Hybrid RNN(Long Short-Term Memory) with CNN (Densenet201) model using EEG signals in detecting epileptic seizure in a human being

Puja Dhar[1]
Research Scholar, Lovely Professional University, Punjab, India

Dr. Vijay Kumar Garg[2]
Associate Professor, Department of Computer Science Engineering, Lovely Professional University, Punjab, India

Abstract

According to the researchers, the population has gradually increased, and the WHO - World Health Organization (WHO) released that epilepsy affects about 65 million people. Various investigations have been conducted in order to identify epilepsy using electroencephalogram - EEG signals that help to record the patient details that have the capability to collect the signals received from electrodes. These signals are presented with the spatial distribution of specific fields focused on the brain. In the current research, we have utilized a hybrid technique with the integration of a Dense Convolutional Network (DenseNet201) and LSTM - Long Short-Term Memory for epileptic seizure identification utilizing EEG data to choose appropriate features utilizing WOA - Whale Optimization Algorithm and PSO. The main focus of the current study is to reduce the time-consuming process during the detection of disease and enhance the accuracy of the prediction that helps physicians to start the treatment earlier as possible.

Keywords: PSO, Whale Optimization, CNN, RNN, Epileptic Seizure Detection, EEG Signal.

1. Introduction

In most of the scenarios, EEG is considered as valuable equipment mainly concentrated on spatial-temporal dynamic characterization of the neuron activities taking place in the brain; therefore, the signals are observed manually, which is considered as sensitive work that eventuated with practical equipment for the study that is utilized in seizure detection diagnosis. Most of the existing research is focused on epileptic seizure identification, and these topics still need more concentration. It is important to use various ML or DL methods, including PSO - Particle Swarm Optimization, CNN-Convolutional Neural Network, Fuzzy-based Concept, and much more in the health industry. Certainly, different epileptic seizure detection methods are utilized with EEG signals [1].

Moreover, epilepsy symptoms can be identified because of the abnormal synchronization and various neuronal activities occurring in the brain. This is a chronic disorder happened in the brain neurological that impacts millions of people around the world because of the electrical activities done in excessive amounts, and these are distinguished by epileptic seizures. Hence, these result in physiological, cognitive, and neurological impacts that result in death or Dizziness if not properly treated and diagnosed [2]. These studies exhibit that this type of disease is incurred due to the hyper-synchronous and other abnormal activities occurring in neuron cells that affect the patient's physical and mental health. The EEG - Electroencephalography tools are utilized to identify the seizures of occurrences. This is a clinical-based test conducted in various scenarios that capture the abnormal activities that happened in the brain neurons that were recorded using EEG. The recordings are complex to understand due to the biomedical signals, and it is not possible for manual investigation. However, the main issue faced during manual EEG signal inspection is the unavailability of neurologists during long-term EEG recordings. Therefore, it is a time-consuming and challenging process that needs expert knowledge in order to identify the seizures precisely. However, these issues are solved by employing automatic EEG signals. To capture the signals automatically, ML -Machine Learning techniques are utilized in order to test and train the acquired datasets [3].

Furthermore, the EEG plays a significant role in the health industry, especially in brain activity monitoring for an epilepsy diagnosis. The subject's expertise helps to analyze EEG recordings in order to identify epileptic activity. To overcome certain issues that persist in the existing research, CNN - Convolutional Neural Network has been utilized in [4], which was experimented based on EEG signals rather than utilizing feature extraction that has been utilized to differentiate interictal, preictal, and ictal segments for identifying epileptic seizure. It is important to provide an efficient automated detection method in the clinical community to overcome the issues that persist. Developing an effective bio-marker tool that applies to real-time and offline clinical techniques is significant in the healthcare industry. Further, the CADFES tools developed in [5], which is the automated detection method that helps to auto-locate epileptic seizures, and the Bern-Barcelona database had been used with the EEG data for the experimentation process along with the feature extractions including statistical domain, frequency, and time. Hence, potential features were chosen to utilize NCA - Neighbourhood Component Analyses.

