International Scientific Journal of Engineering and Management (ISJEM) ISSN: 2583-6129
Volume: 05 Issue: 04 | April – 2026 DOI:10.55041/ISJEM06027
An International Scholarly || Multidisciplinary || Open Access || Indexing in all major Database & Metadata

Epileptic Seizure Prediction using Deep Learning

Mr. L. Kiran Kumar
Assistant Professor.
Department of
Information Technology
Department
Maharaj Vijayaram Gajapathi Raj
College of Engineering(A)
Chintalavalasa, Vizianagaram,
Andhra Pradesh, India.
kirankumar@mvgrce.edu.in

Jagarapu Joshna
Department of
Information Technology
Maharaj Vijayaram Gajapathi Raj
college of Engineering(A)
Chintalavalasa, Vizianagaram,
Andhra Pradesh, India.
testmailjoshna@gmail.com

Madisa Abhilash
Department of
Information Technology
Maharaj Vijayaram Gajapathi Raj
college of Engineering(A)
Chintalavalasa, Vizianagaram,
Andhra Pradesh, India.
abhilashmadisa@gmail.com

Besetty Shubham
Department of
Information Technology
Maharaj Vijayaram Gajapathi Raj
college of Engineering(A)
Chintalavalasa, Vizianagaram, Andhra
Pradesh, India.
shubhambesetty@gmail.com

Gudivada Avinash
Department of
Information Technology
Maharaj Vijayaram Gajapathi Raj
college of Engineering(A)
Chintalavalasa, Vizianagaram, Andhra
Pradesh, India.
22331a1233@gmail.com

***Abstract*—** Epilepsy is a neurological disorder characterized by sudden and recurrent seizures caused by abnormal electrical activity in the brain. Early prediction of seizures is crucial to improve patient safety and enable timely medical intervention. Traditional seizure detection methods rely on manual analysis of Electroencephalogram (EEG) signals, which is time-consuming and prone to human error. This paper proposes a deep learning-based epileptic seizure prediction system using Long Short-Term Memory (LSTM) networks. The system processes EEG data through preprocessing techniques such as noise removal, normalization, and feature extraction. The LSTM model learns temporal patterns in EEG signals and predicts seizure occurrence with high accuracy.The model achieved an accuracy of 98.53%, precision of 0.9837, recall of 0.9873, and ROC-AUC score of 0.9967, demonstrating strong predictive performance. A user-friendly interface is developed using Streamlit, allowing real-time prediction by uploading EEG data. This system provides an efficient, accurate, and accessible solution for seizure prediction and monitoring.

***Keywords*—** Deep Learning, EEG, Epileptic Seizure, LSTM, Prediction, Streamlit**.**

I. Introduction

Epilepsy constitutes a single of the most widespread neurological illnesses, affecting around 50 million individuals globally. It is marked by repeated, spontaneous seizures that originate from aberrant electrical activity throughout the brain [1]. Early treatments for epilepsy ranged from herbal medicines to surgical procedures, and the condition has been researched for centuries. However, because seizures can happen at any time, diagnosing and predicting them has proven difficult. Over a period of time electroencephalography (EEG) has established a routine method for measuring brain activity and diagnosing epileptic abnormalities. Traditional techniques of seizure identification relied on analysis performed manually by physicians, which was laborious and subject to human error [2]. With improvements in artificial intelligence (AI) and deep learning, automatic seizure forecasting techniques have attracted substantial interest, delivering faster and more accurate predictions.

Traditional seizure detection models like Support Vector Machines (SVM), Decision Trees, and Random Forests need extensive feature development and often fall short to capture the temporal relationships present in EEG signals [3]. Recent developments incorporate neural network methods like Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), which are capable of extracting patterns from raw EEG data. Current seizure detection systems primarily depend on rule-based algorithms, signal processing methods, and machine learning models trained on EEG data. However, CNNs are less successful for sequential EEG data because they are unable to maintain long-term dependencies, while ordinary RNNs have problems with vanishing gradients. These drawbacks show that a more reliable deep learning model is required in order to accurately forecast seizures by analyzing dependence over time in EEG signals. In order to overcome these obstacles, this paper suggests an Epileptic Seizure Detection System that makes use of Long Short-Term Memory (LSTM) systems, a specific kind of RNN that successfully captures long-term relationships in sequential data and gets over the vanishing gradient issue. To improve model performance, the system goes through extensive exploratory data analysis (EDA) and preparation, which includes handling missing values, normalizing EEG characteristics and identifying pertinent patterns [4].

