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Research Article

An Integrated Deep Learning Framework for Epilepsy and Basal Ganglia Disorders Detection using Feature Extraction Technique

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ABSTRACT

Introduction: Around 1% of the world's population suffers from epilepsy. The semiology of seizures provides important clinical signs that can be used by neurologists to classify disorders. Developing automatic seizure detection techniques is needed to improve the diagnosis and monitoring of patients. Although the use of machine learning methods has been used to treat epilepsy and basal ganglia (Parkinson disease), it still requires manual adjustments for the classification procedure.

Objectives: This paper represents an integrated model combined with convolutional neural networks and long short-term memory that is designed to perform the feature extraction and classification.

Methods: The experiments were conducted to perform the binary and multi-class epilepsy normal and abnormal classes. During the process, 10 and 100 epochs count is considered during the model training and evaluation.

Results: Finally, the hyperparameter tuning helped the present work to get optimal solutions of 98.15% classification accuracy for epilepsy when compared with the other models like CNN, DNN, and 1D-CNN+LSTM.

Conclusions: The present study also worked on the feature extraction and classification process of basal ganglia disorders using a proposed 1D-CNN+LSTM model. Due to the complex data features, the proposed model is trained for 700 epochs to achieve 91% of classification result.

Keywords: Basal Ganglia Disorder, Convolutional Neural Networks, Deep Learning algorithms, Epilepsy seizure classification, Feature extraction.

INTRODUCTION

Both epilepsy and the basal ganglia are disorders that affect how the brain functions. For people with epilepsy, the condition can have a significant effect on their lives. People who experience basal ganglia disorders will develop psychiatric symptoms together with movement disorders. The central nervous system brings focus to epilepsy-related electrical activity yet basal ganglia dysfunction endorses seizure development [1-8]. Multiple neurodegenerative illnesses can appear simultaneously with Huntington's disease which shows both seizure and movement disorder symptoms. The specialists need to apply the most suitable treatment methods for managing these conditions depending on each condition's specific factors. Deep learning (DL) treatment methodologies are increasingly adopted to manage disorders of the basal ganglia and epilepsy [9]. These diagnostic and prognostic methods produce better outcomes for assessing these disorders. These systems achieve data analysis by studying medical information coming from brain scans and EEG signals [10]. Epilepsy treatment and diagnosis benefits from deep learning models that analysts can employ in practice. Epileptic seizure detection occurs through the analysis of EEG machine data by CNNs and LSTMs along with similar models [11]. The models reveal patterns of brain activity which experts might not notice otherwise.

By using deep learning technology, a predictive model detects the most likely time for a seizure to occur. A predictive system based on EEG time-series data supports clinicians to do both drug dosage adjustments and neurostimulator device activation before seizures occur. Detailed analysis of EEG and genetic information of MRI scans enables an algorithm to personalized therapeutic systems for patients through DL technology. Through examination it can recommend suitable non-drug treatment approaches that match the specific medical condition of

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the patient by advocating ketogenic diet plans. Models utilizing DL algorithms to MRI and fMRI and PET scans deliver precise seizure localization thus minimizing surgery-related dangers after training. The models utilize pre-surgical data to calculate operation success rates besides incorporating historical patient prognosis statistics from similar cases. The capabilities of deep learning extend beyond specific disease management since it provides detection methods for other basal ganglia diseases including Parkinson's disease and Huntington's disease. The list of diseases includes both Tourette's syndrome and dystonia. CNNs enable deep learning to interpret fMRI together with MRI data which helps identify conditions for treatment purposes. Deep learning enables the creation of models which distinguish different movement disorder types. The algorithms identify Parkinson's disease apart from other tremor causes. Non-invasive medical imaging tools enable healthcare providers to detect and monitor disorders of the brain which affect epilepsy patients along with those affecting the basal ganglia. Cortical and neurochemical information becomes accessible to healthcare providers through these techniques whereas direct brain entry is unnecessary. The utilization of such techniques allows neurologists to develop specific treatment strategies which support patients suffering from movement disorders and epilepsy. Through these assessment techniques medical professionals can locate the best patients requiring surgical procedures. Medical professionals use MRI along with PET and fMRI scanners to determine if patients qualify for surgical procedures. Imaging techniques enable how disease advances assess the treatment approaches through the achieved. Professional adjustments of drug amounts and rehabilitation programs are made by medical providers through analysis of patient health status [11]. Through the integration of AI-based and DL techniques can enhance treatment accuracy.

