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Research Article

Epileptic Seizures Detection from EEG Signals using Improved Hybrid RNN-CNN Feature Extraction Approach

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ABSTRACT

Epileptic Seizures(ES), a neurological condition, presents significant challenges in both diagnosis and management. This is crucial in ensuring early detection and treatment before the negative impacts surface and improving patient experiences. In this paper, an automatic method implemented using deep learning hybrid architecture (CNN-RNN) integrates "feature extraction" methods such as DWT, LBP, EMD, and FIT to detect ES from EEG signals. The suggested approach deals with the EEG signals. Thus, CNNs are used to extract the spatial features, and LSTMRNN considers the temporal features of EEG data and model, therefore, handles the short-term and long-term features of the EEG data effectively.
Evaluation of the planned hybrid CNN-RNN model shows promising results surpassing those of MultiSVM by a considerable size in the accuracy measure (98.38%), precision (83.24%), and recall (83.25%) as well as specificity of 95.81% and F1 score of 82.61%. By only having 4.19% false positives and an average specificity, the decisions made by this model are poised to accurately identify clinical seizures in real-time with the minimized likelihood of wrong classification.
This method could be used for continuous, binary seizure identification and integrated into wearable EEG monitoring for constant use. Further work should be done on improving the model, including some effects of noisy data and inadequacy of data sets, and extending the model across a patient's different sexes for better applicability of such a system.
Keywords: Long Short Term Memory (LSTM),Electroencephalograph (EEG), Dense Convolutional Neural Network, Epileptic Seizures (ES), Machine Learning (ML), Feature Extraction.

INTRODUCTION

Epilepsy affects more than 50 million people worldwide (Megiddo et al., 2016), which is 60% of the population of the world (Anugraha et al., 2017). The most common epilepsy symptom is "Epileptic Seizures" (ES), which can take place at all times (Ahmadi et al., 2018). Epilepsy patients already face impulsive, convulsive conditions that can result in significant neurological impairment, such as abnormal behaviours, diminished memory and hypersensitivity. ES affects mostly more advanced countries. Numerous misinterpretations and apprehensions of contempt and dishonour impede the timely provision of medical assistance to the affected individual—excessive electrical discharges in cells in the brain cause a seizure. The lesion may occur in any part of the brain. The seizures can occur at any frequency now. These seizures can happen on several occasions during one day or occasionally once a year and can affect people of all ages in different ways. "Electroencephalogram" (EEG) signals have been regarded as patients' most suitable seizure detection method. In addition, distributed continuous sensing methods are used to obtain high temporal resolution scalp EEG data at multiple input channels.

Electroencephalography (EEG) technology is used for epileptic episode capture using EEG recordings. Detection of neurological diseases, especially epilepsy, relies upon EEG data analysis. An electroencephalogram (EEG) is a machine that records and tracks the function of the brain's neural system as an electric signal. EEG measures the brain's activity and assigns patterns as normal or abnormal. Sensors located on the scalp are applied to take data to generate an EEG, which is a pattern of brain waves. The researchers obtain the given signals and analyze them for seizure detection from EEG data and other disease-related info, including type of seizure and number of seizure recurrences. EEG signal analysis remains a complex and labor-intensive problem because it requires hours of manual inspection of the recordings from a patient by a neurologist (Fürbass et al., 2015; Thodoroff et al., 2016). To overcome the traditional methodology's limitations, several researchers have proposed applying automated methods for detecting ES. In medical practice, seizures are not manually identified due to the heterogeneous morphology of these diseases. The prior methodologies try to identify different patterns in brain activity reflected in artefact-free EEG recordings. However, such strategies produce unsatisfactory results when confronted with processes of the brain that are elaborate and impossible to predict(Cao et al., 2025).

In addition, other approaches to reducing dimensions, filtering, and feature selection do not allow adding new design features and cannot recognize new patterns. However, these constraints usually do not make it effective. Recently, DL and ML methods were applied to overcome the shortcomings of traditional tools. Using machine and deep learning algorithms, meaningful information might be obtained to identify and classify ES. Several studies have proved that machine learning algorithms effectively produced the patient-specific model for the detection of ES. In the past, epileptic convulsions have been characterized by manually constructed attributes. The basis for other researchers' work proposing the use of deep learning-based models for seizure detection is due to the advancements in EEG techniques.(Birjandtalab et al., 2017; Cao et al., 2017).

Among many deep learning models, Convolutional Neural Networks (CNNs) have been primarily used in classification and object detection (Türk&Özerdem, 2019; Madhavan et al., 2019; Mousavi et al., 2019; Kaya, 2020). This ability of CNN to analyze delicate patterns from preprocessed data, extraction of features, and dimensionality reduction leads to this. Because of the exceptional properties of CNNs, they are applied in this study to identify ES.

2. RELATED WORKS

Many studies have analyzed different detection methods to classify EEG data for detection (Mohseni et al., 2006;De Lucia et al. 2008; Chen et al. 2015; Zahra et al. 2017; Chen et al., 2017). Current seizure detection techniques based on conventional feature extraction techniques are designed manually to find EEG data's time and frequency domains (Pei et al., 2018; Acharya et al., 2013; Yan et al., 2017). Then, the classifier extracts features on EEG signal patterns to dichotomize different EEG signal signals. Conversely, the adoption of their enhanced precision in classifying and forecasting epileptic episodes from EEG has dramatically increased for classifiers that involve machine learning and deep learning (ML and DL).

