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A FUZZY–DEEP LEARNING APPROACH FOR MEASURING EPILEPSY SEVERITY USING EEG SIGNAL

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Abstract: Epilepsy is a neurological disorder that affects more than 75 million people in the world. It has resulted to increase in mortality rate, especially in Sub– Saharan Africa due to the lack of experienced medical expert to diagnose the disease leading to misdiagnosis and time–consuming diagnosis. EEG signal is found to be one of the suitable tools to investigate brain disorder by measuring the electrical activities between the brain cells. Hence, this paper used a deep learning Long Short–Term Memory (LSTM) algorithm and fuzzy System is proposed using Electroencephalograph signals (EEG) with 24 epileptic subjects containing 18–EEG channels each were used. The EEG signals were pre–processed to remove artifacts generated during EEG recordings using Notch filter for band stop of 64hz and band pass of 32Hz. The deep–learning model based on LSTM is used for training of 100– segments per channel Epileptic signals and 33– segments used for recognizing Epileptic signals with performance metrics of Accuracy, time, precision, Recall and F1 Score used to evaluate performance. The extracted parameters from the epileptic signals, Signal Energy (SE) and Logarithmic Band Power (LBP) serves as input to the fuzzy Inference system. A triangle membership functions that fuzzifies the extracted features to establish intensity scales using nine (9) fuzzy rules in fuzzy inference system (FIS) were used to characterize each of the disease severity as low, medium, and high in the FIS and the result showed that the proposed model has potential in classifying Epileptic EEG signals.

Keywords: Electroencephalograph–signals, Epilepsy, Fuzzy Inference system, Logarithmic Band Power, Long Short–Term Memory

INTRODUCTION

Electroencephalography (EEG) signals referred to neural signals utilized for diagnosing brain-related disorders. EEG serves as a valuable tool for classifying various neurological impairments, including, Epilepsy, sleep disorders, brain death, autism spectrum disorder and dementia, among others. These signals are capable of giving patient's psycho-physiological state information and exhibit distinct patterns associated with different mental states. The amplitude and patterns of the EEG signal indicate the amount of general stimulation while representing the electrical activity of the brain [3]. This excitement changes significantly during sleep and wakefulness and is affected by the activity of the reticular activating system in the brainstem [9].

Epilepsy is a neurological disorder applied to “provoked or acute epileptic symptomatic seizure which may represent brain injury. Epilepsy is a neurological disorder that refers to provoked or acute symptomatic seizures, often indicative of brain injury. It affects over 70 million individuals worldwide and occurs as a temporary disruption of normal brain function, leading to recurrent unprovoked seizures [4]. These seizures arise from excessive and hypersynchronous firing of cortical neurons and can be focal or generalized. Epilepsy may affect muscles, sensory perception, or both, potentially resulting in complete loss of consciousness [11], [10], [19].

LITERATURE REVIEW

Recently, classification of Epileptic EEG signals has been conducted by different researchers. [1] proposed a method for detecting epileptic seizures using a dynamic wavelet network. Epileptic EEG containing 500 EEG segments from five epileptic patients, band pass filtered at 1-70Hz, 15min with 4-channels digitized at a rate of 200 samples per second were utilized. The EEG was decomposed into frequency sub-bands using discrete wavelet transform, and these sub-band frequencies were used as input to an ANN for classification. The ANN provided two discrete outputs: normal and epileptic. The performance of the Feedforward Error Backpropagation Artificial Neural Network (FEBANN) was compared with that of the Discrete Wavelet Network (DWN).

The results showed that DWN identified epileptic seizure better by accurately with 93.1% specificity and 92.8% sensitivity and FEBANN with 91.3% specificity and 90.4% sensitivity. In [19] developed an Epilepsy diagnosis system using a particle swarm optimization-learned artificial neural network. Epileptic EEG containing 800 EEG segments from five epileptic patients, band pass filtered at 0.53-40Hz, 15min with 128-channels digitized at 173.61 samples per second, was utilized. A PSO-based neural network (PSONN) model was varied based on different versions of PSO. The PSO-based training methods were compared with the backpropagation algorithm by evaluating classification accuracy. The performance of the developed networks (PSONN and BPNN) showed an accuracy of 99.25% and 90.75% respectively for epilepsy recognition. In [5], A Neuro- fuzzy Approach for predicting Epilepsy using EEG signal. The Epileptic EEG used was obtained from CHB -MIT database which contained both epileptic and healthy EEG data, each containing 100 single-channel EEG segments, with each segment lasting 23.6 seconds. The model used Haar wavelet for pre-processing the EEG signal to eliminate noise, wavelet analysis was applied to decompose signal into frequency bands which serves as input to the fuzzy system.

