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CLASSIFICATION OF EEG SIGNALS USING DEEP LEARNING TECHNIQUE

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Abstract*:* When the brain experiences repeated seizures, epilepsy results. The human brain is harmed by frequent epileptic seizures, which can lead to memory loss, mental illness, and other problems. The electroencephalogram (EEG) test is a significant tool for learning about brain activity and for diagnosing neurological disorders, such as epilepsy. An automated seizure detection approach has been effectively introduced in this study. The investigation uses LSTM, CNN and KNN to analyze the EEG signals from an online database for binary categorization. Seizures are detected using two of the five sets from set A (normal) to set E (abnormal). Using MATLAB Tool, the simulations are run with a range of activation functions, optimizers, and loss models to assess the performance. Future suggestions will be formulated with the assistance of the proposed study, which will also assist academics in discovering how deep learning algorithms are implemented for the classification of EEG signals.

I. INTRODUCTION:

The cerebral cortex of the human brain has a remarkable and rich spatiotemporal dynamics that is specific to humans. In the brain, chemical and electrical impulses are exchanged between millions of neurons. Seizures are abnormal electrical disturbances that occur in the brain. When the brain experiences repeated seizures within short duration of time, epilepsy results. Proper examination of the electroencephalogram (EEG) can reveal important details about brain activity and be helpful in the diagnosis of brain disorders, particularly epilepsy. An abnormal brain condition can cause an EEG to show unusual electrical discharge. Meaningful communication is provided by measuring the frontal pole (Fp), frontal (F), parietal (P), temporal (T), and occipital (O) regions of the brain. Treating epileptic patients well is more important than diagnosing them accurately, so future research must focus on automated seizure detection. Machine learning is a key component of expert systems, enabling the creation of systems that support autonomous decision-making.

Just as the human brain learns via information and study, so too can a machine learn from data. In two steps, machine learning performs a specific task to classify the data. The machine is initially trained using pertinent features and the matching categorical labels of the data in the training stage. In the testing stage, the machine is examined using unknown data that has similar features. The unknown data must be classified by the classifier into the proper class. The percentage of test data that the classifier correctly classifies is used to evaluate the classifier's performance. Effective use of machine learning algorithms such as LSTM, CNN, and KNN allows for the making of judgment's based on input.

II. METHODOLOGY

The current investigation used the EEGs of five patients, all of whom had successfully undergone resection of one of the hippocampal formations, which allowed for the accurate identification of the epileptogenic zone. 100 single channel EEG segments, each lasting 23.6 seconds, were arranged into five sets (designated A–E) for the study. Segments from surface EEG recordings, made on five healthy participants utilizing a standardized electrode placement scheme, made up Sets A and B.The volunteers were awake and calm, with their eyes open in (A) and closed in (B).Segments from the hippocampal formation of the opposing hemisphere of the brain were recorded in set C, whereas segments from the epileptogenic zone were recorded in set D.

Set E solely included seizure activity, whereas sets C and D only included activity recorded during seizure-free intervals. Here, a selection of segments.

Displaying ictal activity were made from all recording sites. After then, the recordings were put through a number of classification methods.

1) Discrete Wavelet Transform:

By breaking the signal down into approximation and detail information, discrete WT (DWT) with the fourth-order daubechies (db4) and sixth-order daubechies (db6) wavelet functions analyzes the signal at different frequency bands, with varying resolutions. DWT is employed in both preprocessing and decomposition of the EEG signals. The raw EEG has been cleaned up of noise by using filters. For seizure detection, the noise-free signals are examined and trained.

2) Time Domain Analysis:

For all real numbers at different discrete times, or in the case of continuous time, the value of the signal or function is understood in the time domain. Using time domain analysis, the six statistical features—mean, RMS, peak value, standard deviation, SNR, and THD—are retrieved from raw EEG data in this study in order to identify distinctive patterns from the original data for consistent classification.

3) frequency Domain Analysis:

The analysis of computations or signals in relation to frequency is known as frequency domain. About a range of frequencies, the frequency domain shows the percentage of the signal that is present inside a specific frequency band. In order to obtain distinctive patterns for reliable frequency domain analysis classification of EEG signals, four statistical features—Median frequency, Mean frequency, Band power, and Power bandwidth—are extracted here at a sample rate of 256.