Learning mechanisms of these classifiers are used to learn how to automate the process of detection and, therefore, find out where epileptic episodes take place. Hamad et al. (2017) have used a hybrid methodology that has been developed to express the grey wolf optimization (GWO) combined with enhanced support vector machines (SVMs) for classification purposes. The characteristics from the EEG were extracted, and the SVM classifier and RBF were used for training. The capability of the SVM GWO in identifying eES was also shown. In Subasi et al. (2019), a method is applied to optimize the SVM algorithms using two-hybrid optimization methods: genetic algorithm (GA) and particle swarm optimization (PSO) algorithm. The SVM model is an excellent seizure-detecting mechanism for EEG recording. However, as additionally discussed by (Wang et al., 2016), these methodologies are based on a manual extraction of features. This is a significant disadvantage of existing methods. The extraction of features is a vital phase of seizure classification on EEG recordings. The system helps to increase the precision of the classifier and detector. This has the advantage of executing classification without sophisticated feature extraction and is covered by the capabilities of deep learning algorithms to simplify this process. Different deep learning methods such as Decision Trees (Albaqami et al., 2021) Support Vector Machines (SVM, Zhang & Chen, 2016) and Random Forests (Zhang et al., 2018), recurrent Neural Networks (RNN) techniques are routinely used for the detection of epileptic cases (Gini & Queen, 2021; Verma&Janghel, 2021). Before classification, feature extraction is essential, as it resolves the direct processing of EEG signals before input into the classifier. This will help simplify the categorization process and make it more accurate. However, some recent studies still do not perform feature extraction and the deep learning models were directly trained on EEG signals (Acharya et al., 2018). Hussein et al. (2018) stated that most EEG signal classification studies used the time domain signal, whereas some were based on the frequency domain data. Previous works suggest that the EEG signals have their properties regarding time and frequency domains.

3. RESEARCH METHODOLOGY

In this study, various sensible feature extraction techniques are combined “Recurrent Neural Networks” (RNN),“Convolutional Neural Networks: (CNN) and “Long-Short-Term Memory” (LSTM).

EEG Signal Acquisition
↓
Preprocessing (Filtering & Segmentation)
↓
Feature Extraction (LBP, DWT, FFT, EMD, etc.)
↓
CNN (DenseNet-201) for Spatial Feature Learning
↓
RNN (LSTM/GRU) for Temporal Pattern Learning
↓
Fully Connected Layer (Classification: Epileptic vs. Non-Epileptic)
↓
Performance Evaluation (Accuracy, Sensitivity, Specificity, etc.)
↓
Final Decision (Epileptic Detection & Insights)

3.1 Dataset Description

For training and evaluation, this work used the ES Recognition Data Set, which was comprised of more than 11,500 cases and 179 attributes, as well as multivariate, time series data. The purpose of choosing this dataset is that they contained many EEG signals collected under multiple settings of relaxed and seizure-free states and extensive application in seizure detection research.

The data were collected using more than 10 electrode systems and, thus, provided a substantial spatial description of cerebral activity. Each collection refers to a single channel and EEG signal within a predetermined time range. The data was grouped into five groups associated with distinct brain states and seizure occurrences. Healthy individuals in relaxed and eyes-open conditions are considered as Set A and Set B. For Set D, all the signals are for the seizure-free intervals, Set C for the hippocampus formation of the brain, and Set E for the seizure activity signals.

3.2 Data Preprocessing

Preprocessing of EEG signals is an important step before extracting its features for an automated decision. The preprocessing pipeline involves purifying raw tokens (EEG tokens) from noise and artefacts in order to deliver only the important ones to the next analysis.

This is for the raw EEG data; it is passed through bandpass filters first to remove low-frequency noise (muscular artefact, electrical interference, etc.) and then high-frequency noise (muscular artefact, electrical interference, etc.). Implementation of a 1–50 Hz bandpass filter is a common scheme used in EEG preprocessing, as most seizure-related activity is contained within this frequency spectrum.

The EEG signals were split into fixed-length windows with overlapping sections to deal with the temporal character of the data. Last, each window was normalized to uniform amplitude. Based on the cross-validation, the hyper parameters of the models were adjusted, and the models were prevented from overfitting.

3.3 Feature Extraction

Then, at this stage, the feature values of this segment of the input signal are diminished by extracting relevant features from the specific segment of the input signal. The raw EEG waves exhibit properties that are of varying quality and have varying duration. Additionally, they contain ambiguities brought by motion artefacts and background noise while recording EEG signals. This problem means taking the feature extraction approach and choosing only the essential features. Furthermore, the EEG signal mimics low dimensions, which are further reduced through deep learning-based learning-based methods. Such models based on deep learning allow feature extraction, opting for the good trick by incrementing the minimal computational time available for analysis via processing extensive feature sets. In this study, four sophisticated feature extraction approaches are chosen, namely: “Local binary patterns” (LBP), “Fast Fourier Transform” (FFT), “Discrete Wavelet Transform” (DWT), and “Empirical mode decomposition” (EMD). These approaches can capture EEG data regarding the time or frequency domain, which helps classify seizure episodes against non-seizure episodes(Bhadra et al., 2024).