The proposed model is novel for the selection of data features derived for the recognition and classification of normal/abnormal epilepsy and basal ganglia conditions. In this present wok, an effective and integrated CNN-LSTM model is derived to recognize and classify the epilepsy and normal conditions using EEG signals. The proposed model encompasses different stages like data collection and preprocessing, feature extraction and selection, and classification. The proposed model is evaluating in two stages like binary and five-class classification for 10 and 100 epochs to detect the best epoch value while obtaining the optimal classification accuracy.

The main contributions of the present research are:

- Data Acquisition and preprocessing to fine-tune the input data and generalize the overall process of diseases prediction.
- To develop a novel integrated framework that provides support in recommending the treatments strategies.
- Implementing several deep learning algorithms that can help in classifying the diseases
- To optimize the efficiency of the proposed framework with high level of performance.

The remaining sections of the paper are organized as literature review to summarize the state-of-the-art in the field, proposed method describing the step-by-step process of developing the recommendation framework, results and discussion to present the experiments conducted and results obtained followed by conclusion, challenges and future directions.

LITERATURE REVIEW

The life-threatening condition known as epilepsy is a type of brain disorder that causes uncontrollable seizures. It is caused by changes in the brain's chemical composition. For many years now, there have been studies that support the automatic classification of epileptic seizures. This section aims to review the literature on this topic. The review only investigated the most common extraction techniques and the classifiers that can be used to accurately categorize epileptic seizures. It was conducted through a review of the literature from various sources, such as the MDPI, SpringerLink, and IEEE Xplore. The proposed deep learning framework detects two types of epilepsy seizures between frontal and temporal lobe seizures. The system employs infrared camera technology to study seizure videos which makes it available for hospital monitoring units. The system combines human action recognition technology with large object detection technology which includes Kinectics-400 and ImageNet. The classification framework in the paper demonstrates a 5-fold cross-validation f1 score. The system allows healthcare professionals to make diagnoses, so it has potential applications in epilepsy monitoring through online platforms. The technology has potential for integration with EEG and 3D depth information to enhance its future applications [15,16]. This research aims to create a combined CNN and LSTM network model which performs multi-class operation on epilepsy EEG for binary and ternary processing tasks. Statistical results confirmed that this method reaches accuracy rates of 98% and 97.4% and 98.3% and 96.8% for the three-class category [17]. An array of classifiers performed the data classification process for this research. Random Forest proved to be the most accurate classification method which outperformed Logistic Regression together with K-Nearest Neighbour and Decision Tree. A critical assessment occurred to analyze the performance of all classification parameters relative to different methods. The reviewers analyze the sensitivity

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capabilities of certain classification models to measure their effectiveness in epilepsy data analysis [18]. Research analyzes the development of automated epilepsy detection through ML and DL techniques which are described in the paper. The UCI-Epileptic-Seizure-recognition dataset serves as the foundation for conducting both training and validation procedures of the system. The proposed model relies on combination of DL and ML algorithms and long-term memory function. During validation testing the proposed LSTM model achieved an accuracy level of 97%. The method achieved better results than those demonstrated by other approaches presented in the study [19].

The goal of this paper is to develop a method that can be used to detect epilepsy in early stages. It involves extracting important classification and features data. The experimental results of this approach revealed that it provided superior performance compared to the existing methods. In the testing phase, a combination of the RF and PCA classifiers performed well. The combination of the RF and PCA classifiers performed well in the testing phase. The former was able to achieve an accuracy of 98.09%, a precision of 99.1%, a recall of 93.9%, and an F1 score of 96.21%. On the other hand, the latter was able to achieve an accuracy of 98.98%, a precision of 99.16%, and a recall of 95.69% [20]. The paper presents a machine learning model that can predict the behavior of seizures and categorize them. It was evaluated on different models, such as Random Forest, XGBoost, and Extra Tree Classifier. The proposed methods were then subjected to various tests, such as recall, precision, and F1 score. According to the results, Random Forest was able to achieve an F1 score of 0.943, while XGB came in at 0.933. In terms of accuracy, Random Forest was able to achieve a rate of 0.977 [21]. A PMM network serves as a system for automatic signal classification from epileptic patients. A reinforcement process enables the network to understand the relationships between both regional and whole-network features. The network achieves superior performance than contemporary state-of-the-art methods according to experimental results [22]. This research introduces a CNN-LSTM model operating along one dimension which signifies its ability to discover epileptic seizures automatically. The model performance evaluation takes place through public UCI dataset assessment for detecting epileptic seizures. The examination data established that the new approach delivers superior recognition performance across five-class as well as binary categorization. A comparison of the proposed method exists against three deep learning approaches including k-nearest neighbours, decision trees and support vector machines. CNN along with typical deep neural networks served to demonstrate their better performance capabilities [23]. Researchers developed a method for automatic seizure identification in epileptic patients. The research applies deep neural networks to study the performance of two fusion approaches: the Choquet integral and ensemble combination method. The research outcomes demonstrate that the former method achieves superior results compared to the latter [24]. This research seeks to enhance epilepsy seizure and basal ganglia disorder recognition through deep learning architecture development. Researchers train nine different neural network models through techniques which altered data preprocessing methods. Test accuracy reached its highest level when the study used architecture layers with dropouts. Test accuracy from the LSTM architecture reached 0.986. Both Bidirectional and GRU models achieved success where the former delivered 0.983 accuracy while the latter reached 0.984 [25].