Consequently, different issues are faced during the development of classification techniques and automatic detection tools for epileptic seizures. The CAD-based methods on arithmetic coding and the DWT - discrete wavelet transform [6] are utilized in research to distinguish epileptic seizure signals obtained from seizure-free signals. This method decomposes the coefficients and EEG signals utilizing DWT during rejecting non-significant coefficients with the threshold standards. The benchmark datasets are utilized to validate the developed methods. Usually, the EEG signal decomposition has been utilized in research to identify the focal signal behaviour with radiologists via the extracted features from every layer (decomposed subband).

Further, EMD - Empirical Mode Decomposition, nonlinear mode decomposition, and linear prediction decomposition, which are also known as conventional methods, have been utilized in the research [7] to predict the EEG signals of non-focal and focal behaviour. Therefore, three modules have been employed on the EEG signals, including feature classifications, feature computation, and transformation. These used features are categorized by a system classification method known as "neuro-Fuzzy inference) has been utilized in EEG signal classification with the non-focal or focal signal. Various Screening techniques used to predict epilepsy stages and neuroimaging modalities have been used and gained more attention from specialized views in the health industry. Primarily, the neuroimaging modalities used in the epileptic seizure diagnosis process involve functional and structural models. These modalities are primarily based on EEG signals that consist of IEEG - intracranial EEG and SEEG - scalp EEG [8]. Even though these techniques have several benefits, such as lower cost and simplicity, the physicist needs a long record along with the EEG patient's signal. Basically, the EEG signal has different artifacts and channels that cause challenges while diagnosing epileptic seizures.

2. Literature Review

In [9], EESC - epileptic-EEG-signal classification has been utilized in the research for accurate classification of various epileptic states, which includes significant data on the electrical activities that occurred in the brain for analysis purposes. Initially, this method will transmute EEG signals to PSDEDs - power-spectrum-density-energy diagrams, and then it employs transfer learning and DCNN - Deep Convolutional Neural Network that automates the extraction features processed from the PSDED. Eventually, the epileptic states are categorized into 4-categories, including seizure, preictal, and interictal. This method provided efficient results when compared to the other terms when it comes to efficiency and preciseness. Normally, it obtains 90% classification accuracy with the utilization of CHB-MIT epileptic EEG data. However, it is significant to enhance the EESC method to provide better epilepsy treatment.

In [10], a hybrid method that includes PSO - Particle Swarm Optimization and GA - Genetic Algorithm has been utilized in the detection of an epileptic seizure. Normally, the PSO method helps to define the SVM - Support Vector Machine optimization parameters, especially for EEG data classification. Therefore, SVM is considered an effective ML method and has been utilized in different applications. The SVM kernel parameters processed in the training phase impact the accuracy of classification. The current research used PSO and GA-based techniques in order to increase the SVM parameters in optimization. When it comes to comparison, PSO-based methods are processed in an effective way than GA algorithms. The existing hybrid SVM method provides better accuracy and procured 99.38% with the EEG datasets. However, the hybrid classifier run-time should still be minimized in the future for better performance.

In [11], an analysis system has been utilized in the research for epileptic seizure detection processed from EEG signals that utilize statistical features in accordance with the optimum allocation - OAT method and the LMT - logistic model trees. Hence, this analysis includes employing the OAT to choose specific EEG signals during the entire database processing. Thus, the extraction of statistical features taken from the EEG signals, further the acquired features, should be processed in the LMT classification method for epileptic seizure detection. Certainly, the utilized method consistency has been tested with the investigation chosen on the selected benchmark EEG dataset. Eventually, the procured outcomes exhibit high detection when it comes to performance evaluation for every selected class.

In [12], hybrid DCNN methods have been utilized in the research for EEG-based seizure identification. This study includes a 13-layer DCNN algorithm developed especially for the analysis that is automated. The hybrid DCNN method has procured 88.7% accuracy with 95% sensitivity and 90% specificity. Therefore, compared to other methods, this method procured lower results in terms of specificity, sensitivity, and accuracy. Further, the benefit of the technique is that it segregates the feature extraction steps without the utilization of the feature selection step in work. However, the major limitation of the utilized technique is that it is unable to proceed with the huge database (EEG).