Local Binary Pattern (LBP)

There is a robust approach to texture feature extraction, termed Local Binary Patterns (LBP) that was first developed for image analysis and later, we have made some modifications to its use in a signal processing application. LBP stands for local texture and encodes the regional structure of a signal from each sample compared with adjacent values as a binary digit. The hallmark of this approach is to record local amplitude fluctuations from EEG signals for differentiation of normal versus seizure activity (McCool et al., 2012).

$$LBP_{LHS}(x[n]) = \sum_{k=0}^{L-1} S(x[n+k-L]-x[n])2^{2L-1-k} \quad .....(1)$$

$$LBP_{RHS}(x[n]) = \sum_{k=L}^{2L-1} S(x[n+k+1-L]-x[n])2^{2L-1-k} \quad .....(2)$$

$$LBP(x[n]) = LBP_{LHS}(x[n]) + LBP_{RHS}(x[n]) \quad ......(3)$$

Where x[n] defines the sample of EEG signals, L represents the entire number of samples, for which the LBP is evaluated.

$$S(p) = \begin{cases} 1 & \text{if } p \geq 0 \\ 0 & \text{otherwise} \end{cases} \quad ....(4)$$

Taking a contrast of the value of the sample of the data EEG signal with values of its surrounding values results in the Local Binary Pattern (LBP) of the signal and, thus, captures the fluctuation of the signals. The histograms of all the signals are consolidated to reach the final representation of the signals. LBP has performed in an expected way to successfully apply microscopic signal abnormalities in many domains, including texture differences and small debitage in signal behavior. When used for EEG recordings, LBP may have issues with high-frequency noise and artefacts if preprocessing is insufficient. Although LBP can accurately capture local fluctuations, LBP is very sensitive to the total signal magnitude. If the fluctuations of EEG signals are highly variable or significant baseline shifts caused by motion artefacts or electrical noise (Kumar et al., 2015), its success performance might decrease.Using our CNN-RNN architecture with an LSTM network, we alleviate this constraint, which could not be alleviated by integrating LBP with models specifically built to encode temporality relationships.

FFT

The FFTanalyses a usual EEG signal based on its frequency domain. FFT can be used to analyze specific frequencies which cannot be identified easily in the time domain (Wang et al., 2017); (Somasundaram & Gayathri, 2012). FFT coefficients are presented to study the relative power spectral density. Thus, EEG signal features are extracted, which are further classified using deep learning techniques to identify epileptic signals. The high pass filter is multiplied with the FFT, and 516nalyzin and noise-free filtered signals are acquired. The FFT method uses a thresholding method in which the filtered signals' low intensity is removed.The Fourier transform of a signal f (I, j) is defined as shown in equation 5.

$$F(k,l) = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} f(I, j)\, e^{-i2\pi(\frac{ki}{N}+\frac{lj}{N})} \quad ....(5)$$

f(I,j) here is a signal instance. This exponential component is a basis function for each specified Fourier region F(k,l) point.

$$f(i,j) = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} F(k, l)\, e^{-i2\pi\left(\frac{ki}{N}+\frac{lj}{N}\right)} \ldots\ldots(6)$$

Although FFT is an excellent characterization of EEG signal frequency characteristics, FFT assumes that the signal is stationary over time. Due to the non-stationarity intrinsic to EEG signals during seizure occurrences (Kumar et al., 2014), EEG signals are not constant over time but exhibit a varying frequency composition. The conclusion from this constraint suggests that FFT is inadequate for seizure detection, potentially missing detections, or false negatives when there is a transitory activity alteration.

In addition, the FFT does not give the timing of frequency components, which is essential to 516nalyzing EEG signals, as EEG signals recorded exhibit temporal dynamics of seizure occurrences. To resolve this problem, other techniques of this study, like DWT and EMD, are more appropriate for handling the nonstationary components and also provide time-frequency information(Jothi. B, Dr. D Jayaraj, 2024).

DWT

(DWT) (Kumar et al. (2014) is a powerful approach for detecting ES by its ability to characterize dynamic and impulsive features of EEG signals. This DWT has a fluctuating window size, allowing it to provide precise data on the related frequency. In comparison with Fourier analysis, DWT has one of the temporal resolutions; DWT obtains all the image-related information at its space location, the same as Fourier transformation. In contrast, the high-frequency functionality in the input image is represented in the four sub-bands of high frequency: whichLH, L and HH. Like the DWT, the disparity is computed on an image of the low sub-band compared to the image. Finally, the difference is calculated, and interpolation is carried out to transform the high-frequency sub-bands into two bands.Also, regarding this convolution operation, the DWT is defined as follows:

$$x[n] * h[n] = \sum_{k=-\infty}^{\infty} x[k] * h[n-k] \quad \text{....(7)}$$

Equation 7 defines the convolution operation. After the interpolation in the Discrete Wavelet Transform, the subsampling procedure reduces the image without loss of any image parts while conserving the quality of the image. Equation 8 depicts this procedure.

$$y[n] = \sum_{k=-\infty}^{\infty} h[k] * x[2n-k] \quad \text{....(8)}$$

In filtering operation, only high-frequency samples are retained after rejecting considerable redundant signal information, and these samples are then sub-sampled at the rate of 2.

$$y_{high}[k] = \sum_{n} x[n] * g[2k-n] \ldots (3)$$

$$y_{low}[k] = \sum_{n} x[n] * h[2k-n] \ldots (4) \quad \text{....(9) \& (10)}$$

DWT decomposes EEG signals into many sub-bands of frequencies to give a complete time-frequency representation of the data. However, DWT can have boundary effects that may be especially problematic when small window sizes or seizures are irregular. I.e., the choice of wavelet function and decomposition levels can significantly affect performance, and inappropriate choices can even result in losing important information (Kumar et al., 2014).