Additionally, by reducing reliance on costly and intricate EEG monitoring procedures, this AI-powered system makes seizure prediction more accessible and inexpensive for those living in distant or underserved locations [5]. This approach supports continuing efforts in neurological condition management, AI-driven diagnostics, and customized medicine by fusing deep learning with practical healthcare applications. The urgent need for an effective, precise, and real-time seizure detection technology that can greatly enhance the standard of life for those with epilepsy is what inspired this effort. The low accuracy, high rate of false alarms, and restricted real-time application of many current techniques make them unusable in real-world situations. Because seizures are unpredictable, it is essential to create a strong AI-based system that can offer early warnings and useful insights [6]. In order to ensure that people with epilepsy can live safer and more independent lives, this effort attempts to close the gap between seizure detection research and practical implementation by utilizing the developments in deep learning, LSTMs and powered by AI healthcare solutions.

II. LITERATURE SURVEY

Using predictive modeling and signal processing methods on EEG data, several previous studies investigated the detection of epileptic seizures. To find seizure-related patterns in brain data, traditional methods mostly used feature extraction techniques including wavelet transformations, Fourier evolves, and statistical evaluations. EEG data were classified into seizure and non-seizure categories using traditional machine learning models, such as Support Vector Machines (SVM), Random Forests, Decision Trees and k- Nearest Neighbors (KNN). These models were less effective for massive, real-time seizure detection since they required manual engineering of features, despite their moderate accuracy [7]. Furthermore, because of inter-subject heterogeneity, handcrafted features frequently did not generalize across patients, which led to poorer prediction performance in real-world scenarios. Farooq et al. predicted using machine learning techniques, primarily by feature extraction and classification using different classifiers. By reviewing the body of research and developing a taxonomy, this work offers a methodical literature assessment of feature selection and classification performance [8]. Additionally, it studies the operation of classifiers and looks at impartial and benchmark datasets. The study finds gaps, obstacles, and chances to forecast the future. Tran et al. examines the use of machine learning techniques for epilepsy prediction, looking at benchmark datasets, classifier operation, feature selection and classification performance [9].

Hajjar et al. examines and compiles state-of-the-art machine learning applications for epilepsy detection. By incorporating predictive algorithms for data processing and collecting, the Internet of Medical Things (IoMT) is transforming the healthcare sector [10]. Issues like epileptic seizure surveillance and identification have been successfully addressed by this integration in conjunction with IoMT. Convolutional neural networks (CNNs), recurrent neural networks (RNNs), and mixed models have been adopted for automated seizure detection as a result of recent developments in deep learning. While RNNs, namely Gated Recurrent Units (GRUs) and Long Short-Term Memory (LSTM) systems, have been used to capture temporal dependencies in sequential EEG data, CNNs have shown successful in extracting spatial characteristics from EEG spectrograms. To improve feature learning, some research has also combined Transformer models with attention mechanisms [11]. Notwithstanding these developments, the high computing costs, overfitting brought on by limited datasets, and requirement for intensive hyperparameter tuning are some of the problems that plague current deep learning models. Furthermore, the majority of seizure detection systems are not implemented in real-time and have unintuitive user interfaces, which restricts their applicability for both clinical and individual use.

III. DATA COLLECTION & PREPROCESSING

The data set used in the study consists of EEG signals from people who are experiencing epileptic seizure. The data set is collected from publicly available databases that are used in various seizure detection studies. The seizure as well as the non-seizure state is represented in the data set through various channels of EEG signals collected during various time periods. Before the implementation of the model, the artifacts, vibration, and missing values present in the EEG signal must be addressed. For the analysis of signal patterns, the identification of outliers, and the understanding of the range of seizure occurrence, exploratory data analysis, abbreviated as EDA, is used. The frequency dimension of the EEG signal is analyzed through the implementation of the Wavelet Transform as well as Fast Fourier Transform (FFT) techniques, which reveal important patterns associated with epileptic episodes.