Further, DCNN has the capacity to classify and identify epilepsy seizures in accordance with the EEG- spectrogram images. The EEG dataset, which is publicly available online, has been utilized in the research, and this method procured 98.22% accuracy during the EEG classification. Nevertheless, this method has slow execution and high complexity, and this technique is not appropriate for huge databases.

3. Research Methodology

In the current research, we have utilized a hybrid technique with the integration of a Dense Convolutional Network (DenseNet201) and LSTM - Long Short-Term Memory for epileptic seizure identification utilizing EEG data to choose appropriate features utilizing WOA - Whale Optimization Algorithm and PSO. The main focus of the current study is to reduce the time-consuming process during the detection of disease and enhance the prediction accuracy that helps the physicians start the treatment as early as possible. The proposed hybrid method framework has been illustrated in 3a.

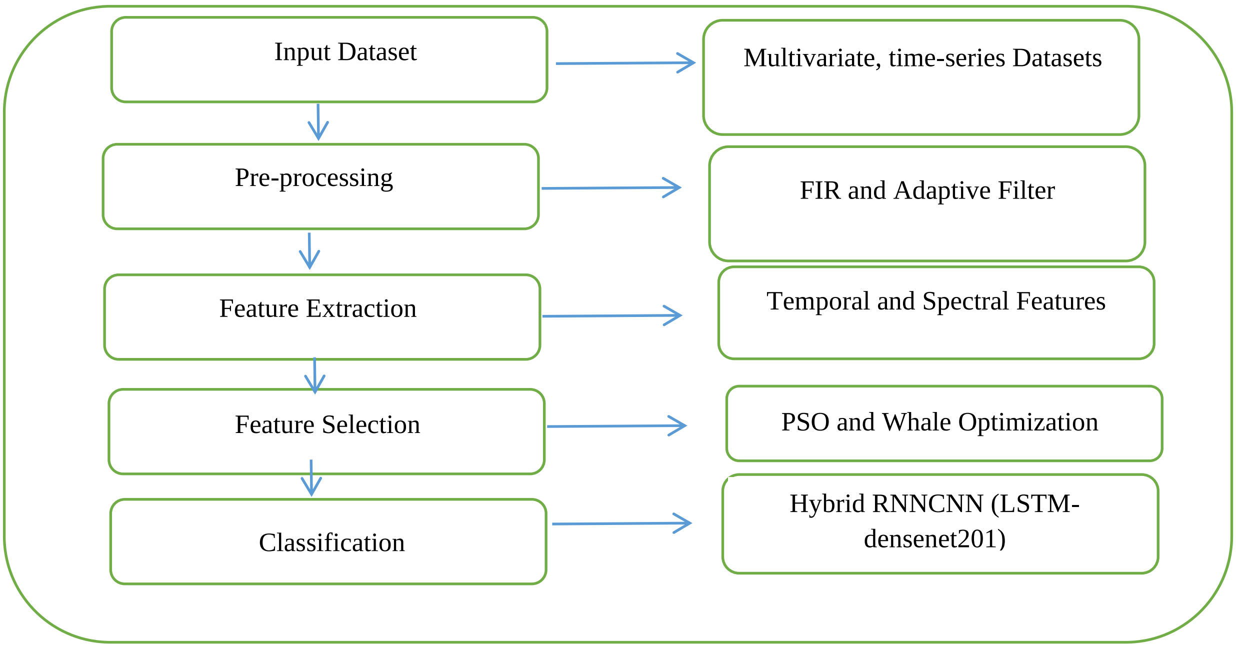

Figure 3a - The framework for the proposed Hybrid Method

3.1 Data collection

Firstly, appropriate datasets should be collected from proper sources to initiate the experimentation. In the current research, we have utilized the datasets that consist of 11500 records gathered from different Time-series and Multivariate data that includes specific information such as Recording_of_Seizure_Activity, Tumor_Located, Healthy_Brain_Area, Eyes_closed, and Eyes_open. These are the data values that are preprocessed for further execution.