The results showed that the developed model (wavelet analysis and Adaptive neuro fuzzy (ANFIS) when compared with SVM have a better accuracy of 98.4% and 97.68% for SVM. [9] carried out EEG signal analysis for diagnosing neurological disorder Using Discrete Wavelength Transform and Intelligent system. The EEG dataset comprises five sets labeled A, B, C, D, and E, each containing 100 single-channel EEG signals. Each signal has a total duration of 23.6 seconds and is sampled at a frequency of 173.61 Hz. They investigated with different EEG feature extraction and classification techniques for diagnosing autism spectrum disorder and epilepsy. The best approach that showed the highest accuracy was found to be combination of logarithmic band power (LBP) and Support Vector Machine gave the highest diagnosis overall Accuracy of 96.14% for Epilepsy classification.

In another study by [3], epileptic seizures were determined from EEG signals using Python programming and three different machine-learning methods from artificial intelligence techniques namely ANN, Gradient Boosting (GB), and Random Forest (RF). Energy and normalization processes of EEG signals were performed and results showed in the performance analysis, indicated normalizing the signals and calculating the energy values were more successful. ANN algorithm is predicted a success rate is 96.56% to detect epileptic seizures using three different attributes, the Gradient Boosting with a success rate of 95.60% and Random Forest with success of 95.00%.

METHOD AND MATERIAL

Dataset Description

The EEG data was collected from EEG children Hospital Ikeja, Lagos Nigeria using EEG data acquisition system called BE PLUS PRO LIGHT amplifier and a processing software that runs using the Microsoft SQL-based Neuro Works database as shown in the figure 2 over the period from April 2021 to August 2022. It included EEG signal of anonymous twenty-four (24) children diagnosed with epilepsy according to International League Against Epilepsy (ILAE), between age 3-10years.The total period of each signal segmented at 50sec with the data sampling frequency of 256HZ taking during both sleep and wakefulness. The signal containing 18- single channel Epileptic EEG signal with the band-pass filter settings of 32HZ, and a band stop of 60HZ digitized with 24-bits resolution were used. EEG datasets of Epileptic patients was obtained for detection and clinical diagnosis and also used to determine the severity rating to assists in providing specific individualized interventions rather than more general treatment plans.

Proposed Model

All This model for epilepsy prediction has five modules which includes (1) EEG data collection or acquisition, (2) pre-processing for noise removal and data cleaning using Notch filter, which was for band stop (3) feature learning was done using LSTM to train the system and find patterns in data as well as either epileptic or non-epileptic, and fuzzy logic for handling of vagueness and ambiguity of EEG signal. As shown in figure 1 below:

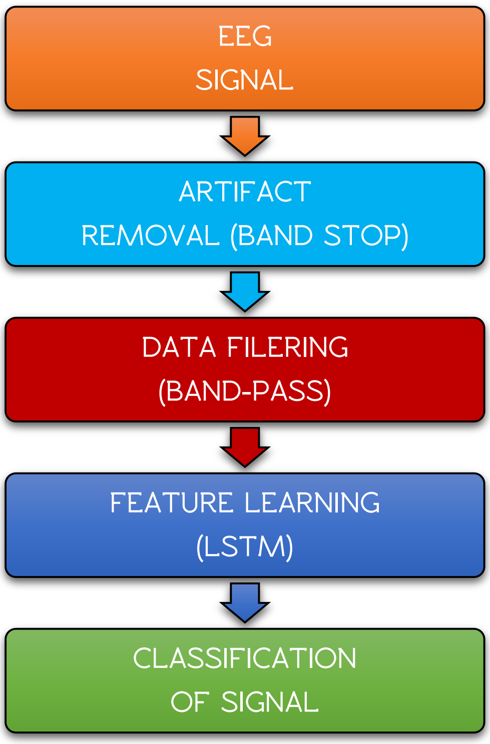

Figure 1: Proposed Block Diagram of the System

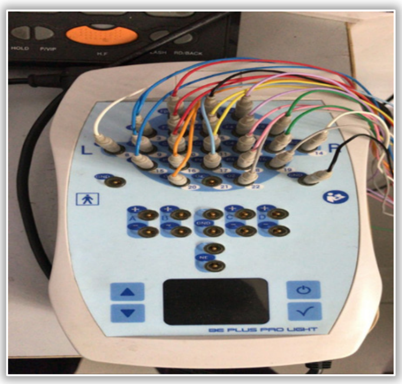

Figure 2: Be plus pro light version

Preprocessing

In this study, Notch filter was used for artifacts removal, to remove generated artifact with the acquired EEG signal. A band-stop filter, including a notch filter, specifically reduces the strength of sounds within a particular frequency range while allowing all other frequencies to pass through unchanged. In the case of a notch filter, this frequency range is very narrow. The stop-band refers to the frequency range that a band-stop filter attenuates. Infinite Impulse Response (IIR) filters, often called notch filters, include feedback and feature an impulse response that doesn't exactly zero out beyond a particular point but instead remains endlessly. These filters' output is influenced by both the previous output and input values as shown in equation 1:

$$(n) = \Sigma_{i=0}^{X} biq[n-i] + \Sigma_{i=0}^{Y} aip\,[n-j] \quad (1)$$

where:
p[n] = signal input
q[n] = signal output
X = filter order feedforward
Y = filter order feedback
bi = coefficients of feedforward filter
ai = coefficients of feedback filter

In order to filter out the noises found in EEG signal; two (2) digital filter structures (Notch and Finite Input Response (FIR) were implemented and the results presented as shown in the tables 1 and 2 below:

Table 1: Performance parameters of noisy epileptic EEG signals and filtered EEG signals using a low pass Notch filter

Order	PSR	CC	MSE
2	131.1899	0.7924	0.0023
4	100.2755	0.9617	0.1195
6	124.3407	0.9342	0.2096
8	84.5903	0.9137	0.2096
10	87.057	0.888	0.3788
12	84.839	0.9273	0.3452
14	96.2304	0.9551	0.1512
16	79.6791	0.9266	0.2532
18	77.4762	0.937	0.2208

Table 2: Performance parameters of noisy epileptic EEG signals and filtered EEG signals using a low pass FIR filter

Order	PSR	CC	MSE
1	44.0812	0.9902	1.102
2	70.0123	0.9635	0.2247
3	92.1056	0.9468	0.1651
4	93.4765	0.9251	0.1888
5	92.0238	0.9250	0.2396
6	84.2136	0.8868	0.292
7	91.2452	0.8717	0.3342
8	100.6584	0.8618	0.3605
9	78.4179	0.8584	0.3688
10	82.8252	0.8604	0.3622

The results showed that band stop NOTCH gives the best results when the filter order is 2 with the minimum MSE of 0.0223. Then to further evaluate the filter performance, parameters (SNR, and CC) are calculated after implementing the filter. Table 1 shows that the band-stop Notch filter outperforms the band-stop FIR filter while rejecting noise artifacts from EEG signals. The analysis parameters used for evaluating the EEG signal also showed significant improvement in SNR values even with band-stop IIR filter structures. The value of SNR and CC of the denoised EEG signal gave 108.1899db and 0.9924 respectively. As the order of the filter increases, the value of SNR and CC decreases. However, after order 2, SNR and CC values start decreasing with a further rise in filter order. This shows the Notch band stop filter with order2 provides an improved result for the EEG signal. Also, the Power Spectral Density (PSD) analysis of the implemented Notch and structures of FIR filter for EEG signal pre-processed is presented in Figure 3 and Figure 4 respectively.

