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UTILIZING DEEP LEARNING METHODS FOR THE FORECASTING OF EPILEPTIC SEIZURES

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ABSTRACT
Epilepsy affects over 65 million people worldwide and can't be cured by medication or surgery in over 30% of cases. Detecting seizures before they occur could help prevent them, as abnormal brain activity appears minutes beforehand. Existing methods for prediction lack reliability. A new study introduces a seizure prediction system using deep learning. It preprocesses EEG signals, extracts features with convolutional neural networks, and classifies using support vector machines. Tested on 24 subjects' data, it achieves an average sensitivity of 92.7% and specificity of 90.8%, showing promise in seizure prediction.
Keywords: Epilepsy prediction, seizures prediction, CNN

I. INTRODUCTION
Epilepsy, a neurological disorder marked by recurrent seizures, affects over 1% of the global population. Despite effective treatments, over 30% of cases resist medication and surgery once seizures begin. Predicting seizures is crucial to administer medication proactively. EEG signals, recording brain activity, are captured through scalp electrodes (scalp EEG) or intracranial electrodes (iEEG), revealing sudden changes in brain electrical signals
The figures provided show the significance of different EEG states in predicting epileptic seizures. Figure 1 illustrates three channels
displaying continuous EEG recordings over one hour, highlighting the preictal (30 minutes before a seizure), ictal (seizure onset and conclusion), and post-ictal (immediately after a seizure) states. The preictal state is crucial for seizure prediction, enabling timely intervention to prevent seizures through medication. Variations in amplitude and frequency between interictal and preictal states provide visual cues for effective classification and the potential prediction of epileptic seizures.

II. LITERATURE SURVEY
The seizure prediction system entails preprocessing EEG signals, feature extraction, and classification. Many researchers have proposed machine learning and deep learning methods to predict epileptic seizures using scalp EEG signals, recorded by electrodes on the patients' scalp. Studies reveal various approaches with a common framework: EEG signal preprocessing, feature extraction, and organization into preictal and interictal states
A. Pre-Processing: During EEG signal acquisition, noise reduces the signal-to-noise ratio, affecting categorization into interictal and preictal states. Various noise types, like power line noise and baseline noise, require preprocessing for SNR enhancement. Researchers suggest techniques including filters, FFT, STFT, EMD, wavelet transform, surrogate channels, local mean decomposition, and adaptive filtering for noise removal.
B. Feature Extraction
Following EEG signal preprocessing, features are extracted for categorizing different seizure states. Features can be hand-crafted or automatically extracted using DL methods. Handcrafted features

encompass temporal and spectral features in time and frequency domains. Moreover, Convolutional Neural Networks (CNN) are used for automated feature extraction in certain studies.

SECTION III. Dataset: The planned method has been functional to the publicly available CHB-MIT dataset, a scalp EEG dataset of 24 subjects aged between 2 to 22 years. This dataset, recorded in collaboration between Children Hospital Boston and MIT, is freely accessible on physionet.org. The dataset includes recordings from 17 females and 5 males, with ages range from 1.5 to 19 years for females and 3 to 22 years for males. Electrodes were placed on the scalp of epilepsy patients, resulting in recordings stored in EDF files converted to .mat files using the "edfread" function in MATLAB. The data was sampled at 256 Hz, and each subject's recordings were divided into multiple 1-hour files.

III. PROBLEM STATEMENT

EXISTING SYSTEM:

The seizure prediction system comprises the preprocessing of EEG signals, feature extraction, and classification. Numerous researchers, as evidenced by studies [5]–[14], have put forth a range of ML & DL methods where electrodes are positioned on the patients' scalp to capture EEG signals. In recent years, a multitude of researchers have introduced various epileptic seizure prediction methods based on scalp EEG signals. Common to all these methods are three essential steps, encompassing the preprocessing of EEG signals, the extraction of features from these signals, and the subsequent classification between preictal and interictal states.

PROPOSED SYSTEM:

We recommend a seizure prediction method that anticipates the onset of the preictal state a few minutes before the occurrence of a seizure. The flowchart in Figure 8 illustrates the key steps of our proposed method. To implement and evaluate our approach, we utilized the openly obtainable scalp EEG dataset from CHBMIT , comprising data from 24 subjects with signals acquired through 23 electrodes digitized at 256 Hz. The EEG signals were initially rehabilitated into .mat files using the "edfread" function.