While these potential challenges exist, the DWT can work with non-stationary data and offer temporal and spectral information, which is necessary for seizure detection.

EMD

EMD is a technique that decomposes a signal sample into several individual components called"intrinsic mode functions" (IMFs) with a residue. The segmentation process is done with the procedure of sifting: Although EMD processes are free of basis functions, they are more appropriate for studying nonlinear and non-stationary data (Nagarajan et al., 2019). The function g1(m,n) is a signal partitioned into 'r1' rows and 'c1' columns.

$G_1(r1,c1)=f(r1,c1)-E_1(r1,c1)$ ....(11)

The proposed equation is tested if it satisfies the mentioned equation for Intrinsic Mode Functions (IMFs), then we are saying that it has the first Intrinsic Mode Function (IMF), named BIMF1(m,n). It continues until all the intrinsic mode functions are obtained. All of the BIMFs are organized to form a reconstructed signal sample.

Since EMD efficiently analyzes non-linear, non-stationary signals, such as EEG data, it is a good candidate for implementation in parallel computer systems. Additionally, it does an excellent job of clarifying the frequency and amplitude of the signal and the characteristics of seizures. The main disadvantage of EMD is that if the quality of the signal within it is not satisfactory (i.e. the signal is corrupted by noise), EMD can decompose it into IMFs that cannot provide helpful information (Nagarajan et al., 2019). In addition, boundary effects are critical in EMD, and the parameters can be misused, which may lead to eliminating important features.However, these problems do not ruin the potential of EMD as a valuable instrument for deriving major components from complicated EEG data.

4. RNN-CNN ARCHITECTURE FOR CLASSIFICATION

The system builds a combined CNN-RNN structure with a RESNET50-inspired convolutional design but changes several layer parameters followed by output from this network. The regular CNN-RNN template functions in three parts: it uses convolutional transformations, updates results with recurrent processing, and creates a result. RESNET50 forms the base of new layers which do not use the standard fully connected classification structures. The convolutional layer creates better visual representations of images in each sample. The system analyzes EEG data through recurrent layers to generate different EEG signal labels.

The joined CNN and RNN form the essential blocks of our proposed hybrid solution for detecting epilepsy symptoms in EEG data. The RNN layers process written information from the convolutional layer to discover different types of signals. The convolutional layers produce better results for local patterns compared to the performance of RNNs. The convoluted nature of CNN processing in RNN helps rapidly distinguish different signal elements during the convolution task. Using customized features within a CNN-RNN system helps boost performance in detecting epilepsy seizures from EEG recordings. The proposed convolutional recurrent neural architecture uses three layers to extract features from every window and a single max pooling layer to shrink their number.

The FC layer converts vector inputs into feature output. Our LSTM implementation merges RNN features with CNN layers and designed feature sets into a single model. New information categories are discovered using complete connection networks. The CNN section includes the following details about its layers: The input signals are initially combined with filters to create vertical and horizontal output values. The next step involves multiplying the input weights and adding the bias term, which produces results similar to those of an electrical signal.

Max pooling reduces the output feature size while performing its important role in CNN design. It eases overfitting problems and decreases the data processing speed and required parameters. At the end of system processing, the FC layer creates links with both the output layer and activating functions from the following CNN levels. Establish the correct number of outputs while generating distinct features and specify which features depend on others.

Softmax units handle results from the fully connected layer and produce feature-based predictions—an examination of the data results in determined chance outcomes for each classification group. The outcome class would become the one that scored highest in probability during analysis.

5. SIMULATION RESULTS

This research tests how well the new CNN-RNN hybrid system can find ES patterns in EEG signals. Our results include multiple performance metrics: correctness, exactness, detection rate, F1 value, selectivity, detection error rate, and false positives count. To display its advantages, this hybrid approach stands beside Multi SVM results and shows the outcomes of combining CNN-RNN architectures.

5.1 Performance Evaluation

The chart in Table 1 explains how the system operates. The CNN-RNN classification system used confusion matrix analysis to test its output, which contained specific components.

- **True Positives (TP)**: We are dealing with the actual positive rate, the number of identified seizure signals.
- **True Negatives (TN)**: The extent of the signals that are non-seizure and which were identified as such.
- **False Negatives (FN):** The quantity of the signals that correspond to seizures but are marked as non-seizure.
- **False Positives (FP):** The number of instances the standard signals were considered seizures.

Table 1. Performance Parameters

Observations	Normal	Epileptic Seizure
Found	Falsely Optimistic (FP)	Positive in all ways (TP)
Nothing was found	True Negative (TN)	Negative False (FN)

$$\textbf{\textit{Accuracy}} = \frac{TP+TN}{TP+TN+FP+FN} \quad \text{.... (12)}$$

$$\textbf{\textit{Recall}} = \frac{TP}{TP+FN} \quad \text{..... (13)}$$

$$\textbf{\textit{Precision}} = \frac{TP}{TP+FP} \quad \text{.... (14)}$$

The F1 score is used to evaluate the accuracy with which the system functions and it is a scalar quantity that ranges from 1 to 0.

$$\textbf{\textit{F1 score}} = \frac{2\,xPrecisionxRecall}{Precision+Recall} \quad \text{.... (15)}$$

The output signals for the five dataset samples are illustrated below figures:

Dataset A ("Healthy people with open eyes")

