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

Ayo Isaac Oyedeji (1*)
Olusogo Julius Adetunji (1)
Ayobami Taiwo Olusesi (1)
Etinosa Noma-Osaghae (1)
Abisola Ayomide Olayiwola (1)
Ignatius Kema Okakwu (1)

Received: 21/01/2026
Revised: 29/03/2026
Accepted: 30/03/2026

[1] Department of Computer Engineering, College of Engineering and Environmental studies, Olabisi Onabanjo University, Ago-Iwoye Ogun state, Nigeria.
*Corresponding Author's Email: ayo.oyedeji@oouagoiwoye.edu.ng

https://journals.ust.edu/index.php/JST https://doi.org/10.20428/jst.v31i3.3610

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Ayo Isaac Oyedeji[1], Olusogo Julius Adetunji[2], Ayobami Taiwo Olusesi[3], Etinosa Noma-Osaghae[4], Abisola Ayomide Olayiwola[5], Ignatius Kema Okakwu[6]

ayo.oyedeji@oouagoiwoye.edu.ng[1], adetunji.olusogo@oouagoiwoye.edu.ng[2], olusesi.ayobami@oouagoiwoye.edu.ng[3], etinosa.noma-osaghae@oouagoiwoye.edu.ng[4], . olayiwola.abisola@oouagoiwoye.edu.ng[5], okakwu.ignatius@oouagoiwoye.edu.ng[6]

***Abstract*—** Epilepsy is a neurological disorder that affects more than 75 million people in the world. It has resulted in an increase in the mortality rate, especially in Sub-Saharan Africa, due to the lack of experienced medical experts to diagnose the disease, leading to misdiagnosis and time-consuming diagnoses. Several automatic epileptic seizure detection methods have been used to extract features from EEG signals but lack the capacity to calibrate the characterizing features of epileptic and non-epileptic EEG signals overlap. Hence, in this paper a deep learning Long Short-Term Memory (LSTM) algorithm and fuzzy system are proposed using electroencephalograph signals (EEG) with 24 epileptic subjects containing 18 EEG channels each. The EEG signals were pre-processed to remove artifacts generated during EEG recordings using a Notch filter for a band stop of 64 Hz and a band pass of 32 Hz. 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), serve as input to the fuzzy inference system. A triangle membership function that fuzzifies the extracted features to establish intensity scales using nine (9) fuzzy rules in a fuzzy inference system (FIS) was used to characterize each of the disease severities 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.

I. Introduction

These electroencephalography (EEG) signals are referred to as 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 patients' 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 [1], [2]. This excitement changes significantly during sleep and wakefulness and is affected by the activity of the reticular activating system in the brainstem [3]. Epilepsy is a neurological disorder applied to a “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 [5], [6], [7].

Consequently, finding a biomarker from EEG data that is scalable for early detection is a challenge due to variability in the presentation of the disorder [8], as is also developing a system capable of detecting epileptic seizures with high sensitivity and precision [9]. Deep learning techniques have been found as most suitable in the field of seizure detection due to their strong classification ability [9], [10], [11]. However, deep learning models tend to frequently struggle with the computational difficulty when analyzing large-scale and complex EEG data because some features characterizing epileptic and non-epileptic EEG signals could overlap, making the detection of severity level unknown [12], [13]. In response to the drawback, fuzzy logic models provide a more efficient method to manage uncertainties and analyze dynamic EEG patterns and the overlapping nature of EEG signals [14], [15], [16]. Recently, classification of epileptic EEG signals has been conducted by different researchers. In [4], A Neuro-fuzzy Approach for predicting epilepsy using EEG signals. The epileptic EEG used was obtained from the 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 a Haar wavelet for pre-processing the EEG signal to eliminate noise; wavelet analysis was applied to decompose the 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 has a better accuracy of 98.4% and 97.68% for SVM. [12] proposed a fuzzy-based epileptic seizure detection model that incorporates a novel feature extraction and selection method along with fuzzy classifiers. It extracts pattern features along with time-domain, frequency-domain, and non-linear analysis of signals and applies a feature selection strategy on extracted features to get more discriminating features that build fuzzy machine learning classifiers for the detection of epileptic seizures. The empirical evaluation of the proposed model was conducted on the benchmark Bonn EEG dataset. It showed an accuracy of 98% to 100% for normal vs. ictal classification cases, while for three-class classification of normal vs. inter-ictal vs. ictal, accuracy reaches above 97.5%. The obtained results for ten classification cases (including normal, seizure or ictal, and seizure-free or interictal classes). [9] The study presents a standard approach for analyzing iEEG signals, including