3.2 Data Sampling or Preprocessing

Data Sampling or Preprocessing is the second stage in the experimentation process, the gathered information from different Time-series and Multivariate has been preprocessed in order to remove background noises and uncertainties from the data. Here, in order to remove noises, the filters such as FIR filter and Adaptive filter have been utilized in the experimentation process as follows:

3.2.1 FIR Filter

Impulse sequences of finite numbers define the digital filter impulse response, and these filters are known as FIR Filters. It enables a frequency range without minimizing its magnitude above below-cutoff frequency and upper-cutoff frequency. Therefore, it rejects the entire frequency amidst upper and lower-cutoff frequencies. Normally, the FIR filter eradicates unwanted noises, EMG noise, and uncertainties along with the cut-off frequencies at 1Hz - 90Hz. Further, the FIR-filter significant features have been used to acquire linear phase, denoted by group delay known as constant time. Therefore it is obtained by the symmetric impulse response,

$$\mathrm{s}\,(\mathrm{u}) = \mathrm{s}\,(\mathrm{U} - 1 - \mathrm{u}) \text{ --------------- } (1)$$

The x-transform of U-point FIR filter is expressed by:

$$\mathrm{S}\,(\mathrm{x}) = \sum_{\mathrm{u}=0}^{\mathrm{U}-1} \mathrm{s}\,(\mathrm{u})\mathrm{x}^{-1} \text{ --------------- } (2)$$

Where S (x) - Output response, s (u) - input response.

The FIR filter has been utilized during the need for the linear phase in such an application. Basically, filter design has been categorized into 2-parts as Approximation problem and the Realization problem.

3.2.2 Adaptive Filter

Adaptive Filter has been categorized as least square estimation, defined as stochastic gradient method, and recursive least square method, which defines least mean square.

3.2.3 LMS

LMS, also known as Least mean square, helps evaluate the gradient vector along with the instantaneous value. These normally vary the tap weights of the filter recursively.

The error estimation defined as e (s) is expressed,

$$\mathrm{e}\,(\mathrm{s}) = \mathrm{c}\,(\mathrm{s}) - \mathrm{w}_{\mathrm{s}}\,\mathrm{y}\,(\mathrm{s}) \text{ ---------------------- } (3)$$

In every iteration, the weights are upgraded by,

$$w_{s+1} = w_s + \mu e(s)\, y\,(s) \text{ ---------------------}(4)$$

For y (s) - input vector, the input time delayed value as,

$$y(s) = [y(s)y(s-1)\ldots..y(s-S+1)]^T \text{ ----------(5)}$$

w(s)- coefficient of adaptive filter at certain period s. μ defines the size, where μ is very small, w_s is small, the final solution will be too large. In case μ provides too large results, w_s becomes unbounded and not stable.

4. Feature Extraction

In the Feature Extraction section, the temporal and spectral features are utilized for the experimentation process. The Temporal features help to choose the time frequency of the filtered data during distribution. At the same time, the spectral features include certain terms such as spectral Centroid, spectral Entropy, spectral Kurtosis, spectrak skewness and spectral Spread, spectral Rolloff Point, spectral Decrease, spectral Slope, spectral Flux, spectral Crest, and spectral Flatness.

4.1Temporal Features

Normally, the temporal feature helps to choose the time-frequency of the filtered data during distribution. In the case of certain conditional temporal situations, a non-stationary signal contains a parameter of time-varying that utilizes in the classification of the delay situation, which includes time. Moreover, these terms are connected to the joint time frequency and conditional-spectral moment. Certainly, the conditional spectrum is considered an integral function used in frequency terms that includes marginal distribution with the provided time. On the other hand, the joint-time-frequency is considered a double integral, where it is totally different from frequency and time.

Normally, the evaluation of the signal conditional-temporal moment used in the non-centralized case is as follows,

$$\langle i^n \rangle_s = \frac{1}{P\,(s)} \int i^n\, P\,(i,s)dt, \text{---------------------- (7)}$$

Where, the centralized conditional-temporal moment as represented as,

$$\mu_i^n\,(s) = \frac{1}{P\,(s)} \int (i - \langle i^1 \rangle s^n\, P(i,s)dt \text{ ----------------------(8)}$$

4.2 Spectral Features

In the spectral features section, the Spectral Centroid, Spectral Entropy, Spectral Kurtosis, spectral skewness and Spectral Spread, spectral Rolloff Point, Spectral Decrease, Spectral Slope, Spectral Flux, Spectral Crest, and Spectral Flatness.