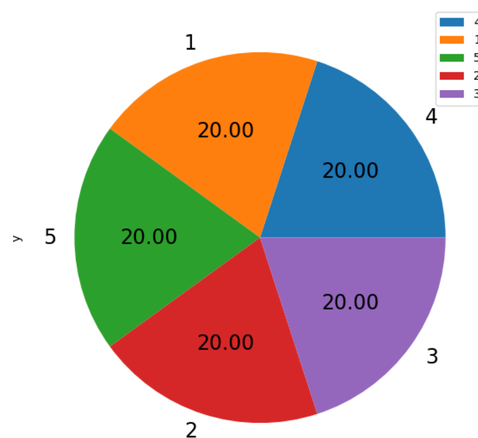

Fig.1 Distribution of Output Class in Data

Significant preprocessing techniques are employed to enhance the quality of the data. Depending on the distribution of missing points, mean imputation or linear interpolation is used to handle missing values in the data set. High-frequency noise and artifacts resulting from external interference or muscle activity are also reduced by applying Butterworth and Chebyshev filters. PCA and ICA are two dimensionality reduction techniques employed to find the most dominant features while reducing the computational cost due to the high dimensionality of the EEG signal [12].

International Scientific Journal of Engineering and Management (ISJEM) ISSN: 2583-6129
Volume: 05 Issue: 04 | April – 2026 DOI:10.55041/ISJEM06027
An International Scholarly || Multidisciplinary || Open Access || Indexing in all major Database & Metadata

In order to resolve the class imbalance issue and enhance the generalization performance of the classifier, various data augmentation techniques such as signal modification techniques, including time shifting, flipping, scaling, etc., as well as synthetic data augmentation techniques with the help of GANs are also employed. In order to ensure uniform scaling of the EEG signal, normalization is an important step to avoid certain features dominating others due to scaling issues.The EEG signals with amplitude in the range of 0 to 1 are normalized using min-max scaling while maintaining the integrity of the pattern in the signals. To standardize features with zero mean and unit variance, which would help in faster training of the deep learning model, there is a possibility of using Z-score normalization. Feature extraction techniques are critical in order to enhance the capability of the model. To identify fluctuations in the signals during seizure, peak-to-peak, entropy, root mean square, and Hjorth parameters are computed in the time domain. To enhance the capability of the model in discriminating seizure and non-seizure events, spectral entropy and power spectral density are retrieved from the signals in the frequency domain [13].

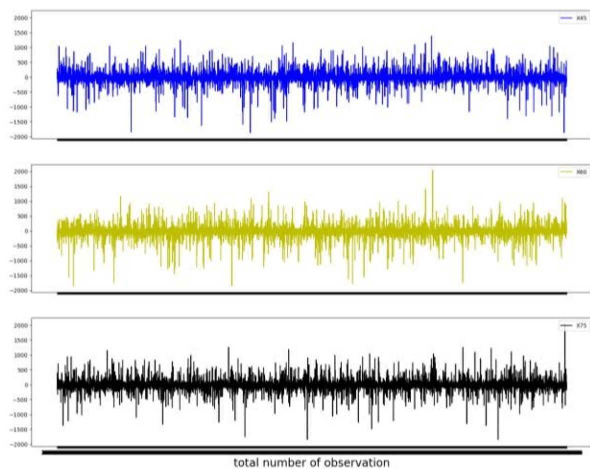

Fig.2 Visual Representation of Different Channels When Stacked Independently

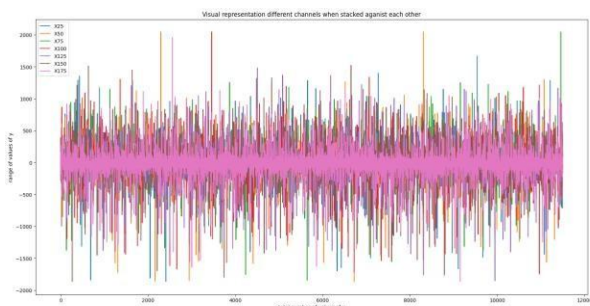

Fig.3 Visual Representation Different Channels When Stacked on Each Other

To guarantee a balanced distribution of seizure and non-seizure samples in both sets, the processed dataset is divided into training (80%) and testing (20%) sets. In order to reduce overfitting and improve generalization, a 5-fold cross- validation approach is used to further assess model performance. This involves frequently splitting the dataset into distinct training and validation sets. Only the training set is subjected to data augmentation techniques in order to preserve the integrity of the test data for objective assessment.