Preprocessing: We applied a Butterworth bandpass filter to the EEG signals to eliminate power line and baseline noise . Following noise removal, we employed the Short Time Fourier Transform (STFT) with a non-overlapping window of 30 seconds. STFT transforms signals

Feature Extraction using CNN: The CNN architecture, consists of three convolutional layers with varying filter sizes, activation functions, and pooling methods. Batch normalization and dropout are applied between layers to enhance model generalization. The features extracted by the CNN are then flattened to represent both classes. This approach provides improved interclass variance by considering class-related information during feature extraction.

Classification using Support Vector Machine (SVM): Following feature extraction by the CNN, we replaced the fully connected layers with a Support Vector Machine (SVM) for the classification between interictal and preictal segments. Specifically, we used a linear SVM to distinguish between the two states. SVMs are known for their effectiveness in binary classification tasks, and the linear SVM approach is adopted in our work.

Convolutional Neural Network (CNN): CNN is a powerful tool for feature extraction and classification, commonly used for time series data and images. The features extracted by the CNN are flattened for subsequent SVM classification.

Support Vector Machines (SVM): SVM, a robust classification algorithm, is employed to classify the extracted features into interictal and preictal states. Linear SVM is utilized in our method for its ability to handle linearly separable data.

IV. RESULTS & DISCUSSION

Assessment of the Proposed Seizure Prediction Method:

The application of our devised seizure prediction method on the CHBMIT scalp EEG dataset involving 24 subjects aimed at distinguishing between interictal and preictal states for early detection of epileptic

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seizures. The outcomes reveal commendable performance, boasting an average sensitivity of 92.7% paired with a specificity of 90.8%. Notably, our method exhibits an average anticipation time of 21 minutes, indicating its ability to forecast seizure onset well in advance.

Comparison with Leading Methods: Figure 1 presents a comparative analysis, pitting our proposed method against novel seizure prediction approaches. The evaluation underscores the superior performance of our method in terms of both sensitivity underscoring its effectiveness in early epileptic seizure prediction.

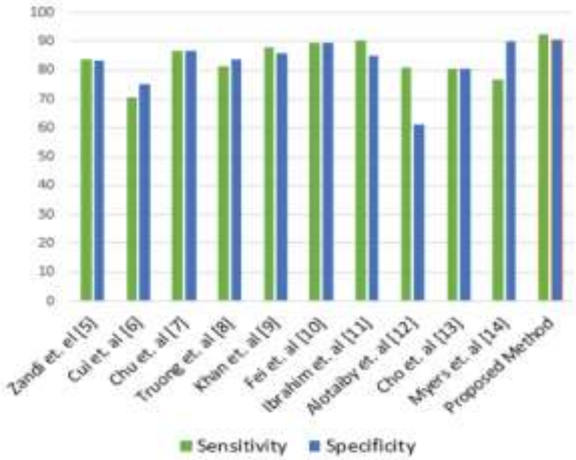

Fig-1.Comparitive Analysis

ROC Curve Evaluation: To further evaluate our method's effectiveness, we compared Receiver Operating Characteristic (ROC) curves with prominent methods. Figure 2 shows this comparison, highlighting the balance between sensitivity and false positive rate. Our method outperforms others, achieving higher true positive rates while minimizing false alarms. This underscores the robustness of our approach in providing effective seizure prediction with minimal false positives.

