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Original Article

Smart Healthcare: Machine Learning-Based Classification of Epileptic Seizure Disease Using EEG Signal Analysis

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Abstract *- At the moment, epileptic disease (ED) is regarded as one of the progressive disorders that affect brain function over a number of months or years. The main prevalent cause of eating disorders is a seizure state. This study employs a Convolutional Neural Network (CNN)-based method to predict epileptic seizures by analyzing EEG data. The approach utilizes the UCI Epileptic Seizure Recognition dataset, with preprocessing steps including outlier removal and Min-Max normalization to enhance data quality. Raw time-series EEG data were used directly for classification, removing the requirement for feature engineering by hand. The suggested CNN model achieved 99% accuracy, 99% precision, 99% recall, and 99% F1-score, demonstrating outstanding performance. Comparative analysis with baseline models Fully Connected Neural Network (FCNN), Random Forest (RF), and Support Vector Classifier (SVC) demonstrated the superior accuracy of the CNN model. These results highlight its potential for integration into real-time smart healthcare systems, enabling proactive patient monitoring and timely intervention in clinical settings.*

Keywords *- Epileptic Seizure Detection, EEG Signal Analysis, Convolutional Neural Network (CNN), Machine Learning, Seizure Prediction, UCI Epileptic Seizure Dataset.*

1. Introduction

The combined strains of an ageing and growing population, a growing need for high-quality treatment, and constrained resources are driving the rise of smart health care in the digital era [1]. wearables have traditionally been used to promote overall wellness, smart health is also beginning to include the Although treatment of acute illnesses. The automated real-time control of seizures using smart health care is one example of such an endeavor [2]. Frequent, unplanned seizures are a hallmark of epilepsy, a neurological disorder. An aberrant hyper-synchronous disruption of a population of neurons causes a seizure, which can cause convulsions, sensory abnormalities, and even loss of consciousness. The human brain is a non-linear, very complicated structure. Numerous physiological and pathological illnesses, including the cause of epileptic seizures is anomalies in the human brain [3]. Seizures in epilepsy are brought on by serious electrical abnormalities in the brain pattern [4]. The EEG signal is a useful clinical tool for identifying brain activity in humans. Diagnosing epilepsy starts using EEG signal data to detect epileptic seizures.

The EEG serves as a vital instrument for brain activity evaluation [5]. The device measures brain electrical signals to provide essential information about brain function and unusual activity patterns. The detection of abnormal electrical patterns signaling seizures in epilepsy patients depends on EEG signals for essential diagnosis [6]. Epileptic seizure detection through EEG requires medical experts to perform visual inspections, yet proves both time-consuming and error-prone during continuous monitoring sessions, according to research [7]. Human-based EEG analysis turns out to be both burdensome and inefficient for real-time seizure detection because signals contain complex patterns.

The difficulties within seizure detection and prediction have led to an increasing necessity for automated systems that precisely analyze EEG signals. ML and DL approaches show great promise in automating seizure detection and prediction with enhanced precision, according to research in [8]. Modern algorithms analyze extensive EEG datasets by locating intricate data patterns that are tough for human experts to detect independently [9]. The application of ML and DL methods by researchers yielded successful results in seizure event classification, which strongly improved detection efficiency [10].

1.1. Motivation and Contribution of the Study

The research goal emerges from an urgent demand to create non-invasive data-driven approaches for early seizure detection and monitoring. Worldwide, millions of people live with epilepsy, yet this neurological condition often receives a delayed diagnosis because seizures occur sporadically. The current diagnostic methods depend on clinician-led manual EEG evaluation, but this analysis requires extensive time to perform and displays human subjectivity along with error rates that reduce diagnostic accuracy. Epileptic seizure detection capabilities powered by the combination of massive EEG signal access and ML technology show great promise to benefit clinical decisions and patient outcomes.

The research develops a reliable seizure detection system through deep learning applications applied to EEG signal data analysis. This work introduces the following key findings:

- **Development of a CNN-based Seizure Prediction Model:** This paper introduces a DL model using the CNN algorithm enables precise epileptic seizure anticipation through EEG signal evaluation to improve early seizure detection elements for smart healthcare applications.
- **Innovative Data Pre-processing Techniques:** The study uses advanced pre-processing techniques combined with outlier detection and Min-Max normalization, and feature extraction to achieve enhanced data quality and uniform scaling of EEG signal features for improved model training efficiency.
- **High Performance and Robust Evaluation:** The usefulness of the suggested CNN model in Its exceptional performance, precision, recall, accuracy and F1-score show that it can distinguish between epileptic and non-epileptic EEG data with low false positives and false negatives.
- **Comparative Analysis with Baseline Models:** The study presents a detailed comparative analysis with traditional ML models (FCNN, RF, SVC), highlighting the superior performance of the CNN approach, particularly in capturing temporal patterns of EEG signals for seizure detection.