In order to detect important seizure characteristics, spectral images and heatmaps are created to track frequency changes over time. To examine feature distributions and correlations among various EEG channels, box plots, histograms, and scatter diagrams are employed. Electrocardiogram (ECG) signals are also analyzed in conjunction with EEG data in order to identify possible associations between variations in heart rate and seizure events. These visualizations offer important information that directs the design of the model architecture and feature selection.

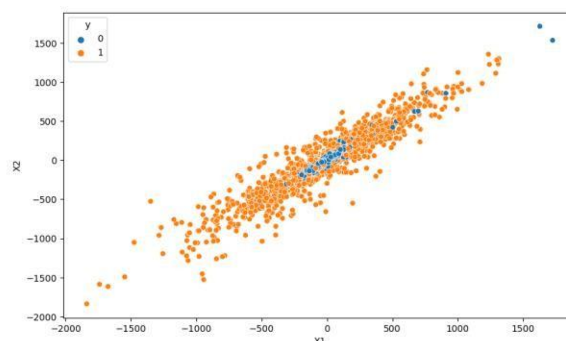

Fig.4 Scatter Plot of Features with Output Column

EEG signals are converted to an appropriate format for the LSTM-based deep learning process, creating an easier route for training the model. The EEG data is converted to time series format, with the signal divided into equal-sized windows. The signal is then represented as one sample. The use of sliding window techniques is also explored to ensure the temporal information is continuous and the seizure onset is well represented. The data is then converted to a 3D tensor to fit the LSTM requirements. Data augmentation is also explored as an approach to enhance the robustness of the system. This includes the addition of Gaussian noise to the data and the use of the Variational Auto-Encoder. The prepared data is then stored in an efficient format for easier loading, such as TFRecord and NumPy array formats. The LSTM is then trained on the prepared data, with the possibility of dropout regularization to prevent overfitting. The test data is used for testing the prepared model only, with no further modifications.This is because the data processing steps ensure the deep learning model is supplied with quality and well-structured data, which enhances the model's accuracy and its capacity to generalize its predictions on the seizures.

IV. PROPOSED METHODOLOGY

After the structured pipeline, the proposed deep learning-based approach for epileptic seizure prediction follows. It starts with data collection, data preprocessing, feature extraction, model training, and finally reaches the prediction phase in real time and the user interface. Preprocessing is done on the raw EEG data set. It involves normalization using Min-Max Scale, removal of artifacts, and removal of noise by means of Fourier filters. In order to sustain the pattern of seizures, the EEG signal is segmented into windows of a specific length. The identification of frequency characteristics of seizures is made easier by exploratory data analysis (EDA), which consists of the creation of a spectrogram, power spectral density analysis, and display of thewaveform.

International Scientific Journal of Engineering and Management (ISJEM) ISSN: 2583-6129
Volume: 05 Issue: 04 | April – 2026 DOI:10.55041/ISJEM06027
An International Scholarly || Multidisciplinary || Open Access || Indexing in all major Database & Metadata

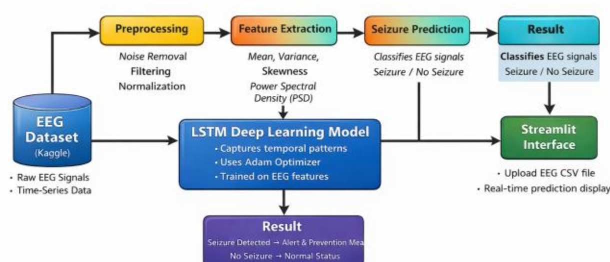

Fig.5 Working Methodology

Once the data is processed, the EEG data is converted into a sequence of data for training an LSTM network, which is fine-tuned using the Adam optimizer. The network is special in that it is able to identify the start of a seizure due to its capacity for recognizing relationships between data. The network also uses ReLU and softmax to maintain a sharp classification and includes batch normalization and dropout for overfitting protection. The network is also connected to a web application via Streamlit and allows the user to upload data in a CSV format. Once the data is processed, the network is able to make accurate predictions regarding the likelihood of a seizure occurring.