PROPOSED METHOD

- **Dataset Sources and Description**

To conduct the feature extraction and classification, two datasets were used for epilepsy seizure disorders. The first dataset is a comma separated file (csv) with 178 features, one target label. The label values are mentioned as one normal class (1) and four abnormal classes (2, 3, 4, and 5). Both the datasets are collected from the public repository [5] and pre-processed the data using scaling technique so that the proposed model can easily understand the data patterns. The second dataset used for basal ganglia disorder (Parkinson disease) is also a .csv file with 77 features and one target label. The target label values are mentioned as normal class (0) and abnormal class (1). The dataset is collected from the public repository [6] and pre-processed using scaling technique to normalize the data so that the proposed model can easily understand the data patterns. Initially the data set consists of 758 records belongs to two classes. Data augmentation techniques are applied to increase the dataset size and make the training and generalization process so well with large amount of data. The augmentation process can also help to overcome the problem of overfitting and increase the classification results as well. The dataset used is a public data source [4] with the brain activity recording samples related to 500 subjects and 11500 EEG data samples. The recordings are subject

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to epileptic seizure conditions along with normal condition recordings. The sample EEG signals data is shown in Figure 1. Figure 2 shows some sample MRI and CT scan images of epilepsy and basal ganglia diseases.

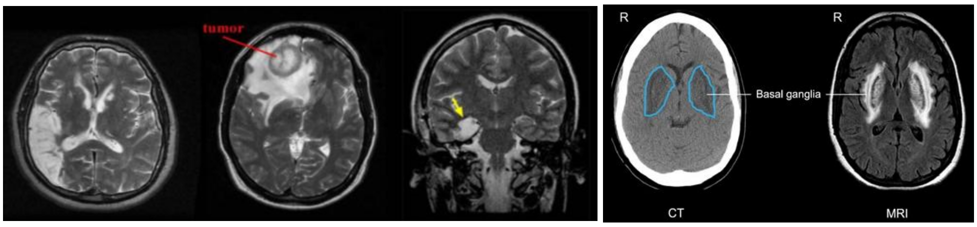

Figure 1. Samples images (a) epilepsy [5] (b) basal ganglia [6]

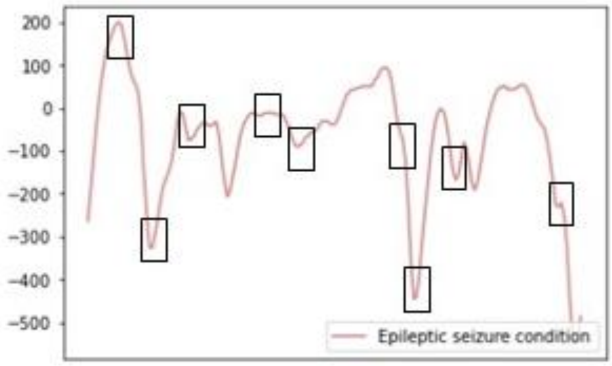

Figure 2. Feature Extraction using 1-D convolution operation

The one-dimensional (1-D) neural network can be able to extract effective features of sequence data (time0series) through convolution operation using several filters. In this work, the convolutional kernels and features maps are represented as 1-D so that they can match the input data (EEG signals). The extraction of 1-D features using 1-D convolution operation are shown in figure 3.

- **Proposed Methodology and Algorithm**

The present study also proposed an algorithm to develop an integrated framework. The algorithm describes the step-by-step process starting from the data collection phase to customizing the framework as per the research objective. Figure 3 describes a pipeline that collects raw medical data from various sources, conducts the preprocessing, application of deep learning algorithms to develop a predictive model, detect abnormalities in medical images, and finally recommend the personalized treatment.