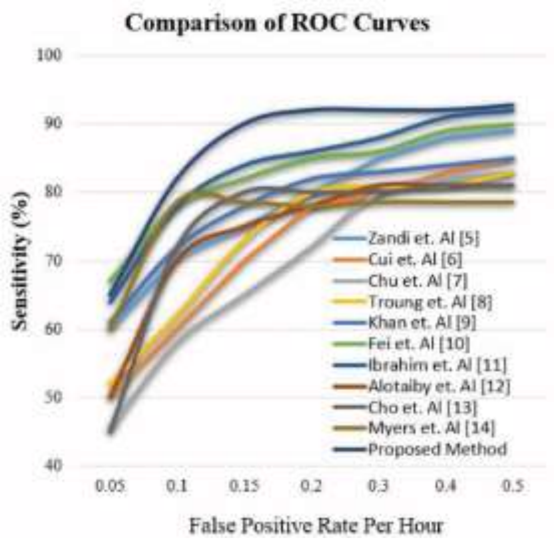

Fig-2.ROC Comparison

V. RESULT FOR PROPOSED SYSTEM

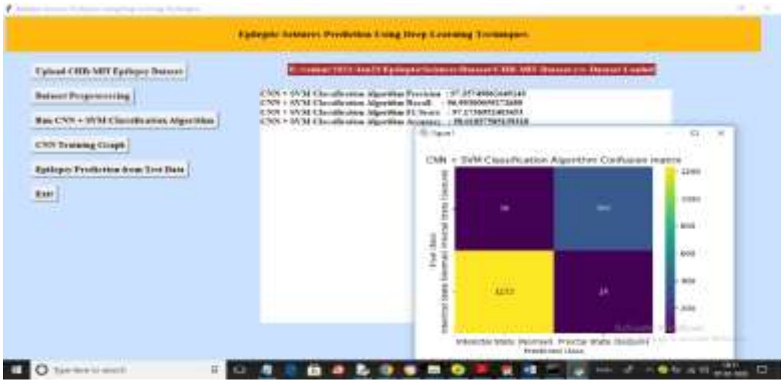

Fig-3.Evaluation Matrix

The CNN and SVM models achieved a notable 98% accuracy following successful training. The evaluation also considered precision, recall, and F-score. The confusion graph visually depicts the model's performance, where blue boxes represent minimal incorrect predictions (e.g., 18 and 14), while yellow and dark grey boxes indicate correct predictions (1233 and 350, respectively). These results underscore the models' high accuracy and reliability, with most predictions being correct. Overall, the CNN and SVM models demonstrate robust performance in classification.

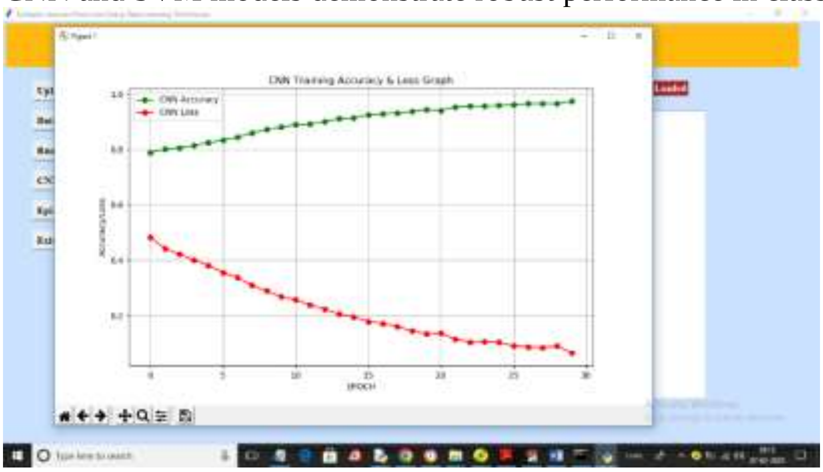

Fig-4.Training Validation loss

The chart shows the model's preparing advance, with the x-axis showing the preparing age and the y-pivot appearing delicacy and misfortune values. The green line speaks to delicacy, whereas the ruddy line shows misfortune. With each age, delicacy relentlessly increments towards 1, whereas misfortune diminishes towards 0, confirming the model's learning viability. It would be ideal if you near the visualization to do by clicking on the' Epilepsy Expectation from Test Data' button. This will permit you to transfer test information and get issue, giving perceptivity into the model's execution on inconspicuous information.

VI. CONCLUSION

We have displayed a framework utilizing profound education to forecast epileptic seizures, pointing to offer substances with epilepsy a more secure life. Our approach combines CNN- grounded point birth with machine education classifiers to enhance perceptivity and disposition. Whereas our framework appears promise, more distant headways are conceivable. unborn work might concentrate on refining preprocessing ways to improve the flag- to- clamor rate and tending to challenges related to the tall number of parameters in DL ways. Whereas our framework offers patient-specific seizure forecasts, unborn investigation ought to explorenon-patient-specific vaticination styles. These bearings have the outcome to development the field and deliver assist strong comes about for epilepsy operation.

VII. FUTURE WORK

Future research focusing on hardware for disease detection shows promise, with practical applications aiding accurate diagnosis. Cloud-based models can be integrated into handheld or wearable devices, enabling timely alerts for conditions like epileptic seizures. EEG-cap technology offers real-time monitoring, while leveraging interictal periods for early seizure detection could revolutionize preventive care. This integration of hardware and predictive models enhances patient outcomes by enabling timely interventions.

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