as a classification among preictal and interictal brain conditions. Here, an alarm is fixed to detect the preictal state between the higher interictal state, which refers to a capable seizure. The prediction duration is a time before a seizure onset if a preictal state has been predicted. In this approach, a different method has been projected to report the seizure prediction issues and manages to gain better classification accuracy in earlier detection. As an EEG signal varies from patient-to-patient because of the difference in seizure type and position, massive seizure prediction models are patient-centric. Seizure prediction by applying EEG signals was examined in the last decades.

[2] applied a Discrete Wavelet Transform (DWT) for the purpose of extracting EEG features and unified the Multilayer Perceptron Network (MLP) with Radial Basis Function (RBF) to classify data. [3] examined seizures with various attributes of wavelet coefficients where the frequency bands from EEG signals are acquired. [4] divided the EEG signals as sub-band signals under the application of wavelet packet transform and employ the SVM model for epileptic prediction.

[5] employed approximate entropy as well as sample entropy as EEG characteristics, correspondingly, and integrated the above-mentioned modules with Extreme Learning Machine (ELM) for computing automated prediction of epileptic seizures. According to pattern recognition, a new model for predicting seizures has been proposed and sampled under the application of the Freiburg database. Then, it is also utilized for symbolic data analysis of EEG signal according to the Ngram model, and probability-based pattern analysis is defined as the existence of symbolic data inside data. Developers presented a technique on the basis of Mean Phase Coherence (MPC). MPC is the value of phase synchronization, which is to reduce the seizure onset. [6] established a framework by integrating patient-based Machine Learning (ML) as well as multivariate characteristics. Afterward, features have relied on eigen-spectra of space delay association as well as covariance matrices as processed in several time delays. Recently, Deep Learning (DL) has accomplished popularity for clinical examination as well as bioelectric signal processing. Using a massive amount of details, it performs well than classical feature extraction and ML approaches in pattern analysis and image examination with respect to classification accuracy.

Generally, DL models like Convolutional Neural Network (CNN) are applied in seizure prediction. For instance, [7] utilized a 13layer depth CNN with EEG signals for detecting seizures and accomplished maximum performance. [8] produced a Mean Amplitude Spectrum (MAS) map from EEG signal and embedded CNNs with SVMs for the purpose of computing feature extraction as well as classification. As a result, maximum seizure prediction accuracy has been attained. Followed by classification accuracy, sensitivity has been employed to estimate the classification function. [9] utilized CNN for learning features from time-frequency maps of EEG signals where classification has been accomplished better sensitivity. Also, [10] employed a CNN structure with a convolution layer for extracting features from wavelets of EEG signals where maximum seizure prediction sensitivity has been obtained. Hence, massive studies have employed domain knowledge for selecting certain channels for examination purposes, whereas data-driven analysis. Furthermore, the efficiency of classifying seizures still remains a dark room for EEG signals with the latest signal processing as well as DL models.

The central premises of this literature are to enhance the classification accuracy by examining EEG signals of diverse epileptic states of the brain where it is helpful in the prediction of seizures. The challenging issues of the traditional model are to compute discriminative attributes which exhibit a class. The processing time required to filter the features are based on complexity which is considered in real-time application. Inspired by these challenges and because of the importance of previous and precise seizure detection, DL based seizure prediction mechanism has been developed and unifies the feature extraction and classification phases as a single automatic approach.

This paper presents a new hierarchical clustering with adaptive momentum (ADAM) optimized Deep Neural Network (DNN), called the HC-DNN-ADAM model. The presented model involves HC-based outlier detection to remove the unwanted data from the input dataset; thereby, the classifier results can be improved. In addition, the HC-DNN-ADAM model utilizes DNN for the classification process where the hyperparameters of DNN are tuned by ADAM optimizer. For examining the effectual classifier results analysis of the HC-DNN-ADAM model, a benchmark Epileptic Seizure Recognition dataset is utilized. The application of HC and ADAM paves a way to achieve better classification outcomes. The simulation analysis of the HC-DNN-ADAM model takes place on the benchmark database, and the results are observed in numerous aspects.