chaos theory, energy in different frequency bands (alpha, beta, gamma, theta, and delta), wavelet transform, empirical mode decomposition, and machine learning techniques such as support vector machines.
Also, modern deep learning algorithms such as convolutional neural networks (CNNs) and long short-term memory (LSTM) were discussed. Detection results were tested on a separate dataset, demonstrating classification accuracy, sensitivity, precision, and specificity of seizure detection. The best results for seizure detection were obtained with features related to iEEG signal energy (accuracy of 0.97, precision of 0.96, sensitivity of 0.99, and specificity of 0.96), as well as features related to chaos, Lyapunov exponents, and fractal dimension (accuracy, precision, sensitivity, and specificity all equal to 0.95). The application of CNN and LSTM networks yielded significantly better results (CNN: Accuracy of 0.99, precision of 0.98, sensitivity of 1, and specificity of 0.99; LSTM: Accuracy of 0.98, precision of 0.96, sensitivity of 1, and specificity of 0.99). In another study by [1], 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, indicating normalizing the signals and calculating the energy values were more successful. The ANN algorithm is predicted to have a success rate of 96.56% to detect epileptic seizures using three different attributes: Gradient Boosting with a success rate of 95.60% and Random Forest with a success rate of 95.00%. [11] proposed a novel method for epileptic seizure detection, leveraging the power of 1-D convolutional layers in combination with bidirectional long short-term memory (LSTM) and gated recurrent unit (GRU) and average pooling layer as a single unit. This unit is repeatedly used in the proposed model to extract the features, which are then passed to the dense layers to predict the class of the EEG waveform.
The performance of the proposed model is verified on the Bonn dataset and employs fivefold cross-validation. The dataset was divided into five subsets, and the model was iteratively trained and tested on different combinations of these subsets, using performance measures, accuracy, sensitivity, and specificity. The model achieved an accuracy of 99-100% for binary classifications into seizure and normal waveforms, 97.2%-99.2%. Accuracy for classifications into normal, interictal, and seizure waveforms: 96.2% - 98.4% accuracy for four-class classification and accuracy of classification 95.81% - 98% for five-class classification. [15] proposed an Electroencephalogram (EEG)-based Fuzzy Logic and Spiking Neural Networks (FLSNN) for Advanced Multiple Neurological Disorders. The diagnosis is aimed at providing a unified, automated solution for detecting multiple neurological disorders such as epilepsy, Parkinson's, Alzheimer's, schizophrenia, and stroke in a single framework. In the Fuzzy Logic and Spiking Neural Networks (FLSNN) framework, EEG data is preprocessed to eliminate noise and artifacts, while a fuzzy logic model is applied to handling uncertainties prior to applying spike neural networking to analyze the temporal dynamics of the signals, making processed EEG data three times faster than traditional techniques. The result showed 97.46% accuracy in binary classification and 98.87% accuracy in multi-class classification, indicating increased efficiency, quality, and speed of diagnostics from the EEG signal.