4.3 Spectral Centroid

$$\text{Centroid (c)} = \frac{\sum_{l=c1}^{c2} f_l s_l}{\sum_{c1}^{c2} s1} \text{ ---------------------- (9)}$$

Where, f_l - frequency (Hz), associated to bin I, s1 - spectral value represented at bin I, c1 & c2 - band edges represented in bins that denoted to measure the spectral centroid. The graph has illustrated the Spectral Skewness in figure 3.3.1.2a.

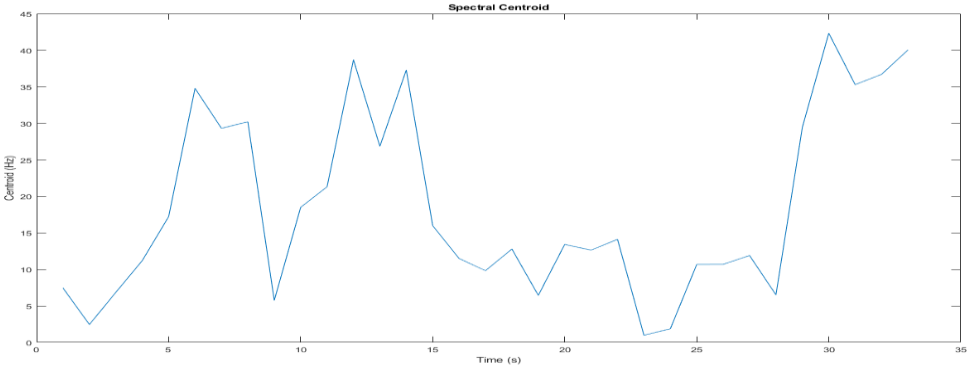

Figure 3.3.1.2 a - Graphical Representation of Spectral Centroid

4.4 Spectral Spread

$$\text{Spread (n)} = \sqrt{\frac{\sum_{I=c1}^{c2}(f_I - \mu_I)^2 s_I}{\sum_{I=c1}^{c2} s_I}} \text{-----------------(10)}$$

Here, Where, fl - frequency (Hz), associated to bin I, s1 - spectral value represented at bin I, c1 & c2 - band edges represented in bins that denoted to measure the spectral spread, - spectral centroid, which helps to measure by the function of the spectral centroid. The graph has illustrated the Spectral Spread in figure 3.3.1.2b.

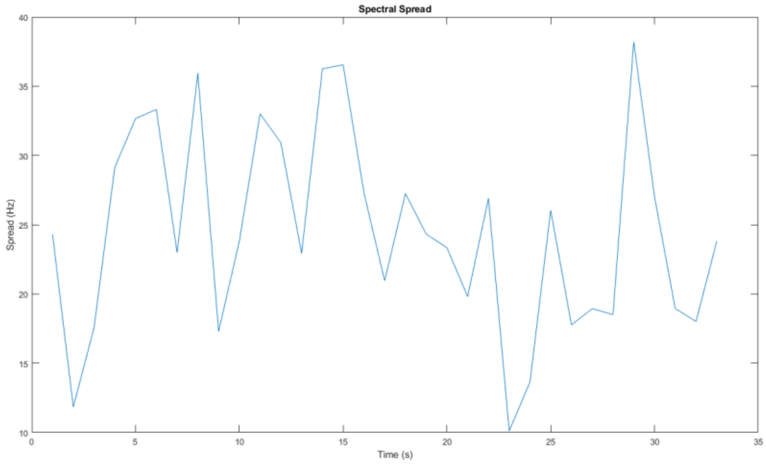

Figure 3.3.1.2 b - Graphical Representation of Spectral Spread

4.5 Spectral Crest

$$\text{Crest (c)} = \frac{\max\left(s_{I \in [c1, c2]}\right)}{\frac{1}{c2 - c1} \sum_{I=c1}^{c2} s_I} \text{--------------------(15)}$$

The graph has illustrated the Spectral crest in figure 3.3.1.2 g.