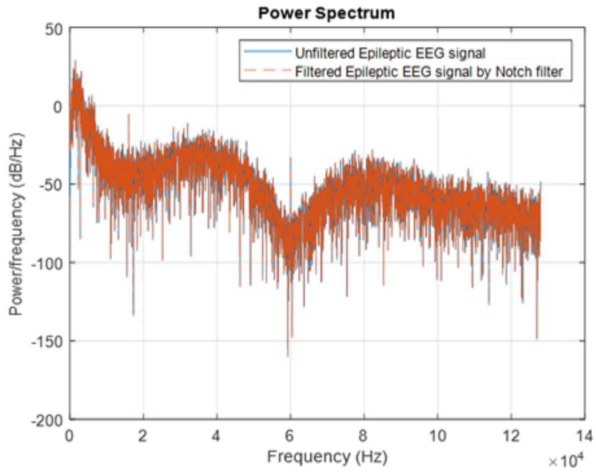

Figure 3: Power Spectrum Density of unfiltered and filtered EEG signal using Notch

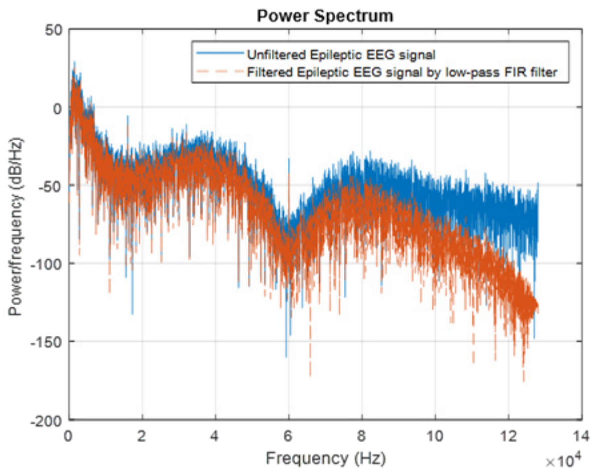

Figure 4: Power Spectrum Density of unfiltered and filtered EEG signal using FIR filter

The amplitude of EEG waves varies significantly across frequency bands. Figure 3 and 4 shows a person's 50-seconds EEG signal and the amplitude change in the lower frequency regions. While the filtered EEG signal using FIR filter has the lowest intensity frequency distribution, the filtered EEG signal using Notch has the most significant intensity frequency distribution. The change in an average

EEG signal between unfiltered and filtered EEG signal is shown in Figure 3 and 4, and the changes seen during an epileptic seizure are shown in figure 3. In general, epileptic seizures appear suddenly, with spikes in the EEG signals, persist for a few seconds, and disappear.

FEATURE LEARNING AND CLASSIFICATION

The Long Short-Term Memory (LSTM) was employed to learn and classify time-series data derived from EEG signals. Recurrent neural networks (RNNs) like LSTM address challenges such as vanishing and exploding gradient problems by incorporating mechanisms for learning both long- and short-term dependencies. LSTM networks consist of cells that propagate their outputs through the network based on the information stored in their previous memory state. As a result of these cells' shared cell state, the chain of LSTM cells as a whole is able to maintain long-term dependence. The input gate (It) and forget gate (Ft) within the network regulate the flow of information, enabling the network to decide whether to disregard the previous state (Ct-1) or adjust the current state (Ct) in response to new data. An output gate (Ot) governs the hidden state or output of each cell, enabling it to compute its output based on the current cell state. The LSTM cell's operation is guided by specific formulas that outline its functionality as n equation 2-6:

$$it = \sigma\ (Wi\ .[ht-1,\ xt] + bi), \qquad (2)$$

$$ft = \sigma\ (Wf\ .[ht-1,\ xt] + bf), \qquad (3)$$

$$Ct = ft * Ct-1 + it * \tanh\ (Wc\ .[ht-1,\ xt] + bc), \qquad (4)$$

$$Ot = \sigma\ (Wf\ .[ht-1,\ xt] + bo), \qquad (5)$$

$$ht = Ot * \tanh\ (Ct), \qquad (6)$$

where $\sigma\ (X)=1/(1+e^{(-x)})$, $\tanh\ (X)=2/(1+e^{(-2x)})-1$, at time step 't', ht represents the hidden state, Ct-1 denotes the cell state from the previous time step, xt refers to the input features provided to the cell. The weights Wf, Wi, Wc, Wo, and biases Bf, Bi, Bc, Bo are determined through backpropagation through time.