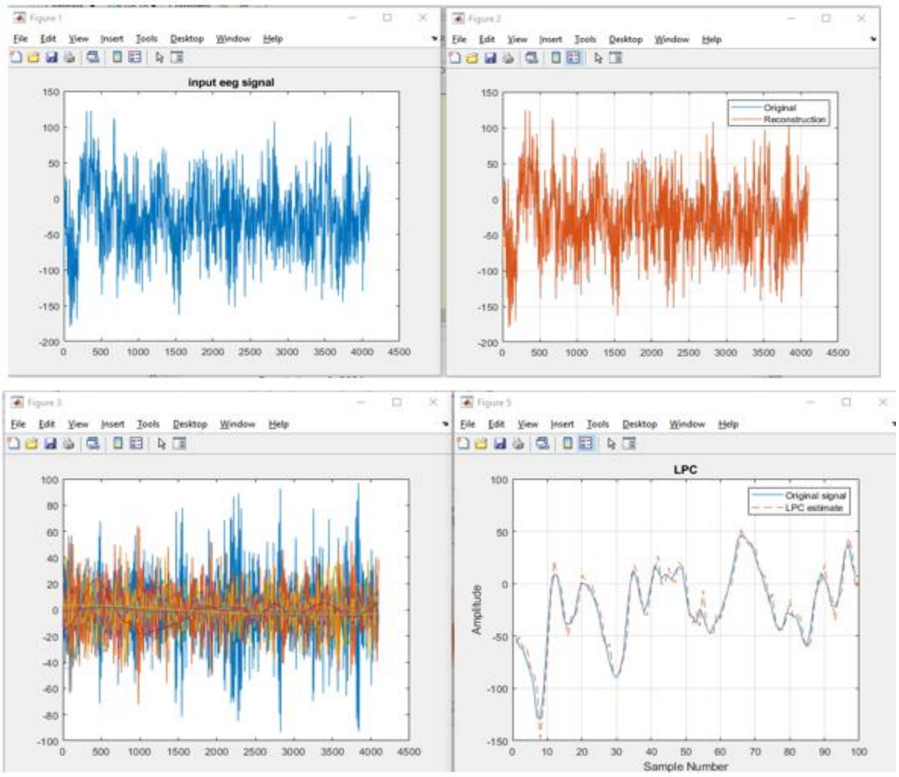

Figure 5.1 Output signals for Dataset A

Dataset B ("Healthy people with closed eyes")

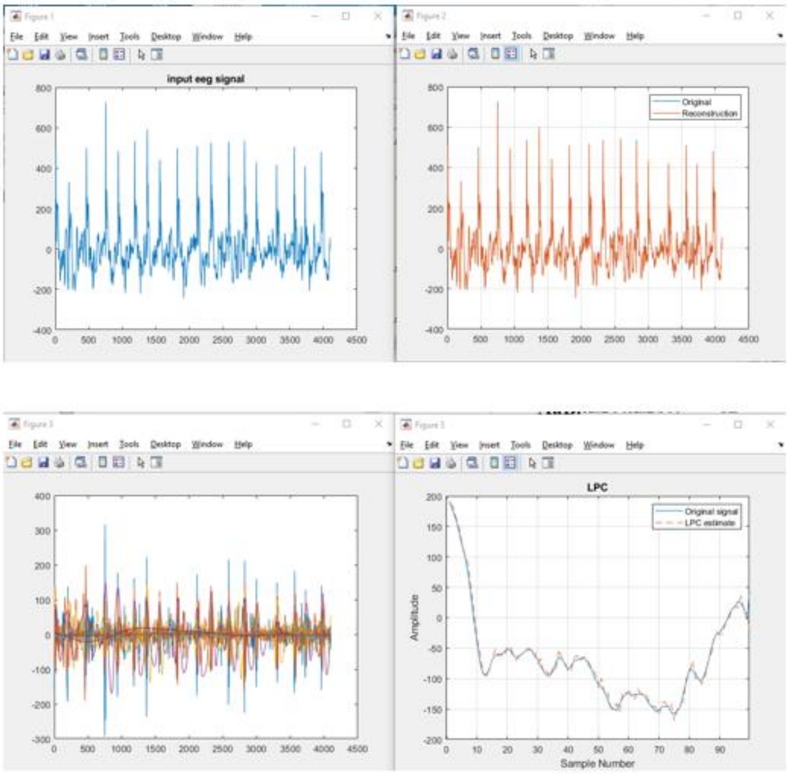

Figure 5.2 Output signals for Dataset B

Dataset C ("Hippocampal formation in the opposite hemisphere of the brain"):