II. The Proposed HC-DNN-ADAM model

Fig. 1 shows the workflow of the HC-DNN-ADAM model involves a set of different processes, such as preprocessing, outlier detection, classification, and parameter tuning. Once the input medical data is preprocessed, the outliers are detected by the HC technique. Then, the DNN-ADAM model is applied for the classification process in which the parameters of the DNN model are tuned using an ADAM optimizer.

A. Preprocessing

Initially, minimum-maximum (min-max) approach was employed for dataset normalization. Here, the low and high values have been assumed in data collection. Every data undergoes normalization into the range of 0 to 1. The key objective of this approach is to generalize low value to 0 and high value to 1, where it distributes the values from 0 to 1. Eq. (1) has been employed for describing the performance of min.-max. Normalization.

$$Min - Max.Norm = \frac{x - x_{min}}{x_{max} - x_{min}} \qquad (1)$$

As a result, class labeling is computed with the samples of EEG signal dataset that has been allocated for proper class labels like 0, 1 named as a binary class and 0, 1, 2, 3, and 4 for multi-class.

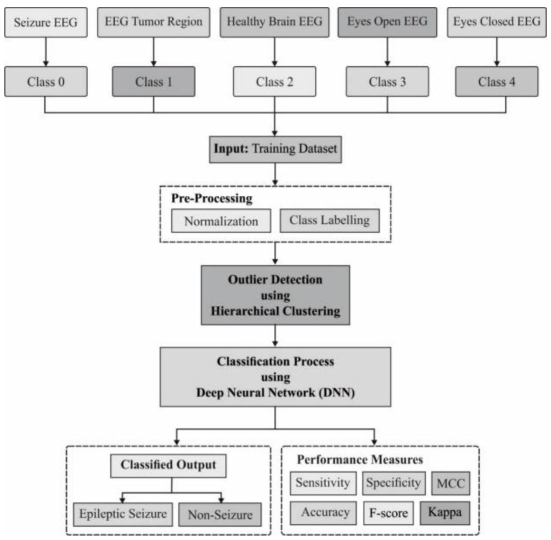

Fig. 1. Block diagram of HC-DNN-ADAM Model

B. HC based Outlier Detection

Outlier or anomalous prediction is considered a significant issue of ML and Data Mining (DM). Noise prediction is an issue of identifying patterns in data which does not ensure the desired behavior. The utilizations of outlier predictions are identified in massive applications like intrusion detection, credit fraud prediction, video observation, climatic forecasting, identification of fraud actions, and so on. In recent times, massive outlier prediction models were developed, such as point outliers, contextual outliers, as well as collective outliers. Here, it is concentrated on deploying point outliers prediction, which is used in various domains. For a dataset with points, a point is named as an outlier when it is varied from the massive count of remaining points. In order to predict outliers, some of the principal approaches used in this study are the classification method, nearest neighbor methods, clustering methods, statistical methods, distance-related methodologies, and so on. This paper makes use of the HC technique for the detection of outliers.

The dissimilarity matrixes, agglomerative hierarchical clustering models [11] have been employed for identifying similar groups of data positions. The agglomerative method is defined as a "bottom-up" technology where a sample position is initialized in a cluster; in all hierarchies, the 2 clusters are similar with bigger clusters till making sample locations into massive clusters. Hence, simulation outcomes are tree-based object representations called a dendrogram. In every step, distances (dissimilarities) from novelty developed clusters and previous clusters are processed in diverse ways; the 3 prominent linkage criteria are Single, Average, and Complete linkage.

In the case of single-linkage hierarchical clustering, distance from 2 clusters G and H is composed of minimum distance among 2 members of 2 clusters:

$$d_{single}(G,H) = \min_{i\in G, j\in H} d_{ij}. \quad (2)$$

In the case of average linkage hierarchical clustering, distance from clusters G and H is the same as arithmetic mean distance from each member in 2 CM:

$$d_{average}(G,H) = \frac{1}{n_G \cdot n_H} \sum_{i\in G, j\in H} d_{ij}. \quad (3)$$

In case of complete linkage hierarchical clustering, distance from clusters G and H equals the higher distance from 2 CM of 2 clusters:

$$d_{complete}(G,H) = \max_{i\in G, j\in H} d_{ij}. \quad (4)$$

It is popular that the single linkage criterion intends to generate long, "loose" clusters. Clusters emerged from the average linkage procedure among long-chain clusters and compact clusters.