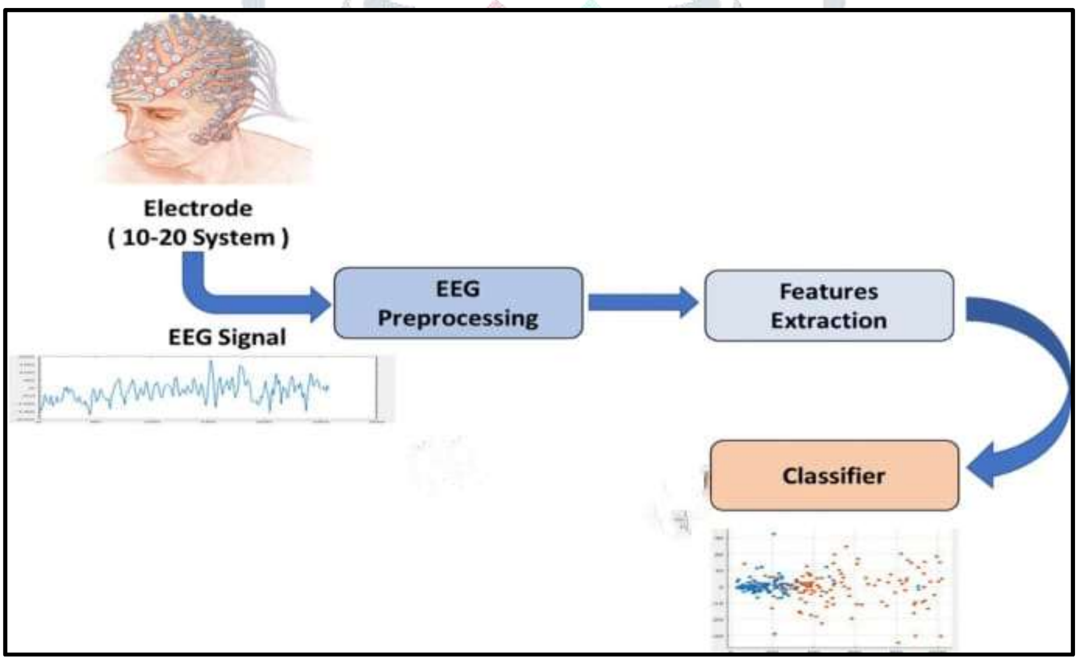

Fig 1: EEG Signals Classification

III. FLOWCHART:

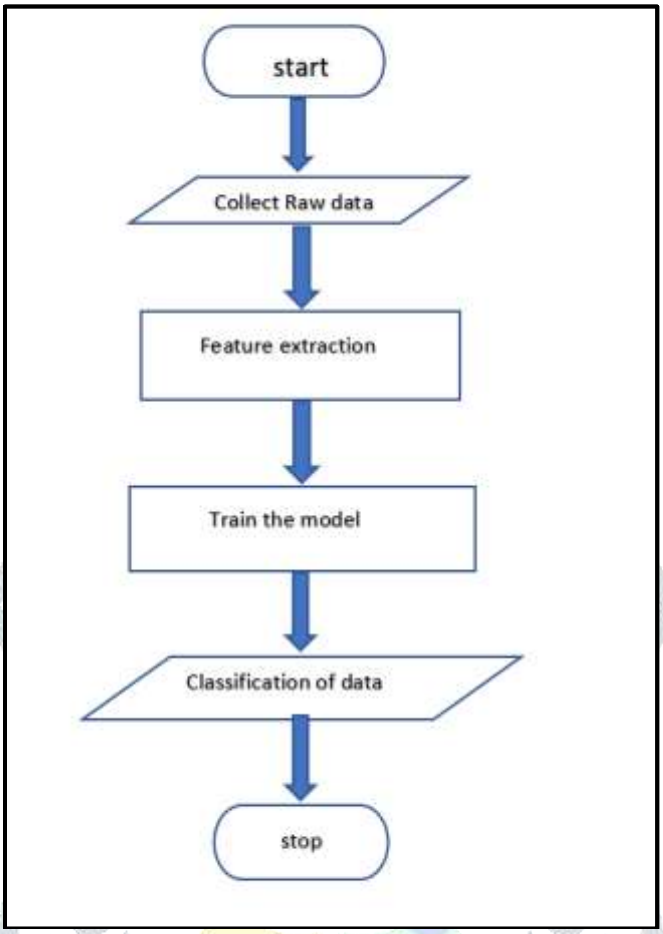

Fig 2: Flowchart of Classification

The dataset for this work is downloaded from Universitats Klinikumbonn[Ukb][1]. Throughout the entire experiment, 20% of the data is designated as the test set and 80% of the data as the training set. A total of 50 training epochs allocated to the deep neural network (DNN), LSTM, CNN, and KNN.A distinct type that has been employed in machine learning for categorization is feature extraction, which lowers the dimension of raw EEG data. Six statistical characteristics are collected from the raw EEG data for the project: mean, RMS, Peak value, standard deviation, SNR, and THD.A crucial phase in the classification process is feature selection. To achieve the best outcome, it is recommended to feed the chosen features. Redundant features can overload the system, which would prevent the best outcome from happening. As a result, reducing the number of features will aid in improving the classifier's learning and performance. Deep Learning Algorithms have been used to train the system with the database and the corresponding class labels during the learning stage. The system is tested using test data for categorization in the second stage. The system's efficiency is assessed based on the proportion of test data that the classifier correctly classifies. Confusion matrix with accuracy as a parameter is used to evaluate the performance of LSTM, BiLSTM, CNN, and KNN.

IV. RESULTS AND DISCUSSION

Here is an illustration of the study's experimentation, analysis, and satisfactory performance for automated seizure identification using pertinent features as an input to compare and choose the best model among the LSTM, CNN, Bi-LSTM, and KNN that classifies with high accuracy.
The classification results by choosing DWT with CNN is indicated in figure 3 and 4.