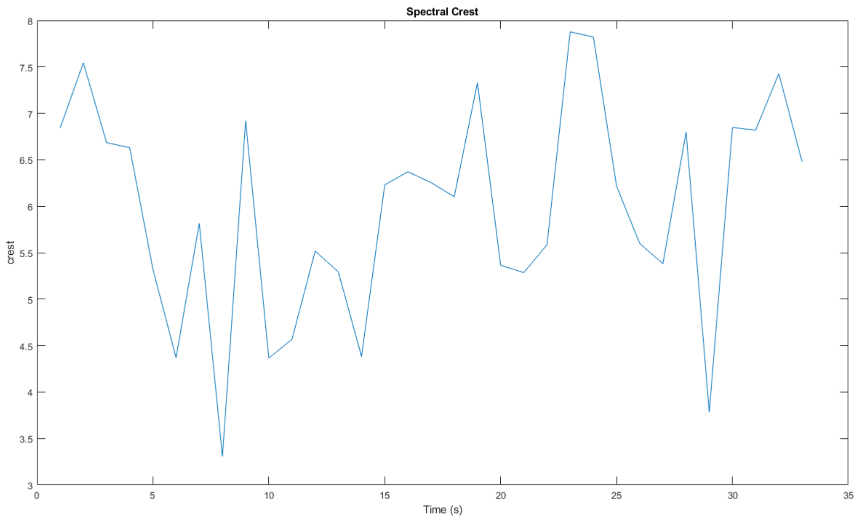

Figure 3.3.1.2 g - Graphical Representation of Spectral Crest

4.6 Spectral flux

$$\text{flux}\ (x) \ = (\textstyle\sum_{I\,=\,c1}^{c2} |s_I\ (x) \ - \ S_I\ (x \ - \ 1)|^N)^{1/N} \text{--------------------(16)}$$

Where, c2 & c1 -band edges in bins helps to measure the spectral flux, N- norm type.

The graph has illustrated the Spectral flux in figure 3.3.1.2 h.