II. Material and Method

A. Dataset Description

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

B. Proposed Model

This model for epilepsy prediction has five modules, which include (1) EEG data collection or acquisition; (2) preprocessing for noise removal and data cleaning using a 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 (4) fuzzy logic for handling vagueness and ambiguity of EEG signals. As shown in figure 1 below:

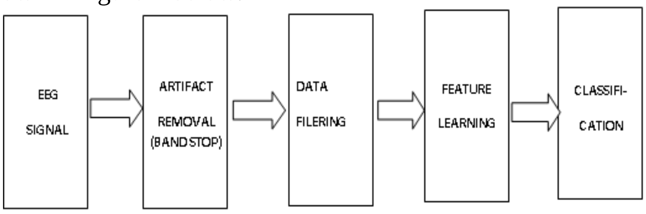

Figure 1: Proposed Block Diagram of the System.

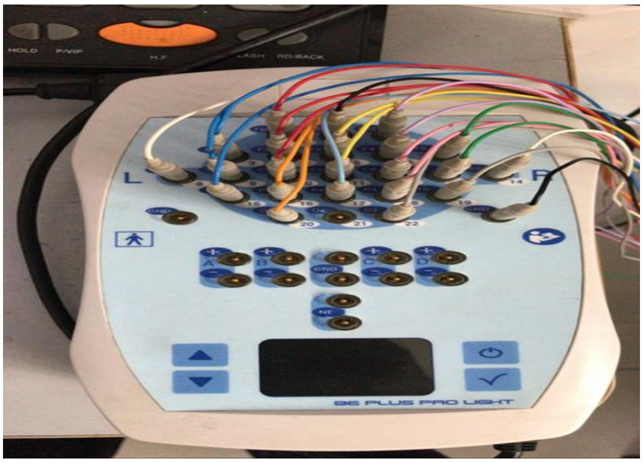
Figure 2: Be Plus Pro Light Version.

III. Preprocessing

In this study, a notch filter was used for artifact removal to remove generated artifacts from 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 stopband 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:

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

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 the EEG signal, two (2) digital filter structures (Notch and Finite Impulse Response (FIR)) were implemented, and the results are presented as shown in tables 1 and 2 below:

Table 1: 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	0.9458	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 the 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 values of SNR and CC of the denoised EEG signal were 108.1899 dB 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 order 2 provides an improved result for the EEG signal. Also, the Power Spectral Density (PSD) analysis of the implemented Notch and structures of the FIR filter for the EEG signal pre-processed is presented in Figure 3 and Figure 4, respectively.

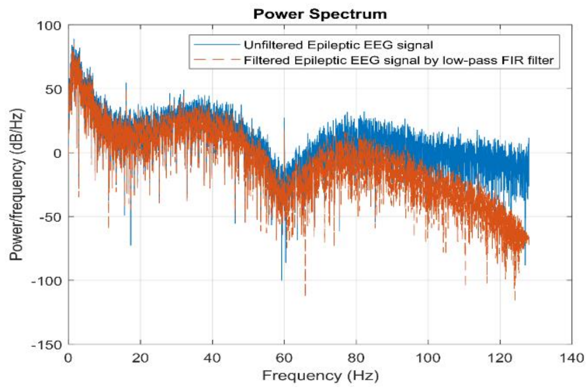

Figure 3: Power Spectrum Density of unfiltered and filtered EEG signal using Notch.

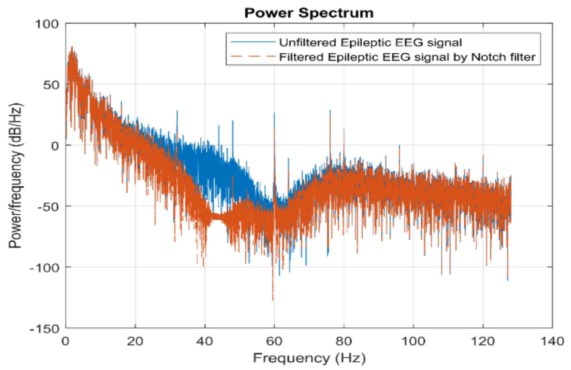

Figure 4: Power Spectrum Density of unfiltered and filtered EEG signal using FIR filter.