A dropout rate of 0.1 was utilized in the LSTM layer and a dropout rate of 0.2 was used in the dense layer made up of 512 units to prevent overfitting of the proposed model. Table 3 provides particular information on the LSTM layer parameters and the model's output dimensions.

Building a deep LSTM network involves configuring various parameters such as kernel dimensions, unit numbers, activation functions, and stride values. In this research, the validation method was employed to determine the appropriate values for these parameters. By continuously testing different combinations of parameters, the optimal values were identified. This approach ensured that the model was fine-tuned and set up effectively [6], [16]

Table 3: LSTM Parameter

Parameter	Specification
Deep learning network	Long short term memory(LSTM)
Hidden unit	1
Fully connected layer/dense layer	2
Output layer function	SOFTMAX
Sequence input length	1000
Solver/Optimizer	Adaptive moment estimation
Maximum Epochs	100
Learning rate	0.05
PC used for Simulation	64bitOS,Core i55200CPU@2.2GHz,4GB RAM

The model was evaluated using real life EEG data obtained from the patient by the mental health specialist in Nigerian Hospital. The EEG signal recorded was evaluated to know how correctly the developed model can classify Epilepsy data using, accuracy, time, precision, Recall and F1 score as performance metrics and the results compared with the existing methods as shown in Table 4 below.

PERFORMANCE EVALUATION METRICS

The definitions are given below:

- Condition positive (P): The entire amount of signs that the illness is present is known as the condition positive (P).
- Condition negative (N): Signals from all of the healthy control participants, or condition negative (N).
- True positives (TP): The quantity of illness signals that were appropriately classified as such.
- False positive (FP) rate: The proportion of signals coming from healthy control participants that were mistakenly classified as illness.
- True Negative (TN): The proportion of healthy control subject signals that were appropriately classified as such.
- False negative (FN) rate: The proportion of illness signals that were mistakenly classified as healthy control.

The parameters used in this research for evaluation are Accuracy, Precision, F1 score and Recall as in equation 7-10. These definitions provide a framework for evaluating the identification and classification of signals in terms of disease presence and healthy control, the functions are given as:

Accuracy (ACC) is defined as:

$$ACC = (TP+TN)/(P+N) \qquad (7)$$

$$PRE = TP/(TP+FP) \qquad (8)$$

$$F1\ SCORE=2TP/(2TP+FP+FN) \qquad (9)$$

$$REC = TP/(TP+FN) \qquad (10)$$

The proposed system LSTM-Fuzzy when compared with other model that combined ANN with Energy normalization and LSTM with Improved Neural Network (INN) showed an improved accuracy, precision, Recall and F1 of 98.84%, 97.38%,95.41%, 96.35%respectively. ANN showed an Accuracy of 96.56%, precision of 88.62%, Recall of 92.47% and 90.50% as F1 score while LSTM-INN obtained accuracy of 78.92%, precision of 72.98%, Recall of 93.70% and F1 score of 82.05%.

Table 4: Performance of LSTM–FUZZY classifier for brain disorder classification

METHODS	ACC(%)	PRE (%)	RECALL (%)	F1 SCORE(%)
LSTM–FUZZY	98.84	97.32	95.41	96.35
ANN	96.56	88.62	92.47	90.50
LSTM–1NN	78.92	72.98	93.70	82.04

The proposed system LSTM-Fuzzy when compared with other model that combined Support Vector Machine (SVM) with logarithmic band power (LBP) and LSTM with Improved Neural Network (INN) showed an improved accuracy, precision, Recall and F1 of 98.84%, 97.38%,95.41%, 96.35% respectively. LBP-SVM showed an Accuracy of 96.14%, precision of 82.38%, Recall of 85.42% and 89.38% as F1 score while LSTM-INN obtained accuracy of 78.92%, precision of 72.98%, Recall of 93.70% and F1 score of 82.05%.