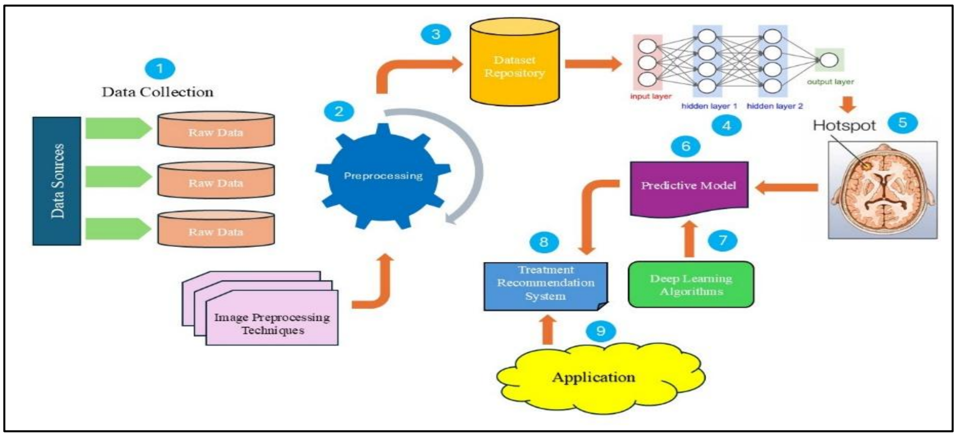

Figure 3. Process Flow Diagram

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Algorithm: Proposed Integrated framework

Step 1: Raw medical data collection from specific sources $D = \{x_1, x_2, ..., x_n\}$, where x_i represents raw EEG signals

Step 2: Apply preprocessing techniques to clean and normalize the data D. Apply $f(x_i)$ where f is a function to perform data normalization

Step 3: Structure the pre-processed data $D = \{x_1', x_2', ..., x_n'\}$, for model application as initially labelled data L(D') = $\{(x_1',y_1), (x_2',y_2), ... , (x_n',y_n)\}$ *where* $y_n \in \{0,1\}$. Split the dataset D' as D'_{train}, D'_{test}, and D'_{val}

Step 4: Implementing deep learning algorithms to identify abnormalities. Use the trained model M_{θ}^{*} to predict abnormalities in the image. Identify the abnormal regions as $H(x_1')$, where $H(x_1')$, represents the pixels with features.

Step 5: Developing an integrated framework to perform the classification task. Apply the proposed system T that maps the predicted disease ($\hat{d}_i$) to the treatment as $\hat{t}_i = T(\hat{d}_i, pi)$ where pi is the patient.

Step 6: Suggest the personalized treatment $\hat{t}_i$.

Step 7: Customize the framework to achieve higher efficiency.

To detect the epilepsy and basal ganglia disorders, the proposed algorithm describes in detail about the process of handling raw data, preprocessing the data, structuring the data into training and testing sets, conducting the detection and classification by implementing deep learning techniques, and improve the classification efficiency.

Raw data collected from different reliable sources typically represents as a time-series data signals, 'N' number of channels, and 'T' number of time points. Data normalization is performed to bring the entire data values into a common scale. This process helps improve the performance of the model training. Data augmentation is also an applicable area which increases the variability that can help in performing the classification well. For example, Let $Y \in \{0,1\}$ be the binary classification, then '1' represents the abnormal and '0' the normal classification label. Splitting of datasets into training and testing helps the learning and generalization process. By using the CNN-LSTM architectures during model design with $f_\theta(X)$ = LSTM(Conv1D(X)) where 'θ' represents the learning parameters and $f_\theta(X)$ the model output. Use the 'Adam' optimizer as a loss function for both binary and multi-class classification. Later, the performance metrics were evaluated to assess the performance of the proposed integrated model. Finally, improve the efficiency of the model by hyperparameter tuning, and applying regularization techniques to prevent the overfitting.

- **Proposed 1D-CNN+LSTM Model**

This subsection describes the development of the proposed one-dimensional convolutional neural networks (CNN) integrated with long-short term memory (LSTM) to perform the feature extraction and classification process. Binary and Five-Class classification is conducted for epilepsy seizure and only binary classification for basal ganglia disorders due to the availability of limited datasets. Figure 4 shows the integrated model with both CNN and LSTM blocks.