Cluster estimation is a major problem in data clustering models. Here, the prominent internal cluster validation indexes are silhouette index. It determines the clustering function according to the pair-wise difference among and inside cluster distances [12]. The best cluster value is that it enhances the index value by eliminating the dendrogram as well. Fig. 2 illustrates the structure of the HC model.

Afterward, the presented clustering schemes ("R1 model is related by a simulation and usage of a real data"), in terms of 2 base methods "N1 method considers spatial data by applying geographical coordinates as excess parameters ("D1 model").

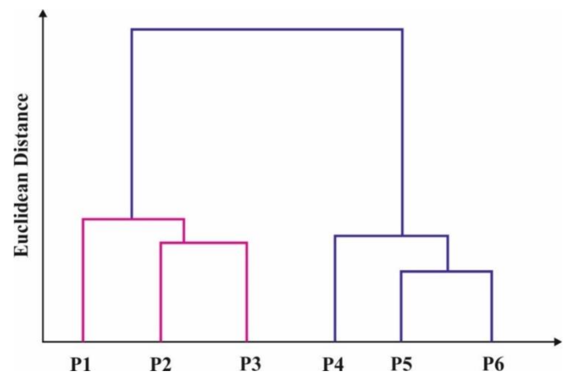

Fig. 2. Hierarchical Clustering

C. DNN based Classification

Once the data pre-processing and outliers are removed, DNN is used to learn the deep features and perform classification tasks [13]. DNN of 3-layer structure is composed of Sparse Auto Encoder (SAE) as well as Softmax classification models. At the initial phase, the simulation outcome has been assumed as an efficient parameter induced as input for upcoming SAE that is a stack-like architecture. Finally, the outcome of the 2nd SAE is considered as a standard protocol when compared with results obtained from the first SAE. Subsequently, the extended version of AE intends to SAE for learning the sparse features in an unsupervised manner using sparsity penalty with AE.

Under the application of this method, the performance of traditional automated encoders has been expanded and employed widely for practical applications. Fig. 3 implies the architecture of the DNN scheme. Hence, AE is comprised of the input layer, a hidden layer, and an output layer. Hence, the final results of the hidden layer are considered to be an optimal feature of unlabeled data by limiting the discrepancy between novelty deployed frameworks. An effective AE is embedded with an encoder and decoder, which have been employed in learning the appropriate measure of hidden layer in recreating the original data at the final layer. In addition, a number of hidden units is assumed to be a major key aspect that influences the simulation outcome of a classification approach. By training SAE, the best attributes of weight and bias were gained in which Back-Propagation (BP) technology limits the expensive cost of the entire process. Hence, weight and bias are maximized in all iterations using Stochastic Gradient Descent (SGD) scheme. In this technique, a softmax classifier which extends Logistic Regression (LR) has been utilized for classification process, which is connected to first SAE and fine-tunes the entire network.

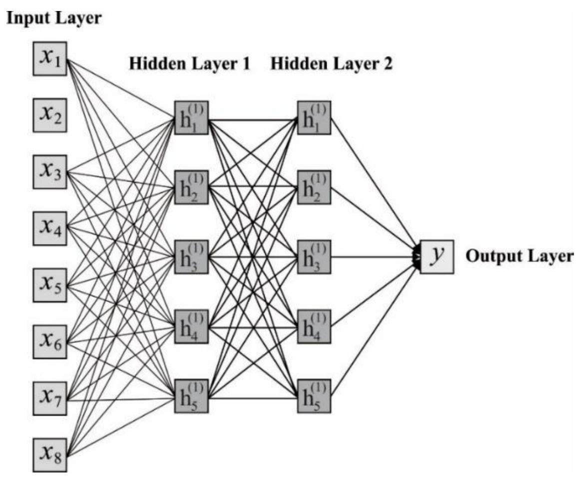

Fig. 3. Architecture of DNN

D. ADAM based Parameter Tuning

The Adam method is applied for estimating adaptive learning value where the parameters are utilized for training the parameters of the DNN model. It is effective and elegant approach for the 1st order gradients with limited memory space for stochastic optimization. Here, the newly presented model has been applied to resolve the ML issues with higher-dimensional parameter spaces and massive datasets which measure the learning rates for different attributes from approximations with 1st as well as 2nd-order moments [14]. Also, the ADAM scheme is applied extensively according to the GD as well as momentum technique, and a difference of an interval. Hence, first momentum has been attained by,