A.Long Short-Term Memory

A long short-term memory network, abbreviated as LSTM, is a specific form of RNN designed in a way that helps these networks avoid the usual problems associated with vanilla RNNs when it comes to capturing long-range relationships in data. The most significant advantage of LSTMs is their gating system, which makes these networks successful in capturing information in long-range data streams—a problem that vanilla RNNs face due to problems like vanishing and exploding gradients. As a result, LSTMs are best used in situations where there is a time component in data analysis, like in voice recognition systems, natural language processing systems, time series forecasting systems, bio-signal processing systems like seizure prediction systems based on EEG signals, etc. The reason people rely on LSTMs when they are required to analyze complex data based on time relationships is due to their capacity to dynamically store information in data streams. Inside a standard LSTM network, there is a component called a gate composed of three gates: the forget gate, input gate, and output gate.

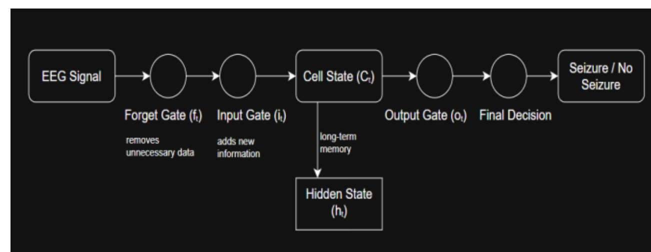

Fig.6 LSTM Architecture

The input gate is also an important part of updating the memory cell, as it determines what information will be added to the cell. This gate has two parts: a tanh function that scales the information to be within -1 and 1 to determine what will be added to the cell, and a sigmoid function that determines how important this information is. This combination ensures that the memory cell remains constant, allowing for a smooth transition to incorporate new patterns in the EEG signal. This combination ensures that the LSTM's interpretation of the EEG signal is constantly adapting, allowing for a more accurate prediction of when a seizure will occur. The output gate determines what information will be passed along by the LSTM. This gate determines how much of the updated cell will be passed to the next time step. This is done with a tanh function to scale the information appropriately, as well as a sigmoid function to determine what information is important.The LSTM model aids the system in generalizing different EEG recordings and prevents overfitting by handling information appropriately.

One of the main components of the LSTM is the cell state, which is a long-term memory. The cell state of the LSTM is updated additively rather than multiplicatively. This prevents the vanishing gradient problem faced by traditional RNNs. This is particularly useful for handling long dependencies in the EEG data, which is a critical requirement for seizure prediction since earlier brain activity influences later activity. The LSTM is also able to process information at every step and adjust its internal state accordingly, thereby processing the EEG data in a deliberate and step-by-step fashion. Each EEG signal is a sequence of time series data, and a set of features is defined for every step.
This is because the LSTM holds the relevant information related to the seizure as it proceeds to the next time steps, checking them one by one. It is because of this characteristic that the LSTM is able to identify the gradual development of the seizure.One major challenge encountered during the training of the LSTM is the hurdle of overfitting. Overfitting is one common challenge encountered in the field of biomedical data, where there is little data to train on.In order to reduce the effect of overfitting in the LSTM model, batch normalization is used. In the context of the LSTM model, the application of the dropout algorithm is to randomly switch off the neurons.

These updates enhance the performance of the seizure prediction model built on the LSTM. Adam, which stands for Adaptive Moment Estimation, is a gradient-based adaptive optimizer. Adam combines the benefits of the Perceptron family of algorithms, such as those that use momentum, and the benefits of the RMSProp family of algorithms. Adam has a different learning rate for each of the model's parameters. Thus, by applying Adam, the accuracy of the seizure prediction model is enhanced, along with its convergence.

Effective data management and acceleration of inference are critical in integrating LSTM-based seizure forecasting into practical applications in real-time. To achieve this, techniques like TensorRT, pruning, and quantization are utilized to reduce memory usage and enhance performance. Parallelization using a GPU is utilized in processing EEG in real-time, significantly reducing latency in seizure forecasting. After these modifications, the LSTM is ready for individual and clinical use, allowing for deployment on various devices and platforms, including mobile and cloud-based healthcare systems.

One of the most critical factors in using deep learning in medicine is interpretability; therefore, some explanations are provided. By visualizing some of the significant EEG patterns associated with seizure forecasting using techniques like prominence maps, SHAP (SHapley Additive Explanations), and Grad-CAM (Gradient-weighted Class Activation Mapping) methods, the decision-making process can be linked to significant EEG patterns rather than random correlations, thus increasing confidence in the system among patients and clinicians.