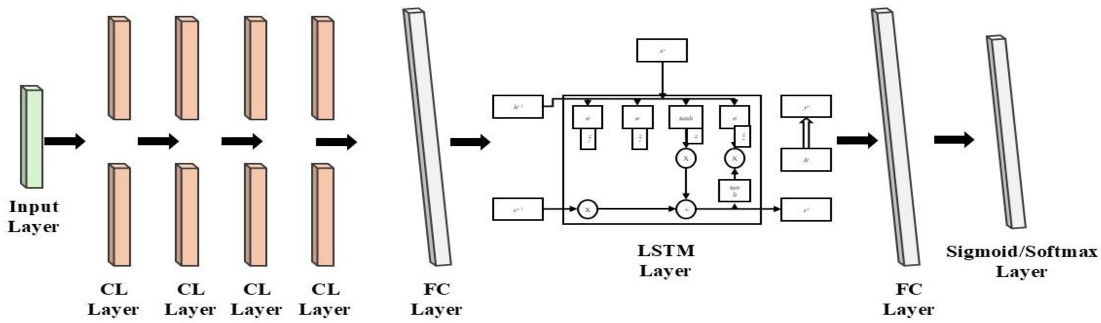

Figure 4. An integrated CNN-LSTM structure

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During the data collection, medical images like EEG readings and patients' data will be collected from various sources and stores in a folder for preprocessing. Second, various data preprocessing tools will be applied to reduce noise, normalizing the data, and handling missing the erroneous data. The pre-processed data is labelled and split into different datasets like training and testing for feature extraction and DL model development. Third, the development and the training process of the deep learning algorithm using labelled data is performed. Hyperparameter tuning and applying regularization techniques are also the part of this step. These techniques will help in understanding the training data well and generalize the testing data. Finally, the processed medical images are selected for image analysis task where the new images are given to the proposed integrated framework to detect the abnormalities. This process will result in annotated images with highlighted disease spots and the classification results. The likelihood of the disease occurrence is processed to predict the disease class. The results of this step are used to recommend the treatment. The system will provide the personalized treatment recommendations based on the model's prediction results. The original dataset has been normalized before feeding into the deep learning model. A 1-D convolutional neural network using long-short term memory (LSTM) structure is implemented to develop the proposed integrated model.

EXPERIMENTS, RESULTS AND DISCUSSIONS

During the entire experiments, the original dataset is split into two with 80% data for training and remaining 20% data for testing purpose. The number of epochs for training is set to 100 to training the 1-D CNN-LSTM model. The entire training and evaluation process is clearly monitored to improve the performance of generalizing the testing data samples and avoid the overfitting. The most used regularization techniques like dropout are used to reduce the overfitting in the proposed training process.

- ***Binary Classification for epilepsy seizure disorder***

The data is randomly shuffled and fed to the networks. During each epoch the accuracy and loss values are calculated to understand whether the model can generalize the testing data and thereby verify the overfitting. During the experiments, several hyperparameters like number of convolutional layers, LSTM layers, learning rate, number of epochs, batch size and dataset split ratio were adjusted to find the best suitable set. The entire experimental process is carried out to perform the multi-label classification of one epilepsy condition and the other four normal conditions.

Table 1. Classification performance of the neural network models

Model	Tr.Ac	Tr.Ls	Ts.Ac	Ts.Ls
CNN	98.11%	4.49%	97.6%	6.45%
DNN	97.03%	8.45%	96.6%	7.87%
CNN-LSTM	97.81%	7.53%	97.73%	6.33%
Proposed Model	**97.52%**	**7.87%**	**98.15%**	**4.48%**

Tr.Ac – Training Accuracy, Tr.Ls – Training Loss, Ts.Ac – Testing Accuracy, Ts.Ls – Testing Loss, P – Precision, R-Recall, FS – F1.Score

From Table 1, the CNN model fits the training data very well with 98.11% accuracy, indicating it has learned patterns effectively. A low training loss, which suggests that the CNN performs well on the training set with just 4.49% loss. The CNN model generalizes well to unseen data provided 97.6% accuracy, though slightly lower than the training accuracy. The testing loss (6.45%) is higher than the training loss, possibly indicating some overfitting. The DNN model is reasonably accurate on the training data achieved 96.6% accuracy but not as high as the CNN. Higher training loss (8.45%) compared to CNN, indicating that the DNN might not have learned as effectively. Slightly lower testing accuracy of 96.6% than training, showing acceptable generalization. Higher loss of 7.87% compared to CNN, indicating the DNN might be less effective on the test set. The CNN-LSTM model achieved high accuracy of 97.81% on the training set, slightly lower than CNN with 7.53% but still good. The testing accuracy of 97.73% is slightly better than the training accuracy, showing strong generalization. Lower than training loss of 6.33%, which is an unusual

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but positive sign of better generalization on test data. The proposed model has achieved a high training accuracy of 97.52%, comparable to CNN-LSTM, though slightly lower than CNN. The proposed model has achieved a training loss higher than the CNN (7.87%) but comparable to CNN-LSTM, indicating it learned moderately well. The highest testing accuracy for the proposed model with 98.15% accuracy among all models, indicating excellent generalization to unseen data. The lowest testing loss of the proposed model, suggesting the model is the best with just 4.48% loss performing on the test set and least prone to overfitting. Figure 5 shows the learning curve of all the four models showing the training accuracy and testing accuracy.