$$m_i = \beta_1 m_{i-1} + (1-\beta_1)\frac{\partial C}{\partial w}. \tag{5}$$

The 2nd momentum is expressed by,

$$v_i = \beta_2 v_{i-1} + (1-\beta_2)\left(\frac{\partial C}{\partial w}\right)^2. \tag{6}$$

$$w_{i+1} = w_i - \eta\frac{\hat{m}_i}{\sqrt{\hat{v}_i + \epsilon}}, \tag{7}$$

where $\hat{m}_i = m_i/(1-\beta_1)$ and $\hat{v}_i = v_i/(1-\beta_2)$. The pseudocode version of this method is as follows in Algorithm 1.

Adam limits the processing cost, demands for lower memory space, and invariant for diagonal rescaling. It considers the problems; however, it is not applicable for massive data sets, hyper-parameters, noisy details, insufficient gradients, and non-stationary issues which require minimum tuning. Adam development variables are alpha α: it is a learning rate, presumably selecting massive estimation with respect to actuality which accomplished a robust learning rather than smaller esteem in which back adapting are accurate in training phase.

Algorithm 1: Pseudo-code of ADAM model.
η: Learning rate $\beta_1, \beta_2 \in [0,1)$: Exponential decay values for moment estimates $C(w)$: Cost function with variables w w_0: Initial parameter vector $m_0 \leftarrow 0$ $v_0 \leftarrow 0$

$i \leftarrow 0$ (Initiate timestep)

while w not converged do

$$i \leftarrow i + 1$$

$$m_i \leftarrow \beta_1 \cdot m_{i-1} + (1 - \beta_1) \cdot \frac{\partial C}{\partial w}(w_i)$$

$$v_i \leftarrow \beta_2 \cdot v_{i-1} + (1 - \beta_2) \cdot \frac{\partial C}{\partial w}(w_i)^2$$

$$\hat{m}_i \leftarrow m_i / (1 - \beta_1^i)$$

$$\hat{v}_i \leftarrow v_i / (1 - \beta_2^i)$$

$$w_{i+1} \leftarrow w_i - \eta \cdot \hat{m}_i / (\sqrt{\hat{v}_i} + \epsilon)$$

end while

return w_i (Resulting variables)

III. Performance Validation

The result analysis of the HC-DNN-ADAM method is applied in Python 3.6.5 tool and the performance outcome has been analyzed with respect to diverse performance measures. For investigation of the HC-DNN-ADAM approach, Epileptic Seizure Recognition dataset has been applied [15]. It is composed of EEG signals under 5 class labels like eyes open, eyes closed, with tumor region, normal brain, and epileptic seizure as depicted in Fig. 4. Moreover, it has collection of 11500 samples with 2300 instances in all class labels. Table 1 illustrates the dataset description. The samples from binary classes are collected with and without seizure movement. Table 2 depicts the sample cluster analysis used binary class dataset. The parameter setting of HC-DNN-ADAM scheme is applied in these studies namely, Optimizer: ADAM, epoch count: 10, Verbose: 1, and batch_size:4096.