DWT with CNN

No. of Epochs (M)=50

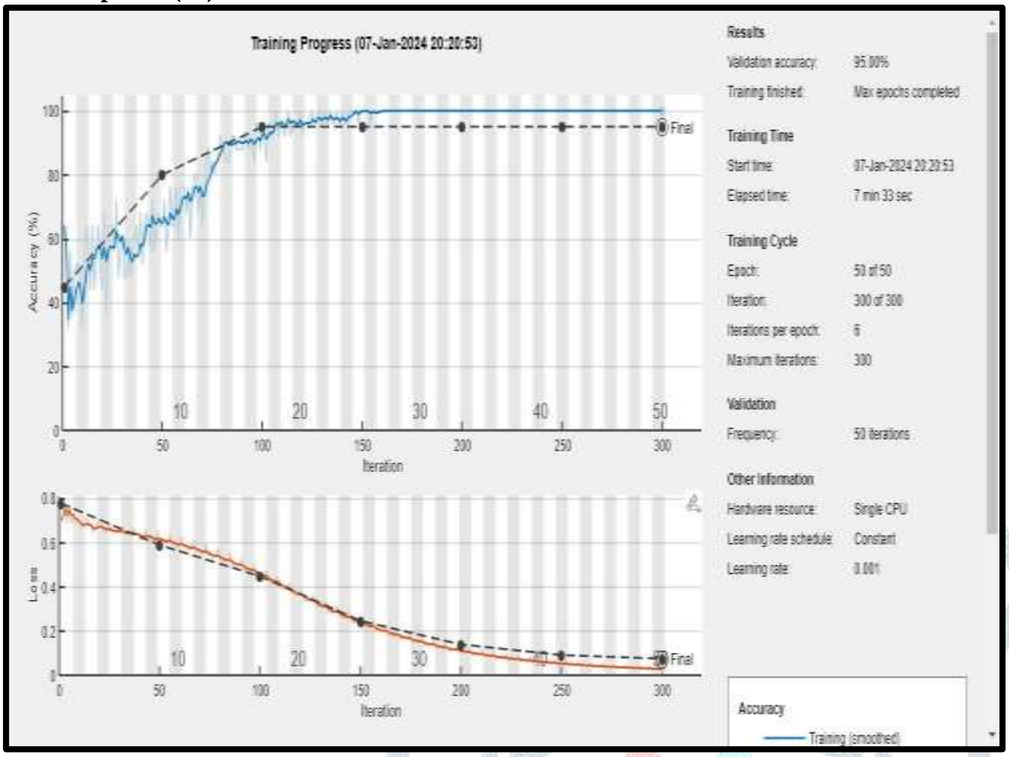

Fig 3: Training Plot

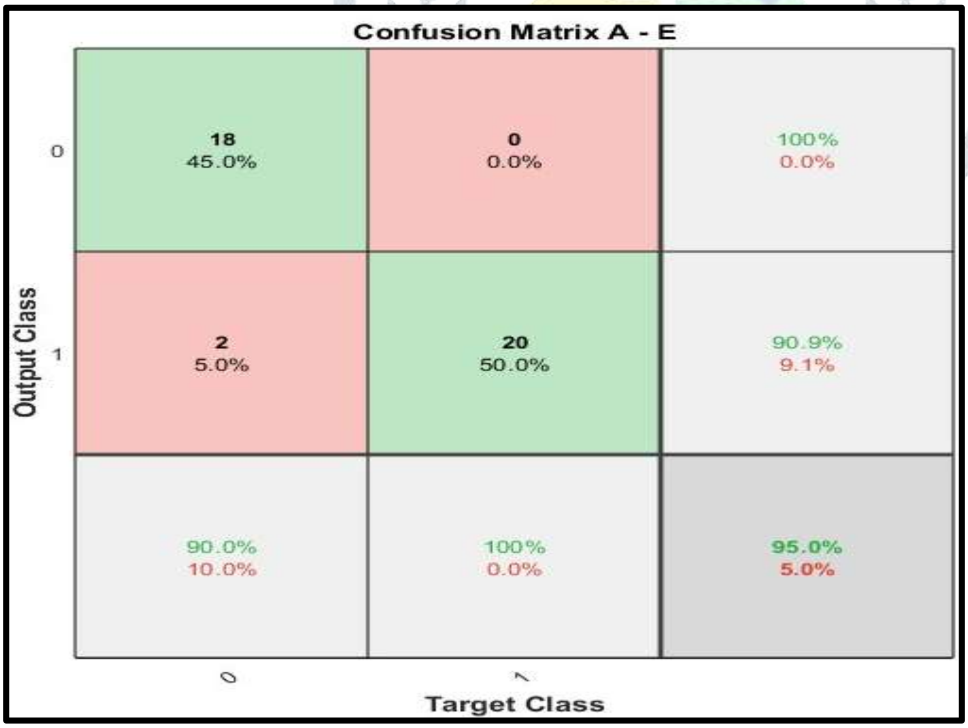

Fig 4: Confusion Matrix

TIME DOMAIN ANALYSIS: Accuracy of classification in time domain with different models is summarized in table 1.

Table 1. Time Domain Analysis with CNN, LSTM, KNN and Bi LSTM models

Classes	Accuracy With CNN	Accuracy With LSTM	Accuracy With KNN	Accuracy With Bi LSTM
A_E	100%	100%	100%	100%
B_E	97.5%	95%	97.5 %	97.5 %
C_E	96.0%	100%	97.5%	97.5%
D_E	97.6%	97.5%	100%	100%
AB_E	96.2%	97.5%	100%	95.0%
CD_E	95.0%	100%	100%	97.0%
ABC_E	95%	100%	99%	98%
ABCD_E	95.6%	92.23%	79%	83%

FREQUENCY DOMAIN ANALYSIS: Accuracy of classification in frequency domain with different models is summarized in table 2.

Table 2. Frequency Domain Analysis with CNN, LSTM, KNN and Bi LSTM models

Classes	Accuracy With CNN	Accuracy With LSTM	Accuracy With KNN	Accuracy With Bi LSTM
A_E	97.5%	62.5%	92.5%	92.5%
B_E	92.5%	80.0%	87.5%	87.5%
C_E	92.5%	92.5%	97.5%	97.5%
D_E	90%	85.0%	95.0 %	95.0 %
AB_E	100%	97.5%	92.5%	92.5%
CD_E	90%	90%	100%	100%