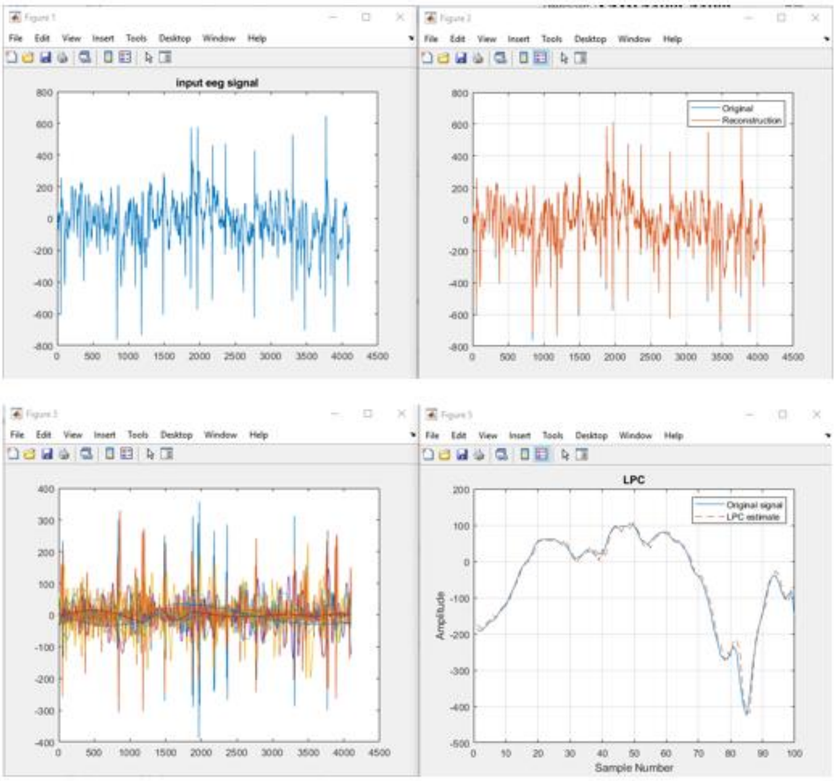

Figure 5.3 Output signals for Dataset C

Dataset D ("Epileptogenic Zone"):

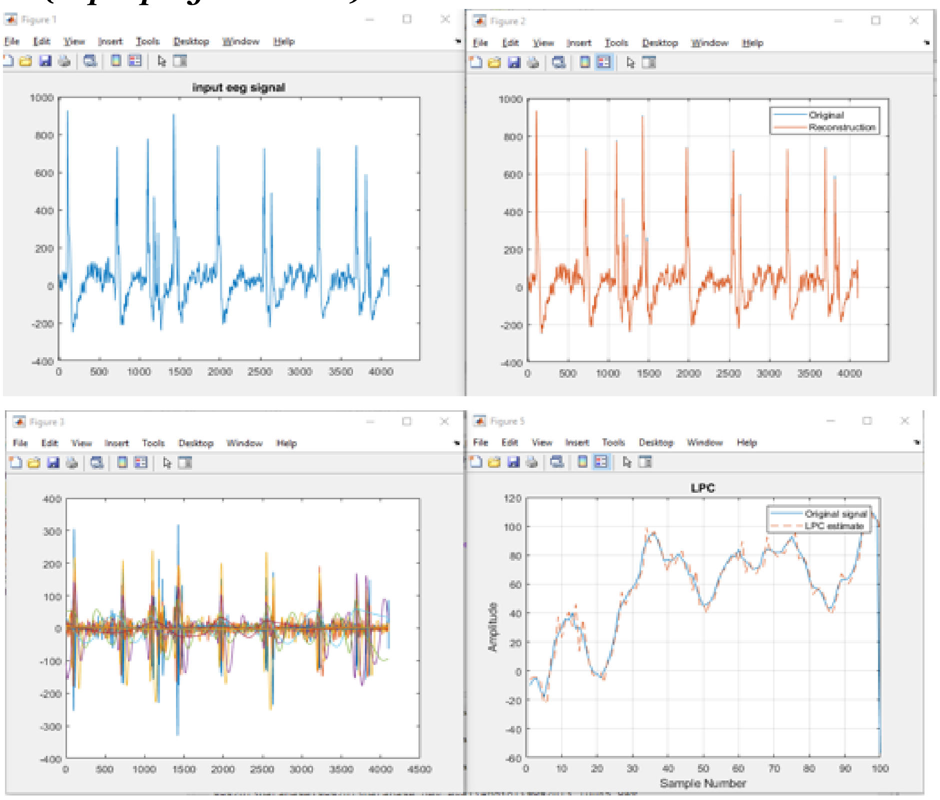

Figure 5.4 Output signals for Dataset D

Dataset E ("Seizure Activity")