FUZZIFICATION APPROACH

The extracted parameters, Signal Energy (SE) and Logarithmic Band Pass (LBP) is used as the input variables to fuzzy rule based using fuzzy logic as in equation 11-13.

$$LBP_{input\_1}(x) = \begin{cases} \text{Low} & \text{if } 0 \le x \le 5 \\ \text{Medium} & \text{if } 5 < x \le 9 \\ \text{High} & \text{if } 9 < x \le 12 \end{cases} \quad (11)$$

$$SE_{input\_2}(x) = \begin{cases} \text{Low} & \text{if } 0 \le x \le 25 \\ \text{Medium} & \text{if } 25 < x \le 40 \\ \text{High} & \text{if } 40 < x \le 60 \end{cases} \quad (12)$$

$$Epilepsy_{output}(y) = \begin{cases} \text{Low} & \text{if } 0 \le y \le 0.5 \\ \text{Medium} & \text{if } 0.5 < y < 0.75 \\ \text{High} & \text{if } 0.75 \le y \le 1.0 \end{cases} \quad (13)$$

The three (3) membership values that was used are; low, medium, high, this process introduces fuzziness to the inputs, and the fuzzy logic rule's outcome is also fuzzified to derive the output, as illustrated in table 6 below. Figure 5-8 displays a membership function that delineates the extent to which the values of SE and LBP align with a boundary or degree of membership. The symptoms weight was assigned with linguistic variable labels and some degrees of membership with the above presented functions. The development of fuzzy Inference System (FIS) was done using the SE and LBP as input parameters for the fuzzy approach in MATLAB R2020a environment. The various weight was assigned ranges, linguistic variables and membership function in the fuzzy system. The membership function was used to make FIS decisions and nine (9) if- then rules.

The extracted features, which are the input variables, are assigned a class as low, medium and high using fuzzy rules. The classification results shown in figure 7-10 for epilepsy, the parameter Signal energy (SE) with interval between 0 to 25 indicated as low, the interval 25.1 to 40 indicated as medium and 40.1 to 60 indicated as high while parameter logarithmic band pass (LBP) with interval between 0 to 5.0 indicated as low, the interval 5.1 to 9.0 indicated as medium and 9.1 to 12 indicated as high score.