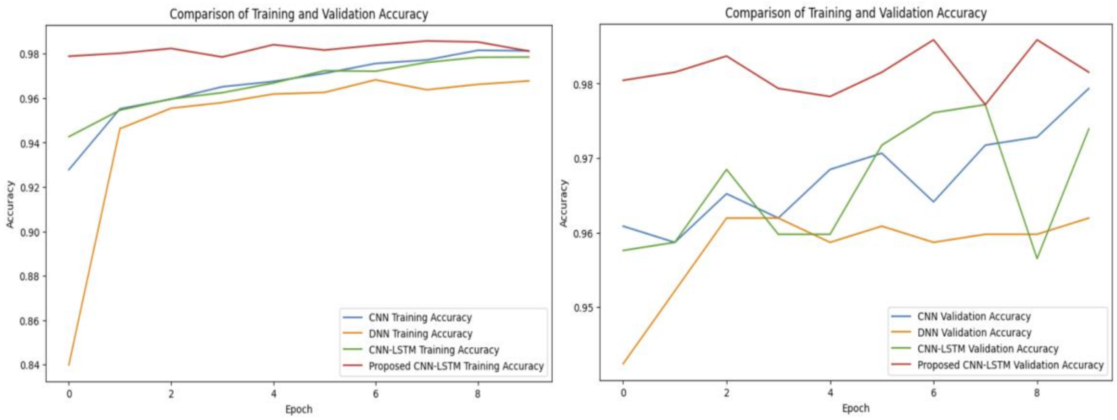

Figure 5. Learning curves of the models for 10 epochs

- ***Categorical Classification for epilepsy seizure disorder***

In this section, the performance of the three neural networks models like CNN, DNN, and CNN_LSTM were compared for analysis. The experiments were conducted in two phases. During the two phase the models were evaluated for 10 epochs and 100 epochs respectively. The results obtained with 100 epochs are not considered for interpretation as the values shows the models overfitting. At each phase several performance metrics like accuracy, loss, precision, recall, and f1-score values extracted and recorded for further analysis. The mathematical notations to extract the performance metrics are introduced below.

$$\text{Accuracy(Ac)} = \frac{TP + TN}{TP + TN + FP + FN}$$

$$\text{Precision(PS)} = \frac{TP}{TP + FP}$$

$$\text{Recall(RC)} = \frac{TP}{TP + FN}$$

$$\text{F1} - \text{Score(FS)} = 2\,X\,\frac{P\,X\,R}{P + R}$$

Where 'TP', 'TN', 'FP', and 'FN' represents true positive, true negative, false positive, and false negative respectively. The training and testing processes of the four models were applied to a five-class classification task and observed that CNN and CNN-LSTM models exhibit the highest classification results. Table 2 shows that the CNN has the highest training accuracy (94.13%), and the CNN-LSTM has the highest testing accuracy (78.4%).

Table 2. Classification performance of the neural network models

Model	Epochs #	Tr.Ac	Tr.Ls	Ts.Ac	Ts.Ls	PS	RC	FS	Performance
CNN	10	71.22	63.18	70.9	65.3	71.6	70.8	69.8	Good Fit
	100	94.13	13.83	74.5	>100	74.4	74.2	74.6	Overfit

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DNN	10	60.8	84.6	66.9	72.7	67.6	66.8	65.4	Good Fit
	100	73.12	57.16	70.21	65.59	70.6	70	69.8	Overfit
CNN-LSTM	10	68.53	66.68	68.56	67.30	69	68.4	67.4	Good Fit
	100	92.32	17.91	77.73	81.86	78.4	77.8	77.6	Overfit
Proposed Model	**10**	**71.95**	**59.47**	**72.65**	**57.05**	**74.2**	**72.6**	**70.8**	**Good Fit**
	100	97.18	8.11	77.34	>100	77.4	77.2	77	Overfit

Tr.Ac – Training Accuracy, Tr.Ls – Training Loss, Ts.Ac – Testing Accuracy, Ts.Ls – Testing Loss, P – Precision, R-Recall, FS – F1.Score

From Table 2, at 10 epochs, the CNN model is moderately trained with 71.22% accuracy, achieving decent accuracy but still underfitting. A high training loss of 63.18%, suggesting the CNN model is still learning. The CNN model generalizes well with 70.9% testing accuracy, but there is room for improvement. A high testing loss of 65.3%, indicating some inefficiency of the CNN model. The metrics like precision, recall, and f1 score are all around the 70% range, showing balanced performance. For 100 epochs, The CNN model has very high training accuracy (94.13%), indicating strong learning. A low training loss of 13.83%, indicating the CNN model has captured the training data patterns well. There is only a slight increase in testing accuracy with 74.5%, indicating potential overfitting. The test loss of more than 100%, further signalling overfitting of the CNN model. The performance metrics like precision, recall, f1 score slightly improved over the 10-epoch results, but the gap between training and testing suggests overfitting.