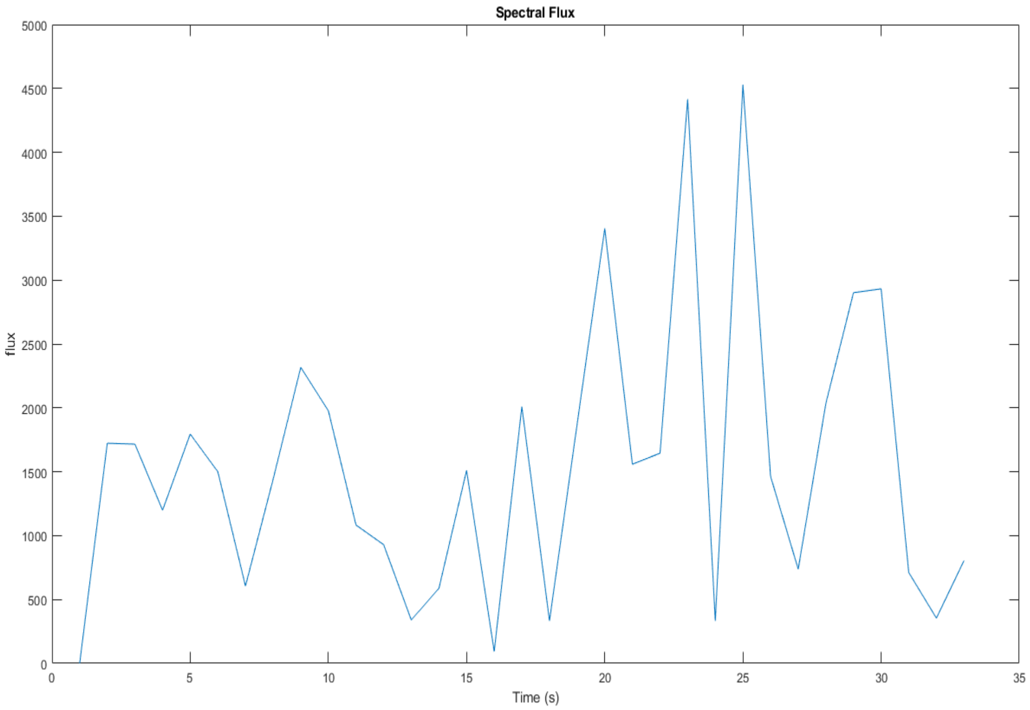

Figure 3.3.1.2 h - Graphical Representation of Spectral Flux

5. Feature Selection

The next step is feature selection, where an effective automated scheme has been developed in order to detect epileptic seizures and classify the EEG signals for epileptic seizures into a particular occurrence that includes post-seizure, seizure, and pre-seizure. These should be appropriately evaluated and identified. In the feature selection step, we utilized whale optimization and PSO techniques. The main benefits of the PSO technique are that it is simple, efficient, easy implementation, and has robustness during controlling parameters. The algorithm of the PSO has been mentioned below, and the outcome of the optimal position has been estimated with the optimal feature subset.

PSO - Optimization algorithm

Input-Feat-Original Feature-set

N1 - Defines the population size

H02 - Feature dimension

Maximum Iteration (MI) - 100 iterations

O/P (Output) - optimal-feature subset

Label (L) - Input Feature Labels

Initiate the particle presents in the population

Evaluatethe correlation matrix coefficients Mamidst features in Fe

Evaluateeveryfeature contributionin Fe by Rr

While - The iteration termination condition is not satisfied certain aspects.

do

For j=j to N1**do**

Evaluatethe particle fitness value utilizing KNN classifier

Historical best-position update of the particle

end for

Velocity of the particle **Update**

Population Optimal position**Update**

For j=I to N1**do**

For j=1 to h02**do**

Finally, the particle position **Update** by integrating the value v of every feature

end for

end for

end while

Further, WOA optimization has been utilized in the research, and it is a population-based method that can avoid certain local optima conditions to achieve a global-optimum solution. Therefore, this technique can solve various unconstrained and constrained issues that occur in the practical application without structural reformation.

WOA Optimization

Input-Feat-Original Feature-set

N1 - Defines the population size

Lb1 - lower_bound - 0

Ub1 - upper_bound - 1

Threshold_value - 1

H02 - Feature dimension

Maximum Iteration (MI) - 100 iterations

O/P (Output) - optimal-feature subset

Label (L) - Input Feature Labels

Initiate the particle presents in the population

Evaluatethe correlation matrix coefficients Mamidst features in Fe

Evaluateeveryfeature contributionin Fe by Rr

While

Every iteration termination condition is not satisfied

For j=j to N1 do

Fitness value Evaluation of the particle utilizing KNN-classifier

Update the agents historical best-position

end for

Update the population optimal position

For j=I to N1**do**

For j=1 to ho1 **do**

Feature

If (fit1<0.5)

Update the current position search agent using equ20

elseif (fit1<1)

Random search-agent selection (rand)

Update the current position search agent using equ21

end for

end for

end while

The current research has utilized PSO and WOA in the feature selection process in order to provide an efficient outcome that helps in the real-time application.

6. Hybrid RNN(LSTM) with CNN (Densenet201)

In the current research, three primary layers have been utilized, stacked together to develop a fully connected CNN that is a dense layer, pooling layer, and convolutional layer. Firstly. The input signal has been interconnected to the convolutional layer to manage the operation utilizing a window (kernel). Therefore, the outcome of the equation, as mentioned earlier, is created as a feature map for the layer presented next. Further, the convolutional layers are presented in between, and a pooling layer will be utilized in order to minimize the feature map size; therefore, it allows fast computation. Certainly, each neuron presented in the pooling layer is interconnected with the neuron presented in the fully connected layer. Here, the high-level features are utilized in the research in input signal classification into different classes. The training image is represented in figure 3.3.2b.