1.2. Justification and Novelty of the Paper

The justification and novelty of this paper lie in the application of CNN using the UCI Epileptic Seizure Recognition dataset to determine if EEG patterns are epileptic or non. This study contributes to the domain of smart healthcare by offering an accurate, automated approach to seizure detection, which is necessary for early diagnosis and treatment planning in the management of epilepsy. Using unprocessed EEG time-series data as input instead of feature engineering enables the CNN model to autonomously learn complex temporal and spatial patterns associated with seizure activity.

1.3. Structure of Paper

This paper is structured as follows: Section II reviews related work, Section III describes the dataset and CNN methodology, Section IV presents results and analysis, and Section V concludes with key insights and future work.

2. Literature Review

This section reviews and highlights advancements in EEG data analysis for epileptic seizure identification with an emphasis on using ML and DL techniques in intelligent medical care.

2.1. Some of the notable reviewed works are:

Grabat et al. (2019) features are taken from the EEG signals' S-transform across predetermined time intervals. These characteristics are taken from three states: ictal (seizures), pre-ictal, and normal. Calculations are made to determine the powers of the various EEG-retrieved characteristics. SVM uses analysis to differentiate between specified time periods of certain states following its implementation. The simulation's results show that S-transform performs well in detection, 94.481% sensitivity and 70.315% specificity on average with the prediction method works accurately, with an average of 72.944% specificity and 96% sensitivity [11].

Billeci et al. (2019) in order to develop seizure prediction systems an initial patient-specific research combining EEG and ECG is presented. The study team collected synchronization patterns, Recurrence quantification analytic metrics from the RR inter-beat series using EEG data, along with time and frequency aspects. The SVM classifier included the properties that were derived from both signals to differentiate midway between the interictal and preictal stages. Predictive results from the proposed integrated analytical approach allowed for the identification of epileptic seizures with 93.3% sensitivity and 80.6% specificity over a 20-minute prediction period. Using wearable and portable electronics, researchers have discovered ways to implement real-time patient-tailored seizure forecasts [12].

Gaho et al. (2019) in order to determine the cause of seizures, spikes, and anticipated epileptic problems in individuals with epilepsy who are sleeping at night, the study team examined these phenomena. The results show that the whole EEG data contains several strong spikes or seizures, especially in the brain's frontal sensory region. According to the research, the left front-central region of the brain, which has large amplitudes at the electrode positions (FC1, Cz), is responsible for sharp waves, polyspikes, and spikes in beta band activity, especially while the patient is asleep. Additionally, for a certain time period, this region has a fixing goodness rating greater than 95% [13].

Rajendran and Kumar (2019) develop a model for an ANN that can identify and forecast seizures before they happen. Using a sensitivity rating of 91.15%, the suggested ANN model predicts and detects seizure events using an easy-to-use and effective architecture. Experiments on the data reveal that, with a significant calculation time (630 seconds), the prediction accuracy is 91%. A common neurological condition known as epilepsy or epileptic seizures affects a large number of people. It happens suddenly and without any indications, which raises the human mortality rate [14].

Acharya et al. (2018) this method is restricted in detecting irregularities, can be time-consuming, has technical artefacts, and yields inconsistent findings depending on the reader's degree of skill. Therefore, it is crucial to create a CAD system that uses ML techniques to automatically determine this EEG data's kind. This is the first attempt to use CNN to analyze EEG data. This study distinguishes between the normal, preictal, and seizure classes using a 13-layer deep CNN approach. The recommended method's sensitivity, specificity, and accuracy were 95.00%, 90.00%, and 88.67%, respectively [15]. Table I presents a comparative analysis of the background literature, categorized by author, methodology, data used, key findings, limitations, and proposed future work.

Table 1: Smart Healthcare and Prediction of Epileptic Seizures Disease Using EEG Signal Analysis

Author(s)	Methodology	Data	Key Findings	Limitations	Future Work
Grabat et al. (2019)	S-transform for EEG feature extraction; SVM classification	EEG signals (normal, pre-ictal, ictal states)	Sensitivity: 94.481%, Specificity: 70.315% (detection); Sensitivity: 96%, Specificity: 72.944% (prediction)	Moderate specificity	Enhance specificity and validate on larger datasets
Billeci et al. (2019)	Combined EEG and ECG features; SVM classifier	EEG and ECG data (patient-specific)	Sensitivity: 93.3%, Specificity: 80.6%, ~20-minute prediction window	Preliminary study with limited dataset	Incorporate wearable and portable technology for practical applications
Gaho et al. (2019)	Pre-processing and source localization using EEG	Night-time EEG data from epilepsy patients	Identified spikes in the left fronto-central region with >95% localization accuracy	Requires extensive pre-processing	Streamline processing for real-time or clinical applications
Rajendran and Kumar (2019)	Artificial Neural Networks (ANN) for the detection and prediction of seizures	EEG data	Prediction accuracy: 91%, Sensitivity: 91.15%, Computation time: 630 seconds	High computation time	Optimize ANN architecture for improved speed and performance
Acharya et al. (2018)	Classifying EEG data using a 13-layer CNN model	EEG signals (normal, preictal, seizure)	Accuracy: 88.67%, Specificity: 90%, Sensitivity: 95%	Time-consuming and subject to artifacts	Develop real-time CAD systems and expand validation across diverse datasets