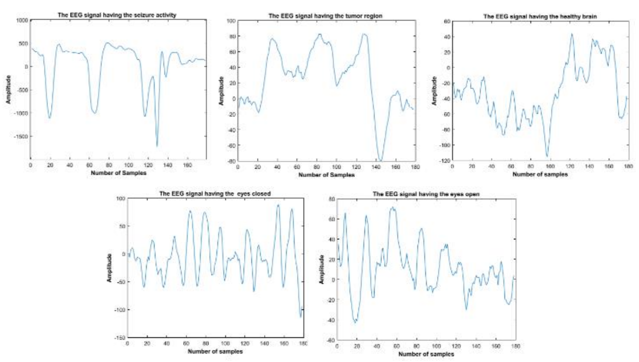

Fig. 4. Raw EEG Signals of Different Classes

TABLE 1 DATASET DESCRIPTION

Class Name	Classes	Instance count
Binary Class Dataset		
EEG signals having seizure activity	0	2300
EEG signals with no seizure activity	1	9200
Multi-Class Dataset		
EEG signals having seizure activity	0	2300
EEG signals having tumor region	1	2300
EEG signals having healthy brain	2	2300
EEG signals having eyes opened	3	2300
EEG signals having eyes closed	4	2300

TABLE 2 SAMPLE CLUSTER ANALYSIS OF APPLIED BINARY CLASS DATASET

Description	Values
Total Number of Instances	11500
EEG signals having seizure activity	2300
EEG signals not having seizure activity	9200
Correctly Clustered EEG signals having seizure activity	978
Correctly Clustered EEG signals not having seizure activity	5807
Incorrectly Clustered EEG signals having seizure activity	1322
Incorrectly Clustered EEG signals not having seizure activity	3393
Total Correctly Clustered Samples	6785

The confusion matrix is generated by the HC-DNN-ADAM scheme on the binary classification of epileptic seizure prediction as projected in Fig. 5. The figure exhibited that the HC-DNN-ADAM approach has divided overall 957 samples under class 0 and 5686 samples under class 1 correspondingly.

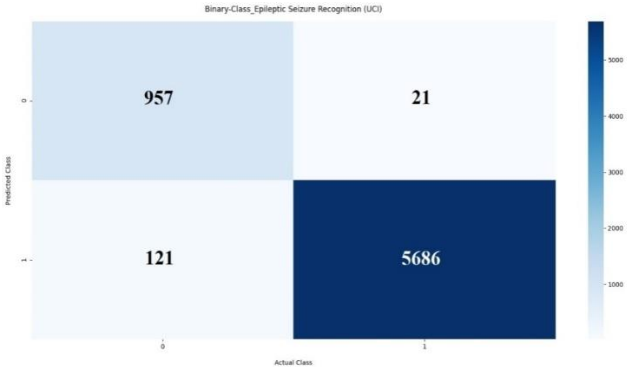

Fig. 5. Confusion Matrix of Proposed HC-DNN-ADAM on Binary Class Dataset

Fig. 6 illustrates the confusion matrix produced by the HC-DNN-ADAM scheme for classifying various classes of epileptic seizures. The figure displayed that the HC-DNN-ADAM approach has categorized a total of 748 samples under class 0, 16 samples from class 1, and 649 samples from class 2 respectively.

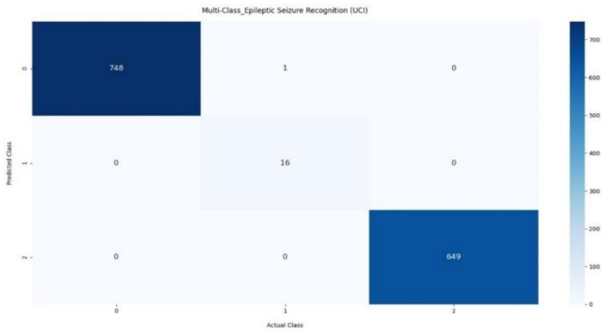

Fig. 6. Confusion Matrix of Proposed HC-DNN-ADAM on Multi-Class Dataset

Fig. 7 offers the examination of simulation analysis by the HC-DNN-ADAM approach by means of accuracy attained in the implementation stage. Fig. 7a depicts that the HC-DNN-ADAM method has achieved maximum training as well as validation accuracy under different count of epochs (total count of 20). Meanwhile, Fig. 7b shows the accuracy examination of the HC-DNN-ADAM scheme under the multi-classification of epileptic seizures. From the figure, it is evident that the verification accuracy is moderate than training accuracy.