V. RESULTS

The seizure forecasting model enables a real-time seizure detection using its high accuracy and reliability. The model, which is based on a deep neural network using LSTM, effectively detects seizure occurrence in real time, as it is trained on a good preprocessed dataset of EEG signals. The model has a high accuracy of 0.9853, F1 Score of 0.9855, precision of 0.9837, recall of 0.9873, and ROC AUC of 0.9967. The model has a high level of accuracy in detecting seizures, as there are fewer false positives and false negatives. The high level of accuracy in class separation is evident from a high ROC AUC value of 0.9967, which indicates a high level of reliability in seizure detection. To evaluate the model comprehensively, various graphs are used, such as receiver operating characteristic curves, precision-recall curves, and confusion matrices. The high level of accuracy of the model is evident from a high value in the confusion matrix, which is 0.9837 precision.

The report also included several metrics for the performance of the model, such as positive and negative real rates and false positive and negative rates. The efficiency of the model in predicting seizures is also indicated by the low number of false positive and negative rates. The precision-recall curve also indicates a good balance of accuracy and recall of the data by the model. The robustness of the model is again confirmed by the ROC curve, which indicates good separation of seizure and non-seizure activity by the model by the proximity of the AUC value to a strong value.1.

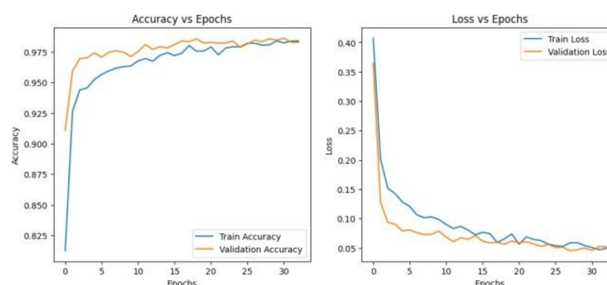

Fig.7 LSTM Epochs vs Accuracy, Loss

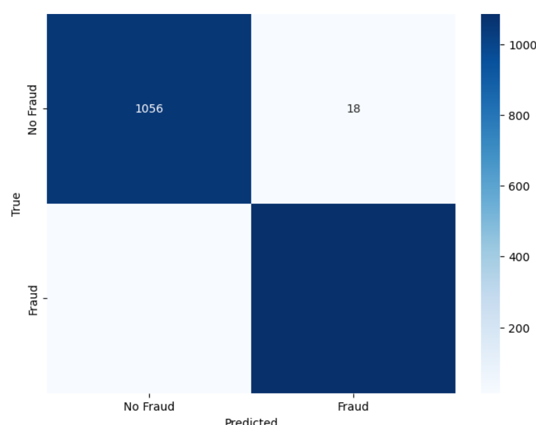

Fig.8 Confusion Matrix

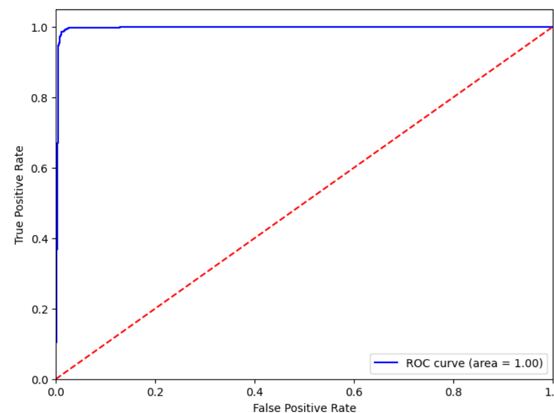

Fig.9 Receiver Operating Characteristic (ROC) Curve

International Scientific Journal of Engineering and Management (ISJEM) ISSN: 2583-6129
Volume: 05 Issue: 04 | April – 2026 DOI:10.55041/ISJEM06027
An International Scholarly || Multidisciplinary || Open Access || Indexing in all major Database & Metadata

Fig.10 Sample Data Page in User Interface

In order to evaluate the performance of the model in terms of its ability to learn during the course of training, we plotted the loss with epochs and accuracy with epochs. From the model, it is evident that the model is learning well without any major cases of overfitting, as the loss is decreasing steadily with epochs. From the graph showing the accuracy with epochs, it is evident that the model is achieving high accuracy, with the accuracy being 98.53%. Moreover, the graph showing the accuracy with epochs indicates that the model is achieving high accuracy with both the validation set and the training set. In order to verify the model's ability to learn the actual patterns in the EEG signals, we carried out the gradient flow assessment.
In terms of deployment, the model is being deployed using the Streamlit framework, which is a lightweight and web-based framework. Streamlit is being used to deploy the LSTM model in the real-time seizure prediction system. It is capable of generating the predictions on the fly by allowing the user to upload the CSV files containing the EEG signals. From the interface, it is evident that the design is simple and user-friendly.The user has the option to upload their raw EEG data, and the model will immediately analyze it to determine if a seizure is currently happening. The user interface will assist patients or caregivers in taking emergency and quick preventive measures when a seizure is detected. Seizure detection can be done not only by doctors but also by people living with epilepsy.