AB _CD_E	80%	74%	86%	86%
ABCD_E	95%	78%	96.0%	96.0%
AC_E	81%	73%	81.7%	81.7%

DISCRETE WAVELET TRANSFORM: Classification accuracy by using DWT and different models is summarized in table 3.
Table 3. Analysis by using DWT, with CNN, LSTM, KNN and Bi LSTM models

Classes	DWT	Accuracy With CNN	Accuracy With LSTM	Accuracy With KNN	Accuracy With Bi LSTM
A_E	db_4 db_6	95% 95%	97.5% 97.5%	95% 95%	97.5% 97.5%
B_E	db_4 db_6	95% 96.0%	100% 92.5%	95% 96.0%	90% 90.0%
C_E	db_4 db_6	97.5 92.5%	95.5% 97.5%	97.5 92.5%	95.0% 95.0%
D_E	db_4 db_6	95% 97.5%	95% 90.5%	95% 97.5%	97.5% 92.5%
AB_E	db_4 db_6	95% 92.5%	97.5% 97.5%	95% 92.5%	97.5% 97.5%
CD_E	db_4 db_6	95% 95%	95% 95%	95% 95%	95% 95%

CONCLUSION:

In the field of EEG signal classification, deep learning algorithms have shown to yield promising results. These models can be trained to generate an automated seizure detection mechanism with labeled sensor data, and they are highly valuable in fields like neuromarketing, clinical and psychiatric studies, and brain-computer interfaces (BCIs).

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