At 10 Epochs, the DNN model has achieved a low training accuracy of 60.8%, showing the model hasn't fully learned the patterns. Very high training loss of 84.6%, indicating the model struggles with the training data. The DNN model could be able to obtain moderate generalization with 66.9% testing accuracy, but performance is low overall. Still a high testing loss of 72.7%, confirming the DNN model's inefficiency at this point. The performance metrics like Precision, Recall, F1-Score are lower than the CNN, reflecting the DNN's struggle. At 100 Epochs all the performance metrics improve but remain lower than CNN. Like CNN at 10 epochs, indicating the CNN-LSTM model is underfitting with a training accuracy of 68.53% and testing accuracy of 68.56%. The training loss is still high loss (66.68%), suggesting more learning is needed. A testing accuracy of 68.56% accuracy slightly lower than CNN but comparable. High test loss of 67.30%, indicating some inefficiency. The performance metrics like Precision, Recall, F1-Score are close to the CNN values, showing similar generalization. At 100 Epochs, a large improvement of 92.32% training accuracy, showing that the model is learning well on the training data. A lower training loss of 17.91%, indicating a better fit of the CNN-LSTM for the training data.

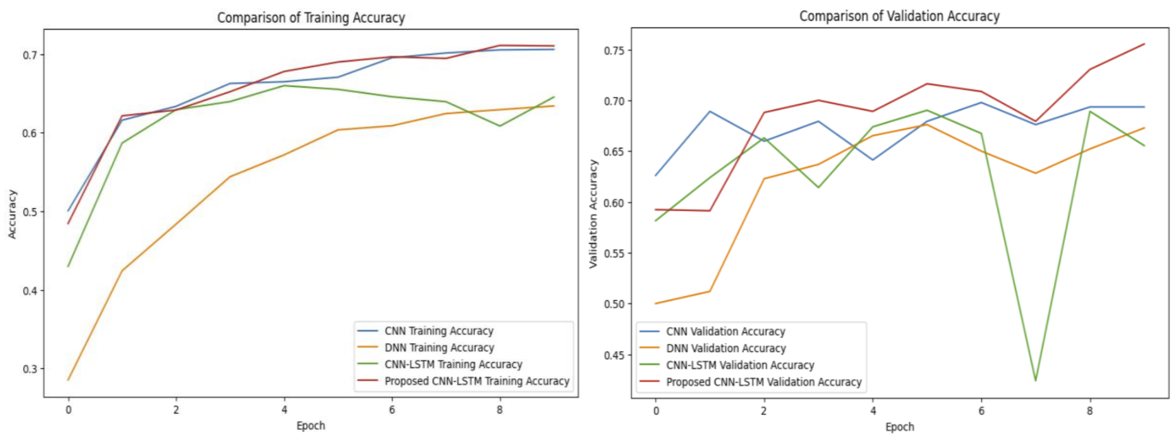

Figure 6. Learning curves of the models for 10 epochs

Like CNN at 10 epochs the training accuracy of the proposed model is 71.95%, showing moderate learning. Slightly lower than CNN with 59.47%, indicating the proposed model learns more efficiently. Higher than CNN the testing accuracy of the proposed model, showing better generalization at 10 epochs with 72.65%. The lowest test loss of

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57.05% among the models at this stage, indicating better efficiency. The best performance metrics like precision, recall, and f1 score among all models at 10 epochs are better. Figure 6 shows the classification performance of four models including the proposed one when executed with 10 epochs.

- ***Binary Classification for basal ganglia disorder***

The data is randomly shuffled and fed to the networks. During each epoch the accuracy and loss values are calculated to understand whether the model can generalize the testing data and thereby verify the overfitting. During the experiments, several hyperparameters like number of convolutional layers, LSTM layers, learning rate, number of epochs, batch size and dataset split ratio were adjusted to find the best suitable set. The entire experimental process is carried out to perform the binary-label classification of one normal and one abnormal basal ganglia disorder class. Due to the complexity in the dataset, the proposed model is evaluated for different epochs to determine the suitable epoch count for achieving higher classification/testing accuracies. Table 3 shows the performance improvement of the proposed model with respect to several epochs. A comparative analysis is conducted to understand the correct suitable training time in terms of epoch count and avoiding the model overfitting with the training data.