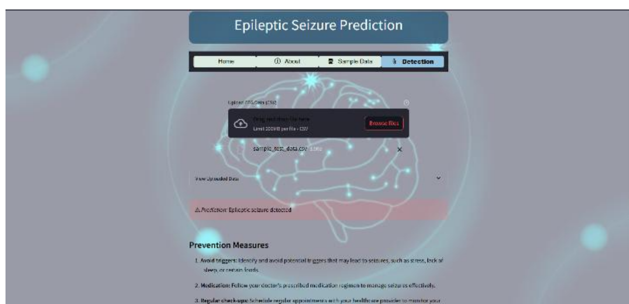

Fig.11 Prediction Page in User Interface

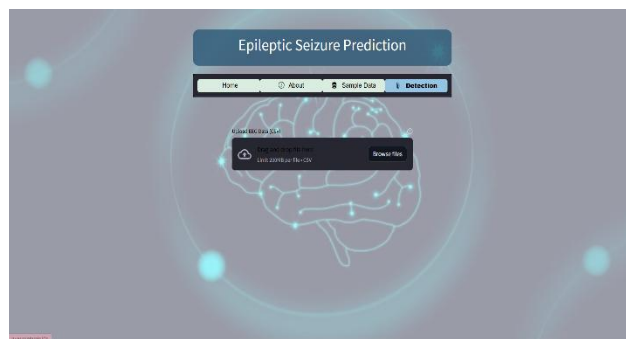

Fig.12 Prediction Page in User Interface

Various features and preprocessing techniques were also explored to better understand the behavior of the model. Initially, frequency-domain-based features such as power spectral density, wavelet decomposition, and Fourier analysis were considered for the analysis of EEG signals. Time-domain-based features such as mean, variance, skewness, and kurtosis were also considered. Feature importance analysis showed that gamma, theta, and delta bands are significant for seizure activity. The team also tried different normalization techniques such as robust scaling, Z-normalization, and Min-Max scaling to find out which method performs better for the problem. The best results were obtained by using Min-Max Scaling, which scales all the EEG features to a fixed range. The final step is to test the model on real-time EEG data and examine its robustness for different conditions of patients. For validation purposes, EEG data from different sources and seizure prediction datasets are considered.The results proved the scalability and versatility of this model in handling unique seizure patterns, which show its generalization capability over different data sets. It effectively trims away extra noise while maintaining high accuracy, despite the fact that the system is dealing with heavily noisy and corrupted EEG signals.

CONCLUSION

With the high level of accuracy being 98.53%, and AUC ROC being 0.9967, the deep learning-based epileptic prediction model is extremely reliable and accurate in the early diagnosis of seizures using EEG signals. It is one of the best tools for the management of epilepsy because it can be implemented in real time using Streamlit. It is efficient because the efficiency can be improved using sophisticated feature extraction, data preparation, and visualization techniques. It can be improved in the future to be accessible to the public by developing a mobile application, using cloud technology for tracking, and making the model adaptable to the immediate streaming data. It can be used to take a more proactive role in the management of epilepsy by using hybrid deep learning techniques, such as the Transformer model, and using data such as heart rates, EEG signals, and other bio-signal data to improve the accuracy of the model.

Conflict of Interest: There is no conflict of Interest

REFERENCES

[1] Kunekar, Pankaj, Mukesh Kumar Gupta, and Pramod Gaur. "Detection of epileptic seizure in EEG signals using machine learning and deep learning techniques." Journal of Engineering and Applied Science 71.1 (2024): 21.

[2] Tang, Jianbin, et al. "Seizure detection using wearable sensors and machine learning: Setting a benchmark." Epilepsia 62.8 (2021): 1807-1819.