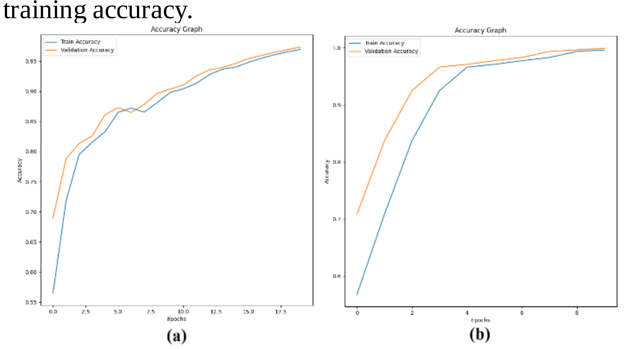

Fig. 7. Result Analysis of HC-DNN-ADAM at Execution Time a) Accuracy Graph of Binary Class Dataset b) Accuracy Graph of Multi Class Dataset

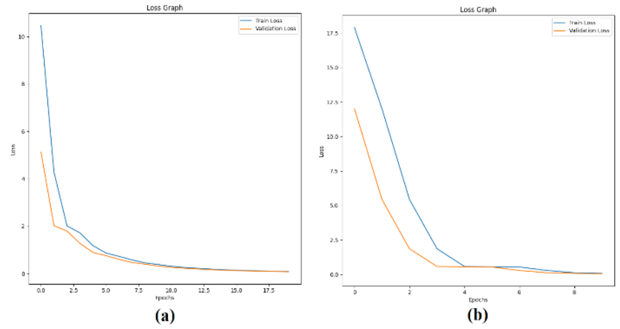

Fig. 8. Result Analysis of HC-DNN-ADAM at Execution Time a) Loss Graph of Binary Class Dataset b) Loss Graph of Multi-Class Dataset

Fig. 8 predicts the function of HC-DNN-ADAM framework in light of loss obtained in execution. Fig. 8a verifies that the HC-DNN-ADAM approach has accomplished lower training and validation loss under different number of epochs (total count of 20). Along with that, Fig. 8b implies the loss analysis of the HC-DNN-ADAM scheme under the multi-classification of epileptic seizures. The figure ensures that the validation loss is slightly lower than training loss.

The confusion matrix produced for several classifications of HC-DNN-ADAM scheme is manipulated by means of TP, TN, FP, and FN, as illustrated in Table 3 and Fig. 9. The values depicted that the DNN-AD approach has showcased effectual function by reaching supreme classification outcomes.

TABLE 3 MANIPULATION FROM CONFUSION MATRIX OF HC-DNN-ADAM ON MULTI-CLASS DATASET

Classes	TP	TN	FP	FN
Label 0	748	665	0	1
Label 1	16	1397	1	0
Label 2	649	764	0	0

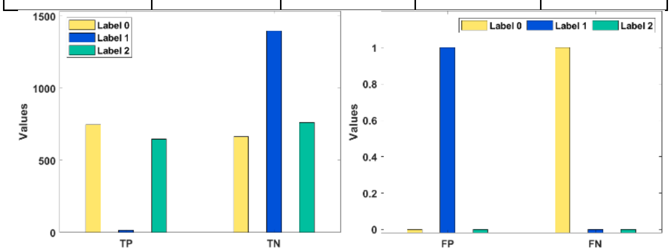

Fig. 9. Confusion matrix of HC-DNN-ADAM model

Table 4 and Fig. 10examine the seizure prediction outcomes of the HC-DNN-ADAM framework on classifying multiple classes. On classifying the samples under label 0, the HC-DNN-ADAM method has accomplished maximum sensitivity of 99.87%, specificity of 100%, accuracy of 99.3%, F-score of 99.93%, kappa of 99.86%, and Matthews's correlation coefficient (MCC) of 99.86%.