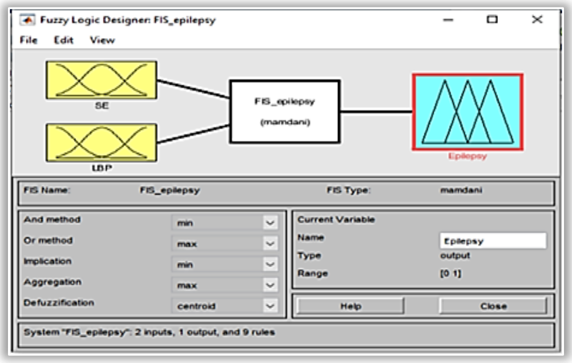

Figure 5: FIS design window for epilepsy classification in MATLAB

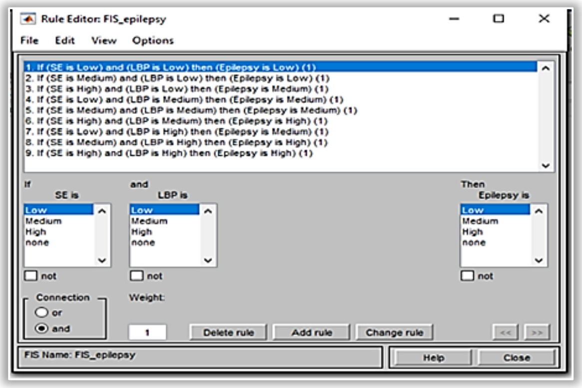

Figure 6: Design of the fuzzy rules for epilepsy signal classification in MATLAB

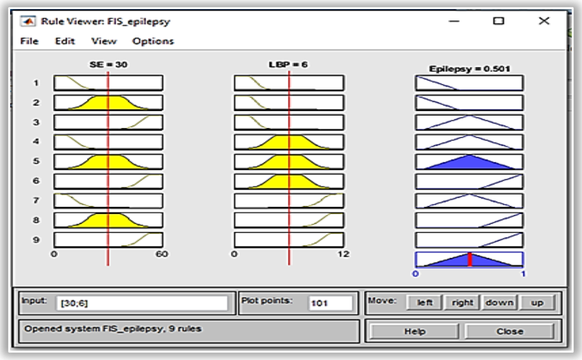

Figure 7: Testing the FIS in Rule Viewer window of MATLAB

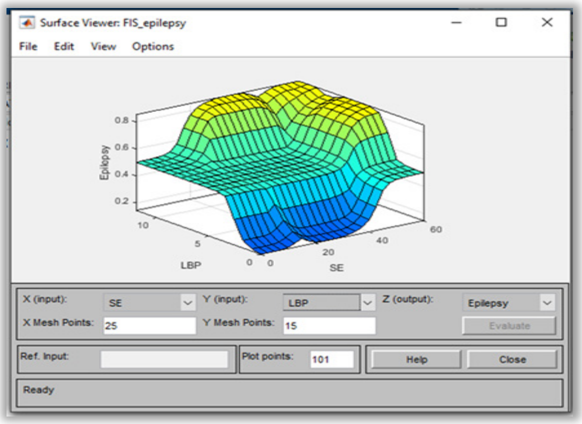

Figure 8. Graphical view of the relationship between the FIS variables in MATLAB

Table 5: Results of the classification of the degree of epilepsy by the FIS

Files containing seizures	SE	LBP	Fuzzy Output	Degree of Epilepsy
chb01_03.edf	44.4497	9.4592	0.6347	'Medium'
chb02_16.edf	41.4861	8.915	0.5613	'Medium'
chb03_02.edf	46.6076	9.7483	0.693	'Medium'
chb04_05.edf	38.1546	7.5582	0.5062	'Medium'
chb05_06.edf	51.7326	10.9042	0.8274	'High'
chb06_01.edf	37.0973	7.9339	0.5094	'Medium'
chb07_12.edf	44.6656	9.7388	0.6623	'Medium'
chb08_02.edf	47.0727	9.8214	0.7105	'Medium'
chb09_06.edf	49.8836	10.8045	0.8152	'High'
chb10_12.edf	40.4426	8.7247	0.5406	'Medium'
chb11_82.edf	40.7809	8.7135	0.5397	'Medium'
chb12_28.edf	52.1745	10.9702	0.8306	'High'
chb13_19.edf	42.9191	8.9339	0.5638	'Medium'
chb14_03.edf	37.6844	8.1042	0.5123	'Medium'
chb15_06.edf	24.0671	4.7878	0.4991	'Low'
chb16_10.edf	44.4857	9.3244	0.6182	'Medium'
chb17a_03.edf	42.4179	8.6075	0.5317	'Medium'
chb18_29.edf	35.2273	7.1754	0.5037	'Medium'
chb19_28.edf	47.7122	9.637	0.7029	'Medium'
chb20_12.edf	36.4122	7.7475	0.5073	'Medium'
chb21_19.edf	47.1144	9.6807	0.6962	'Medium'
chb22_20.edf	46.961	9.7611	0.7018	'Medium'
chb23_06.edf	47.4625	10.2646	0.7575	'High'
chb24_01.edf	46.4039	9.8472	0.6994	'Medium'

The output generated using fuzzy rule and input variables in the FIS as shown in Table 6 outputted the level of severity of epilepsy with interval between 0 to 0.5 as low epilepsy, 0.51 to 0.74 as medium epilepsy and 0.75 to 1.0 is considered as high epilepsy. In the 24-subject used for epileptic EEG, subjects 15, subject 1 and subject 5 is considered as low epilepsy, medium epilepsy and high epilepsy respectively.

CONCLUSION

In this paper, a deep learning algorithm LSTM have been used for EEG signal classification and fuzzy logic used to measure the level of epilepsy severity level. Convectional machine learning SVM and neural network are implemented using MATLAB software to compare the performance. LSTM and fuzzy are proposed for better performance of 98.84% accuracy in EEG classification. Deep learning algorithm helps in getting a better accuracy, precision, recall and F1 score when compared to conventional methods because of its combined effect of feature extraction and classification. Consequently, fuzzy logic also helps in measuring the intensity of the disease as either low, medium and high which formed a better robust system for prediction of epilepsy.

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