[3] Xiong, Wenjuan, et al. "Classification of epileptic and psychogenic non-epileptic seizures using electroencephalography and electrocardiography." IEEE Transactions on Neural Systems and Rehabilitation Engineering 31 (2023): 2831- 2838

[4] Costa, Gonçalo, César Teixeira, and Mauro F. Pinto. "Comparison between epileptic seizure prediction and forecasting based on machine learning." Scientific Reports 14.1 (2024): 5653.

[5] Zubair, Muhammad, et al. "Detection of epileptic seizures from EEG signals by combining dimensionality reduction algorithms with machine learning models." IEEE Sensors Journal 21.15 (2021): 16861-16869.

[6] Zhao, Xuyang, et al. "Epileptic seizure detection by using interpretable machine learning models." Journal of Neural Engineering 20.1 (2023): 015002.

[7] Al-Hajjar, Alaa Lateef Noor, and Ali Kadhum M. Al-Qurabat. "An overview of machine learning methods in enabling IoMT-based epileptic seizure detection." The Journal of Supercomputing 79.14 (2023): 16017-16064.

[8] Tran, Ly V., et al. "Application of machine learning in epileptic seizure detection." Diagnostics 12.11 (2022): 2879.

[9] Farooq, Muhammad Shoaib, Aimen Zulfiqar, and Shamyla Riaz. "Epileptic seizure detection using machine learning: Taxonomy, opportunities, and challenges." Diagnostics 13.6 (2023): 1058.

[10] Natu, Milind, et al. "[Retracted] Review on Epileptic Seizure Prediction: Machine Learning and Deep Learning Approaches." Computational and Mathematical Methods in Medicine 2022.1 (2022): 7751263.

[11] Bazarian, Jeffrey J., et al. "Validation of a machine learning brain electrical activity–based index to aid in diagnosing concussion among athletes." JAMA network open 4.2 (2021): e2037349-e2037349.

[12] Wahr, Joyce A. "Human Error–Cognitive Processes and Interventions to Improve Safety. A Global Perspective." Education for anaesthesia providers worldwide (2024): 7.

[13] Jafari, Mahboobeh, et al. "Emotion recognition in EEG signals using deep learning methods: A review." Computers in Biology and Medicine 165 (2023): 107450.

[14] Apicella, Andrea, et al. "On the effects of data normalization for domain adaptation on EEG data." Engineering Applications of Artificial Intelligence 123 (2023): 106205.

[15] Ali, Amza, et al. "Delivering epilepsy care in low-resource settings: the role of technology." Expert Review of Medical Devices 18.sup1 (2021): 13-23.

[16] Al-Tekreeti, Zeena, et al. "AI-Based Visual Early Warning System." Informatics. Vol. 11. No. 3. MDPI, 2024.

[17] Ritharson, P. Isaac, et al. "DeepRice: A deep learning and deep feature based classification of Rice leaf disease subtypes." Artificial Intelligence in Agriculture 11 (2024): 34-49.

[18] Farooq, Muhammad Shoaib, Aimen Zulfiqar, and Shamyla Riaz. "Epileptic seizure detection using machine learning: Taxonomy, opportunities, and challenges." Diagnostics 13.6 (2023): 1058.

[19] Tran, Ly V., et al. "Application of machine learning in epileptic seizure detection." Diagnostics 12.11 (2022): 2879.

[20] Al-Hajjar, Alaa Lateef Noor, and Ali Kadhum M. Al-Qurabat. "An overview of machine learning methods in enabling IoMT-based epileptic seizure detection." The Journal of Supercomputing 79.14 (2023): 16017-16064.

[21] Boddapati, Mohan Sai Dinesh, et al. "Creating a protected virtual learning space: a comprehensive strategy for security and user experience in online education." International Conference on Cognitive Computing and Cyber Physical Systems. Cham: Springer Nature Switzerland, 2023.

[22] Gowri, Gokul, et al. "Approximating mutual information of high-dimensional variables using learned representations." Advances in Neural Information Processing Systems 37 (2024): 132843-132875.

[23] Martini, Alessandro, et al. "Maximum Entropy Spectral Analysis: an application to gravitational waves data analysis." arXiv preprint arXiv:2106.09499 (2021).

[24] Murray, Derek G., et al. "tf. data: A machine learning data processing framework." arXiv preprint arXiv:2101.12127 (2021).

[25] Zha, Wenshu, et al. "Forecasting monthly gas field production based on the CNN-LSTM model." Energy 260 (2022): 124889.