TABLE 4 RESULT ANALYSIS OF PROPOSED HC-DNN-ADAM METHOD ON MULTI-CLASS DATASET

Methods	Sensitivity	Specificity	Accuracy	F-score	Kappa	MCC
Label 0	99.87	100	99.30	99.93	99.86	99.86
Label 1	100	99.93	99.93	96.97	96.93	96.98
Label 2	100	100	100	100	100	100
Average	**99.96**	**99.98**	**99.74**	**98.97**	**98.93**	**98.95**

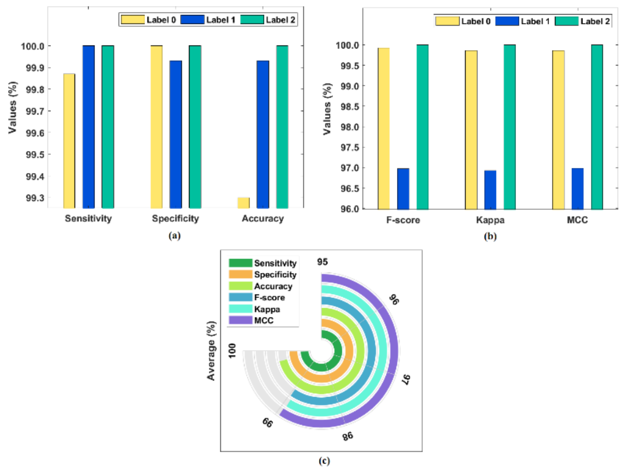

Fig. 10. Multi-Class analysis of HC-DNN-ADAM model

Meantime, under label 1, the HC-DNN-ADAM approach has gained optimal sensitivity of 100%, specificity of 99.93%, accuracy of 99.93%, F-score of 96.97%, kappa of 96.93%, and MCC of 96.98%. At the same time, under label 2, the HC-DNN-ADAM approach has accomplished superior sensitivity of 100%, specificity of 100%, accuracy of 100%, F-score of 100%, kappa of 100%, and MCC of 100%. Eventually, the average analysis of HC-DNN-ADAM technology has obtained maximum sensitivity of 99.96%, specificity of 99.98%, accuracy of 97.74%, F-score of 98.97%, kappa of 98.93%, and MCC of 98.95%. Table 5 and Fig. 11 showcased the investigation of the simulation outcomes of the HC-DNN-ADAM method on classifying binary and multiple class labels. The experimental scores have implied that the HC-DNN-ADAM scheme has divided binary classes with the higher sensitivity of 88.77%, specificity of 99.63%, accuracy of 97.91%, F-score of 93.09%, kappa of 91.86%, and MCC of 92.01%. Followed by, the HC-DNN-ADAM approach has provided intellectual multi-class classification function with the optimal sensitivity of 99.96%, specificity of 99.98%, accuracy of 99.74%, F-score of 98.97%, kappa of 98.93%, and MCC of 98.95%.

TABLE 5 RESULT ANALYSIS OF PROPOSED METHOD ON BINARY-CLASS AND MULTI-CLASS DATASET

Models	Sensitivity	Specificity	Accuracy	F-score	Kappa	MCC
	Binary Class Dataset					
HC-DNN-ADAM	88.77	99.63	97.91	93.09	91.86	92.01
	Multi-Class Dataset					
HC-DNN-ADAM	99.96	99.98	99.74	98.97	98.93	98.95

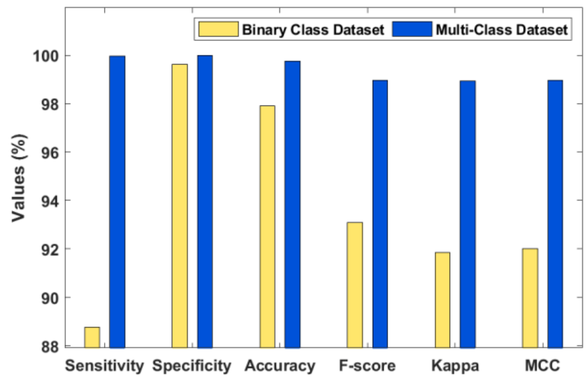

Fig. 11. Result analysis of HC-DNN-ADAM model

Table 6 and Fig. 12 displayed the comparative analysis of the HC-DNN-ADAM method with the previous frameworks with respect to accuracy [16-21]. The figure portrays that the KNN and Linear SVM (MAD-Normal) methodologies have attained lower accuracy of 76% and 76.7% correspondingly. At the same time, the linear SVM (Z-score) and MLP approaches have gained considerable accuracy of 77.1% and 78% correspondingly. In line with this, the KELM (binary class) framework has achieved acceptable accuracy of 80.53% while the M-Gaussian-SVM (MAD-Normal) and M-Gaussian-SVM(Z-score) technologies have resulted in moderate accuracy of 81.4% and 81.7% correspondingly. Besides, the blend of 5 methods like Cubic SVM(z-score), SA-KELM (Binary Class), Cubic SVM(MAD-Normal.), KELM (Multi-Class), and SA-KELM (Multi-Class) have attempted to gain moderate results with the accuracy of 82.3%, 82.49%, 82.5%, 82.62%, and 82.91% correspondingly.