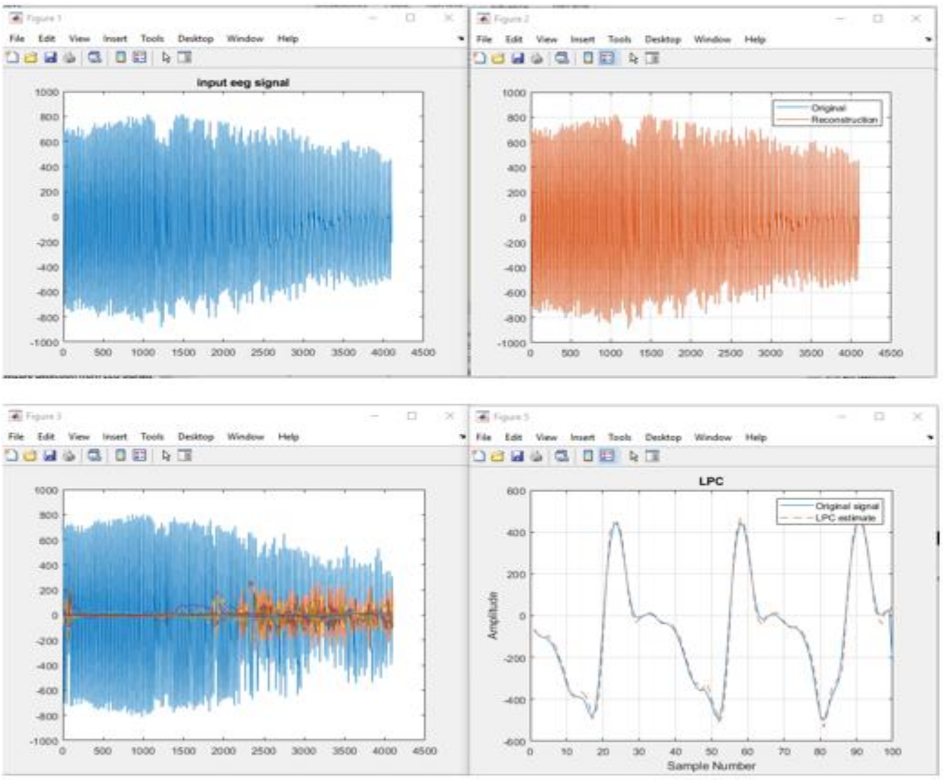

Figure 5.5 Output Signals Detecting Seizures from EEG Signals.

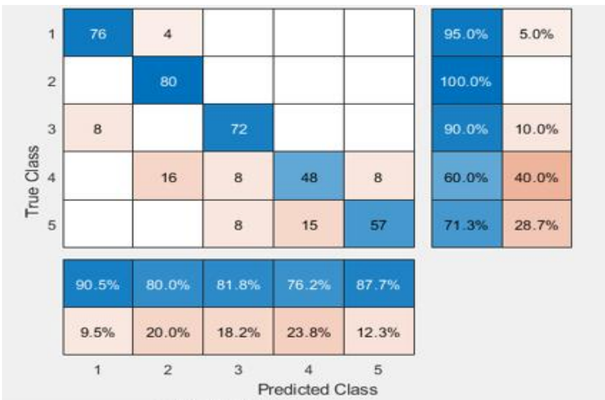

Figure 5.6 Confusion Matrix of Hybrid CNN-RNN classifier

The results analyzed in a way comparable to the various other performance perspectives are presented below in Table 2.

Table 2. Evaluation of different performance metrics

Sl No	Parameters	CNN-RNN
1	Precision	83.23%
2	Accuracy	98.38%
3	Specificity	95.81%
4	Recall (Sensitivity)	83.25%
5	Error	16. 75%
6	F1 score	82.61%
7	False Positive Rate	4.19%

5.2 Comparative Analysis

Table 3 contains the MultiSVMclassifier's performance characteristics, whereas Figure 5.7 is an example of the MultiSVM classifier's confusion matrix.

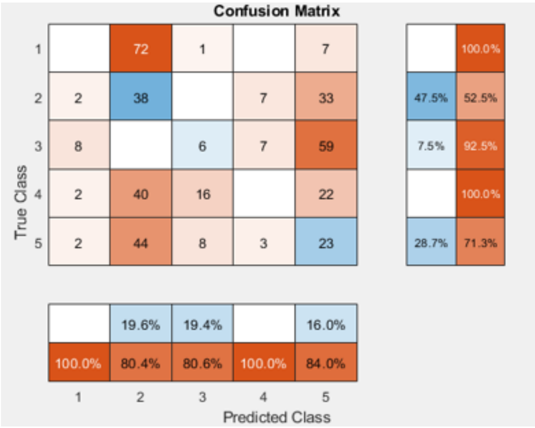

Figure 5.7 Confusion Matrix of the MultiSVM Classifier

The results of the comparisons to achieve different performance are presented in Table 2.

Table 3. Evaluation of different performance metrics

Sl No	Parameters	MultiSVM
1	Precision	76%
2	Accuracy	67.20%
3	Specificity	79.50%
4	Recall (Sensitivity)	18%
5	Error	82%
6	F1 score	66%
7	False Positive Rate	20.50%

Table 4: Feature extraction comparison

Feature Extraction Name	TYPE-A Healthy People with Open Eyes	TYPE-B Healthy People with Closed Eyes	TYPE-C Hippocampal formation of the opposite hemisphere of the brain	TYPE-D Epileptogenic Zone	TYPE-E Seizure Activity
LBP feature	0.0133	0.004	0.012	0.003	0.011
DWT feature	-6.858	0.601	-5.281	-1.504	1.854
FFT feature	0.350	0.689	0.994	2.207	0.980
EMD feature	-0.697	-0.846	2.002	-4.119	0.581
MFCC	0.643	1.003	0.803	1.208	0.516
Wavelet packet entropy	-9.92	-5.54	-9.44	-1.10	-1.13
Wavelet energy entropy	8.91	4.040	6.677	6.1628	8.146
Lorentz plot area	2.959	10.475	9.601	27.667	17.702
Median frequency	2.878	1.662	2.074	8.244	8.691
Mean frequency	1.764	2.045	4.807	2.043	2.047
Standard deviation	45.028	1.53	1.433	4.401	1.59
RMS Value	52.902	1.127	1.445	4.4006	1.598
Band power in the delta band	9.967	6.506	6.4594	6.0448	1.0704
Band power in	6.815	3.097	3.698	6.8154	4.61

theta band					
Band power in the alpha band	1.396	1.709	5.157	1.799	3.298
Band power in the beta band	7.296	2.519	1.147	3.964	9.027
Band power in the gamma band	2.047	1.170	1.800	1.615	2.859

The comparative results of the proposed CNN-RNN and MultiSVM are tabulated in Table 5 and are graphically illustrated in Figure 5.8.