The amplitude of EEG waves varies significantly across frequency bands. Figures 3 and 4 show a person's 50-second EEG signal and the amplitude change in the lower frequency regions. While the filtered EEG signal using the FIR filter has the lowest intensity frequency distribution, the filtered EEG signal using the Notch has the most significant intensity frequency distribution. The change in an average EEG signal between unfiltered and filtered EEG signals is shown in Figures 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.

IV. 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 in equation 2-6:

$$it = \sigma\ (Wi\ .[ht\text{-}1, xt] + bi), \quad (2)$$

$$ft = \sigma\ (Wf\ .[ht\text{-}1, xt] + bf), \quad (3)$$

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

$$Ot = \sigma\ (Wf\ .[ht\text{-}1, xt] + bo), \quad (5)$$

$$ht = O_t * \tanh\ (C_t) \quad (6)$$

where σ (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 [17] [18].

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	bitsOS, 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 were compared with the existing methods as shown in Table 4 below.

V. Performance Evaluation Metrics

The definitions are given below:

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

i. $$ACC = (TP+TN)/(P+N) \quad (7)$$
ii. $$PRE = TP/(TP+FP) \quad (8)$$
iii. $$F1\ SCORE = 2TP/(2TP+FP+FN) \quad (9)$$
iv. $$REC = TP/(TP+FN) \quad (10)$$

The LSTM-Fuzzy system, when compared with other models that combined ANN with energy normalization and LSTM with an improved neural network (INN), showed an improved accuracy, precision, recall, and F1 of 98.84%, 97.38%, 95.41%, and 96.35%, respectively. ANN showed an accuracy of 96.56%, a precision of 88.62%, a recall of 92.47%, and an F1 score of 90.50%, while LSTM-INN obtained an accuracy of 78.92%, a precision of 72.98%, a recall of 93.70%, and an 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**
LBP-SVM	96.14	82.38	85.42	**89.38**
LSTM-1NN	**78.92**	**72.98**	**93.70**	**82.04**

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 were compared with the existing methods as shown in Table 4 below.

The proposed system, LSTM-Fuzzy, when compared with other models 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%, and 96.35%, respectively. LBP-SVM showed an accuracy of 96.14%, a precision of 82.38%, a recall of 85.42%, and an F1 score of 89.38%, while LSTM-INN obtained an accuracy of 78.92%, a precision of 72.98%, a recall of 93.70%, and an F1 score of 82.05%.

IV. Fuzzification Approach

The extracted parameters, Signal Energy (SE) and Logarithmic Band Pass (LBP), are used as the input variables to fuzzy rules based on fuzzy logic as in equations 11-13. The development of a fuzzy inference system (FIS) was done using the SE and LBP as input parameters for the fuzzy approach in the MATLAB R2020a environment. The various weights were assigned ranges, linguistic variables, and membership functions in the fuzzy system. The membership function was used to make FIS decisions and nine (9) if-then rules. The three (3) membership values that were used are low, medium, and 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 5 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 following functions:

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

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

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

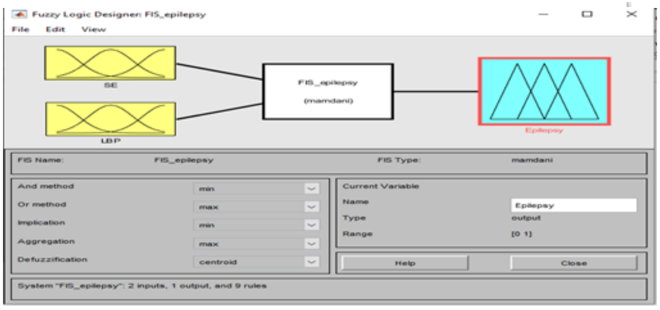

Figure 5: FIS design window for epilepsy classification in MATLAB.