Table 3. Classification performance of the proposed model

Model	Epochs #	Tr.Ac	Tr.Ls	Ts.Ac	Ts.Ls	PS	RC	FS	Performance
Proposed 1D-CNN+LSTM Model	300	85.62%	35.63%	81.66%	36.84%	80%	80.5%	80.5%	Good Fit
	400	82.56%	35.86%	84.72%	35.59%	83%	84.5%	84%	Good fit
	500	84.17%	34.35%	85.76%	31.82%	80.5%	81.5%	81%	Good Fit
	600	87.04%	31.11%	85.83%	35.30%	85%	85.5%	85%	Overfit
	700	**92.80%**	**23.49%**	**90.55%**	**26.47%**	**89.5%**	**91.5%**	**90%**	**Good Fit**
	800	90.72%	24.27%	86.66%	32.31%	85.5%	87.5%	86%	Overfit

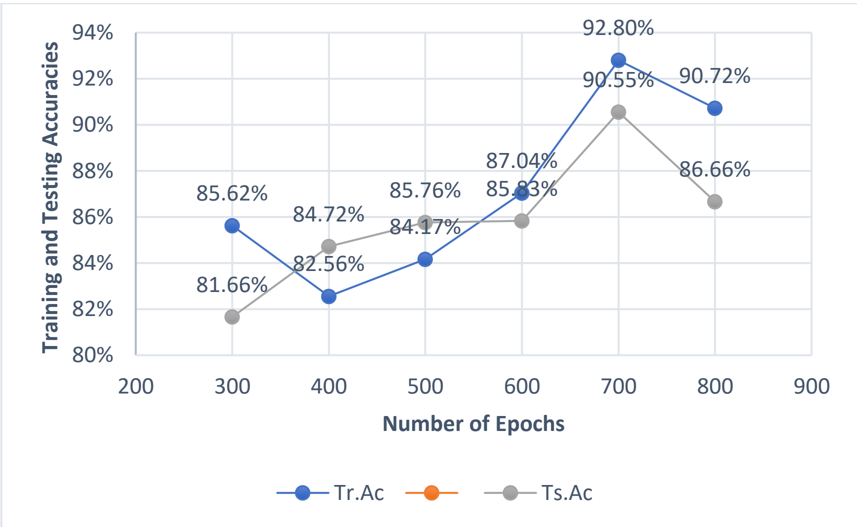

Figure 7. Learning curves of the models for different epochs

From Table 3, it has been noted that the proposed model has sufficient time to learn the data features from the training data while the number of training iterations (epochs) increases. The training accuracy consistently increases to 92.80% at 700 epochs. Reaching the lowest value of 23.49% testing loss describes that the decreasing loss significantly fitting the data better by reducing the difference or error between the proposed model's prediction and the actual training set values. The testing accuracy at 700 epochs started at 81.66% and reached to 90.55% with good

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performance on the unseen dataset. However, at 800 epochs the performance drops to 86.66% suggesting that the model's performance cannot be extended further. Figure 7 shows that the proposed model started acquiring training accuracy of 81.66% at 300 epochs and reached to 90.55% at 700 epochs. Meanwhile, the proposed model has obtained 85.62% generalization accuracy at 300 epochs and reached to 92.80% at 700 epochs. The reduced training and testing accuracies of 2.08% and 3.89% respectively shows that the model's learning process has a downfall. The performance loss describes that the further training process cannot produce the optimal results and lead to overfitting as well.

OBSERVATIONS

- The CNN model shows a reasonable fit with 0.32% variation among the training and testing accuracies at 10 epochs is a good fit for epilepsy seizure disorder.
- The DNN model shows a good fit at 10 epochs, but the outcomes are less when compared with the other models for epilepsy seizure disorder.
- The CNN-LSTM model shows good fit and a room for the improvement at 10 epochs for epilepsy seizure disorder.
- The proposed CNN-LSTM model shows good fit with a balanced learning accuracy of 72.65% at 10 epochs for epilepsy seizure disorder.
- The proposed 1D-CNN+LSTM model performed better around 700 epochs by achieving 90.55% test accuracy.
- The model also achieved a lower test loss, and good precision, sensitivity (recall), and f1-score as well during binary classification for basal ganglia disorder.

CONCLUSION, CHALLENGES, AND FUTURE DIRECTIONS

Despite the promising potential of deep learning techniques, there are still many challenges including the need for high-quality datasets and the ability to integrate them with clinical workflows need to address. The experiments were conducted in two-phases to extract the features from the epilepsy and basal ganglia disorders separately due to distinct data features. Later, the feature extraction process is utilized to conduct the classification of both the disorders. The proposed CNN–LSTM is a balanced model that has a good performance between the test and training sets. During five-class classification, although all models fit the data well at 10 epochs, the proposed model has the best balance between testing and training performance. During the binary classification of basal ganglia disorder, the CNN model along with LSTM model is developed to do feature extraction and classification. The proposed model produced more than 91% testing accuracy with 750 epochs. Developing a treatment recommendation system for both epilepsy and basal ganglia disorders by extending the work of classification process is the future scope of the present study.

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