Table 5. Comparativeresults of CNN-RNN and MultiSVM

Sl No	Parameters	CNN-RNN	MultiSVM
1	Precision	83.2354%	76%
2	Accuracy	98.38%	67.20%
3	Specificity	95.8125%	79.50%
4	Recall (Sensitivity)	83.25%	18%
5	Error	16. 75%	82%
6	F1 score	82.6079%	66%
7	False Positive Rate	4.1875	20.50%

When compared with MultiSVM, the CNN-RNN model's accuracy is much higher, at 98.38%, as opposed to 67.20% for MultiSVM. In other words, this indicates the superiority of the CNN-RNN architecture in accurately categorizing both seizure and non-seizure signals.CNN-RN outperforms MultiSVM since, although having slightly worse precision (83.24%) and recall (83.25%), it is far better than MultiSVM with a precision of 76% and recall of 18%. MultiSVM has such low recall (in its inability to detect seizure signals un accurately), which impedes clinical applications. In contrast, the CNN-RNN model achieves a well-balanced precision and recall such that any missed seizures occur at minimum cost in false negatives.The CNN-RNN model achieves a specificity of 95.81%, which is far more than MultiSVM's resulting specificity of 79.50%. Furthermore, the CNN-RNN model's reduced false positive rate (4.19%) ensures reliability in distinguishing seizure from non-seizure activities, avoiding unnecessary clinical interventions.Its F1 score is 82.61%, which is also superior to the MultiSVM model (66%). Thus, a high F1 score presents better precision, which means that the CNN-RNN model has more accurate results.The CNN-RNN model is capable of incorporating spatial and temporal EEG signals necessary for seizure identification, two characteristics that are not easy to capture with LSTM and MF.

5.3 Feature Extraction Comparison

To help understand performance improvement using the CNN-RNN model, a comparative analysis was performed between the feature extraction methodologies applied in both the CNN-RNN and MultiSVM models. Table 4 delineates the comparison of feature extraction across five distinct EEG dataset categories. A comparative analysis of the feature extracted with the CNN-RNN model's exploitation (the LBP, DWT, FFT, and EMD) can be better than the feature extracted with the Multi SVM model. This CNN RNN model uses the LBP technique for the time domain, DWT and FFT for the frequency domain, and EMD for non-stationary signal analysis, an ability crucial for identifying short-term and long-term organizational structures of the EEG data indicating seizure occurrence.

Comparing the results between different methods of feature extraction in the DWT, it is found that it produces superior Type-E (seizure activity) values over compared methods in detecting frequency changes associated with seizures. Results with the EMD approach show clearly that it is a successful approach to feature extraction for Type E signal, as the method is capable of detecting very small, transient signal changes associated with seizures.

5.4 Graphical Representation of Results

Figure 5.8 shows the performance disparity between the CNN RNN and MultiSVM models in graphical representation and compared with each other to emphasize the wide gap.

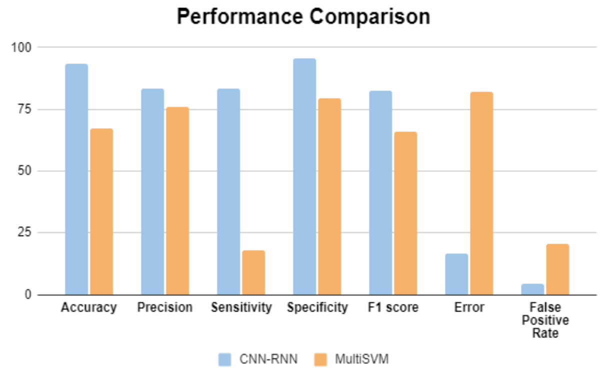

Figure 5.8: Comparative Analysis

5.5 Discussion of Results

There are several critical reasons why the CNN-RNN hybrid model is so exceptionally efficacious in the work presented. The CNN model component performs well at finding spatial patterns within the EEG signals to get local features related to seizure activity. Secondly, the LSTM RNN piece receives temporal dependencies in different EEG segments, which helps the model identify the dynamic evolution of seizures over time. The combined model with these two components shows high sensitivity and specificity to identify seizures.

According to the results, the constrained capacity of MultiSVM to model the temporal dynamics of the seizure occurrences and dependence on less discriminative feature sets may be responsible for its suboptimal performance.The CNN-RNN model employs feature extraction methods, namely DWT and EMD, to improve its functionality in determining how the coal beds can behave as rock break installations. Unlike other methods, conventional techniques developed based on MultiSVM are generally based on the application of relatively simple feature extraction methods, which are usually incapable of capturing the details of the seizure-associated phenomena.

CONCLUSION AND FUTURE DIRECTIONS

The results suggest that the model is feasible to use in clinical settings to track pathologic activity toward real-time surveillance and for something as automated as the identification of a seizure. Also, by reducing the false favourable rates and achieving high specificity, which decreases the need for manual EEG signal interpretation, the CNN-RNN model increases patient care.

This future work should focus on improving the model for clinical use in practice. What is important for practical application is improving model robustness using approaches to handle noisy data, poor datasets and class imbalance challenges. Investigating alternative deep learning architectures may also be beneficial, e.g., using attention processes, transformer models or some combination of the two. Continuous monitoring of the epileptic patient with wearable EEG equipment presents the possibility of early seizure prediction and intervention. In addition, additional data expanding the range of other demographic groups and seizure types could help increase the model's generalisability to different patient populations.

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