TABLE 6 COMPARATIVE RESULTS OF HC-DNN-ADAM METHOD WITH THE PREVIOUS FRAMEWORKS

Author	Year	Methods	Accuracy
Ours	-	HC-DNN-ADAM (Binary Class)	97.91
Ours	-	HC-DNN-ADAM (Multi Class)	99.74
Suguna et al.	2020	KELM (Binary Class)	80.53
Suguna et al.	2020	SA-KELM (Binary Class)	82.49
Suguna et al.	2020	KELM (Multi Class)	82.62
Suguna et al.	2020	SA-KELM (Multi Class)	82.91
Polat et al.	2020	Linear SVM (MAD-Normal.)	76.70
Polat et al.	2020	Cubic SVM (MAD-Normal.)	82.50
Polat et al.	2020	M-Gaussian-SVM (MAD-Normal.)	81.40
Polat et al.	2020	Linear SVM(z-score)	77.10
Polat et al.	2020	Cubic SVM(z-score)	82.30
Polat et al.	2020	M-Gaussian-SVM(z-score)	81.70
Guha et al.	2019	KNN	76.00
Guha et al.	2019	MLP	78.00
Bhattacharyya et al.	2018	LS-SVM	90.00
Usman et al.	2017	CHB-MIT	93.12
Kabir et al.	2016	OAT-LMT	95.33

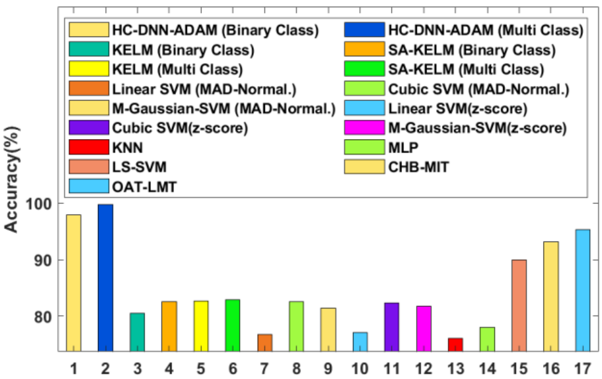

Fig. 12 Comparative Analysis of Proposed with Existing Models in terms of Accuracy

Concurrently, the LS-SVM, CHB-MIT, and OAT-LMT methodologies have exhibited represented acceptable outcomes with accuracy of 90%, 93.12%, and 95.33% respectively. Therefore, the newly presented HC-DNN-ADAM scheme has surpassed the traditional schemes by depicting maximum accuracy of 97.91% and 99.74% on the classification of binary and several class labels correspondingly. By reviewing the pre-defined tables and figures, it is apparent that the HC-DNN-ADAM module is supreme than previous diagnosis of epileptic seizures.

IV. Conclusion

This paper has developed a HC-DNN-ADAM model for the detection and classification of epileptic seizures. The proposed HC-DNN-ADAM model involves a set of different processes, such as preprocessing, outlier detection, classification, and parameter tuning. Once the input medical data is preprocessed, the outliers are detected by HC technique; thereby the classifier results can be improved. Then, the DNN-ADAM model is applied for classification process in which the parameters of the DNN model are tuned using ADAM optimizer.The application of HC and ADAM paves a way to achieve better classification outcomes.The simulation analysis of the HC-DNN-ADAM model takes place on benchmark database and is found to be effective in the detection of epileptic seizures with an accuracy of 99.74% on the classification of multiple classes of seizures. In future, the performance can be further improved by the use of feature reduction techniques.

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