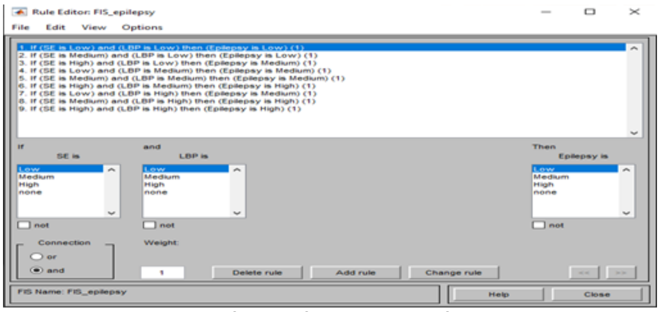
Figure 6: Design of the fuzzy rules for epilepsy signal classification in MATLAB.

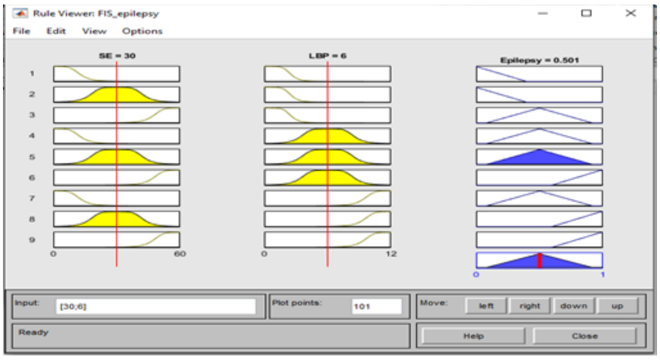
Figure 7: Testing the FIS in Rule Viewer window of MATLAB.

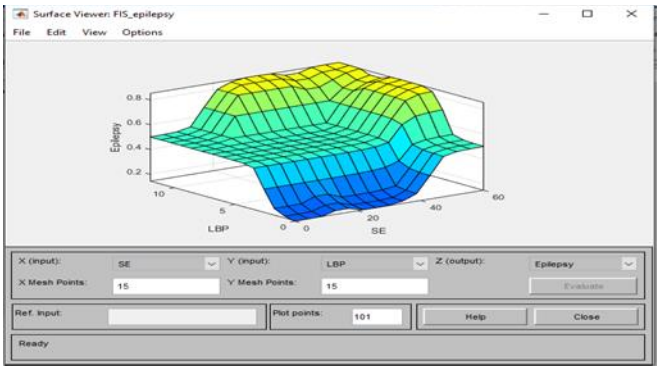
Figure 8 Graphical view of the relationship between the FIS variables in MATLAB.

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	46.5076	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 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 an interval between 0 and 25 indicated as low, the interval 25.1 to 40 indicated as medium, and 40.1 to 60 indicated as high, while the parameter logarithmic band pass (LBP) with an interval between 0 and 5.0 is indicated as a low score, the interval 5.1 to 9.0 as medium, and 9.1 to 12 as a high score. The output generated using fuzzy rules and input variables in the FIS, as shown in Table 5, outputted the level of severity of epilepsy with an interval between 0 and 0.5 as low epilepsy, 0.51 and 0.74 as medium epilepsy, and 0.75 and 1.0 as high epilepsy. In the 24-subject EEG used for epilepsy, subject 15, subject 1, and subject 5 are considered low epilepsy, medium epilepsy, and high epilepsy, respectively.

6.0 Conclusion

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

Author contributions

Name1 Ayo Isaac OYEDEJI: Data curation, Writing-Original draft preparation, Software, Validation., Field study

Name2 Olusogo Julius ADETUNJI: Conceptualization, Methodology, Software, Field study

Name 3: Ayobami Taiwo OLUSESI Conceptualization, Methodology, Software, Field study

Name4: Etinosa NOMA-OSAGHAE Visualization, Investigation, Writing-Reviewing and Editing

Name5: Abisola Ayomide OLAYIWOLA: Conceptualization, Methodology, Software, Field study

Name 6: Ignatius Kema OKAKWU: Visualization, Investigation, Writing-Reviewing and Editing

Source of Funding

No funding received

Conflicts of interest

The authors declare no conflicts of interest

Ethical Approval

Not applicable.

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