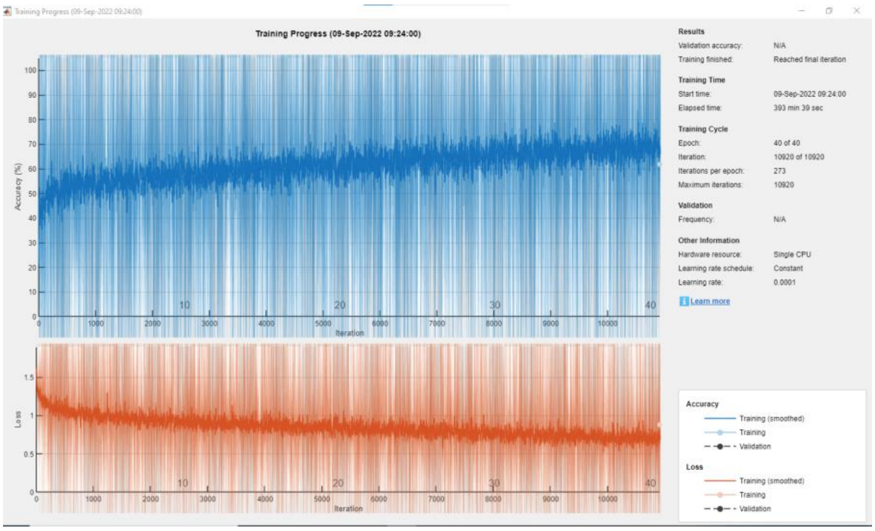

Figure 3.3.2 b - Training image

Moreover, this study utilizes pre-trained NN models known as DENSENET-201 in experimentation with the CNN and 201 layers deep. The total network can be trained by loading pre-trained, and it has the capability to train images captured from the Image Net database. Certainly, the dense201 was modified into RNN and compared with the conventional feed forward network architecture. Further, RNN has the capability to inherit the properties of strong modeling and have the capacity to study sequential data as neurons and transmit feedback signals to the next presented neuron found in the hidden layer.

Eventually, this research integrates the CNN and RNN by developing a DL network for information, including image sequences that include medical images or videos. The sequence input layer has been used to provide the images to the network and employed with the convolutional operations at every step. As a first step, it will convert the image sequences into arrays utilizing the folding sequence layer. Once the operation is executed, restoring the sequence structure and converting the changes arrays to image-sequence is significant. Finally, in order to transform the converted data to feature vectors, we have utilized a flattened layer and then the input vector sequence into LSTM.

7. Results and Discussions

This section compares the results of the hybrid RNN-CNN model with the other existing techniques. The WOA and PSO feature selection and classification are compared with the Hybrid LSTM with Dense201. We utilized RNN-LSTM in the experimentation process for classification, as stated in this section. This proposed method has successfully and efficiently extracted the feature map signals and procured better results than existing research. The PSO Optimization Output comparisons are illustrated in Figures 4a, 4b, & 4c with the feature selection and confusion matrix for RNN-CNN and RNN-LSTM models. On the other hand, The Whale Optimization Output comparisons have been illustrated in Figures 4d, 4e, & 4f with the feature selection and confusion matrix for RNN-CNN and RNN-LSTM models.

Table 4.1a Performance Matrix **Table 4.1b - Performance Measure**

Proposed Model	**Performance Value**	**Existing Model**	**Performance Value**
Accuracy	89.0226	Accuracy	79.1096
Error	27.4435	Error	52.2261
Sensitivity	72.5565	Sensitivity	47.7739
Specificity	93.1391	Specificity	86.9435
Precision	75.6008	Precision	46.8391
FalsePRate	6.8609	FalsePRate	13.0565
F-score	72.7927	F-score	46.9687

Table 4. a and b represent the performance matrix and values for the proposed and existing model with the PSO optimization method. It has been denoted that the proposed method procured better results than the existing method in terms of accuracy (89.0226), error (27.4435), sensitivity (72.5565), specificity(93.1391), precision (75.6008), FalsePRate (6.8609), and F-score (72.7927).

8. Conclusion

In the current research, a novel hybrid DL model that integrates a Dense Convolutional Network (DenseNet201) and LSTM - Long Short-Term Memory for epileptic seizure was identified using EEG data to choose the features of PSO and WOA optimizations. The proposed method first transforms the EEG data into an Adaptive FIR filter. Therefore, it usually chooses the features utilizing WOA and PSO optimization algorithms. Then, we trained the previously transformed image via a hybrid model integrating Densenet201 and LSTM. Eventually, the performance of the proposed method has procured efficient results with an accuracy of 90.34% in WOA and PSO with an accuracy of 89.02% in existing methods.

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