3. Methodology

This project aims to create a precise DL-based model for EEG signal analysis-based epileptic seizure prediction. The aim is to enhance early detection capabilities for integration into smart healthcare systems. This work uses EEG data processing in a methodical manner to anticipate epileptic episodes. The Epileptic Seizure Recognition dataset is where the procedure starts, which undergoes preprocessing involving outlier detection and removal to enhance data quality. Following this, Min-Max normalization is applied to scale the EEG features uniformly within a range of 0 to 1. Features are extracted directly from the normalised time-series EEG data points. To facilitate the model evaluation process, the dataset is then separated into training and testing subsets. A CNN architecture is employed for categorization by leveraging its ability to recognize temporal patterns in EEG data. The model's performance is evaluated using standard measures, such as F1-score, recall, accuracy, and precision. The outcomes are then examined to confirm that the suggested approach works. The suggested methodology's flowchart is shown in Figure 1.

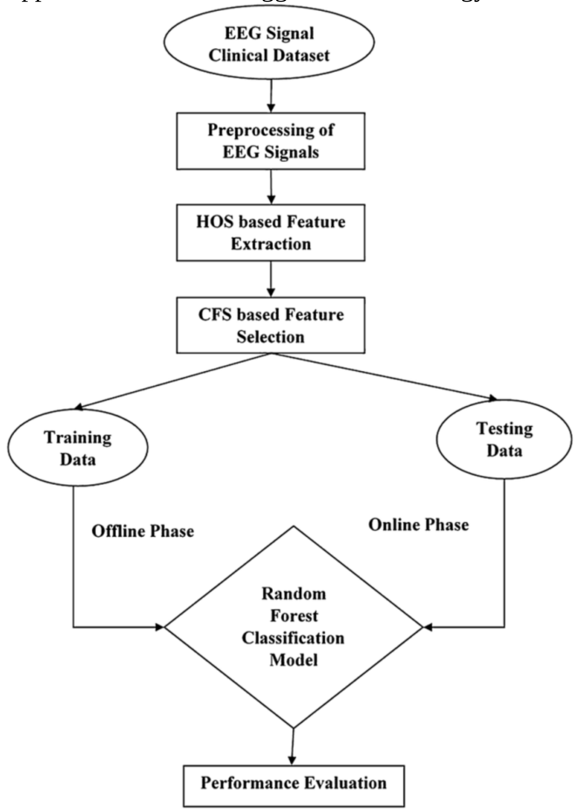

Fig 1: Data Flowchart Diagram for Epileptic Seizure Disease

The flowchart's general steps for epileptic seizure disease are shown below:

3.1. Data Collection

The UCI Epileptic Seizure Recognition dataset was developed. This work uses data from the original Bonn EEG dataset. It includes 500 EEG recordings with 4,097 data points per recording. These recordings were split into 23 non-overlapping segments, each with 178 data points, to yield 11,500 one-second samples. Five classes are created from the dataset: Class 1 denotes the presence of epileptic seizures, whereas Classes 2–5 reflect different non-seizure states. For binary classification purposes, Class 1 was labeled as 1 (epileptic), while Classes 2–5 were grouped and labeled as 0 (non-epileptic), facilitating the development of seizure detection models.

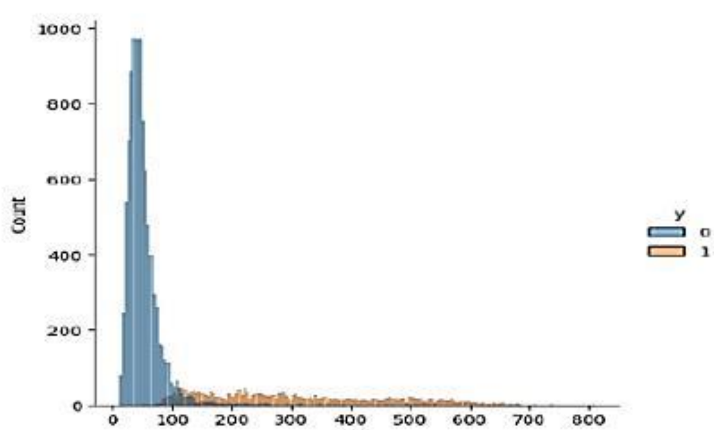

Fig 2: Histogram Representation of the Epileptic and Non-Epileptic Seizures in the Dataset

Histogram showing the distribution of EEG signal values for class labels 0 and 1, shown in Figure 2. Class 0 signals are densely concentrated at lower amplitudes (around 50–100), while class 1 signals are more spread out, indicating higher variability. The overall distribution is right-skewed.

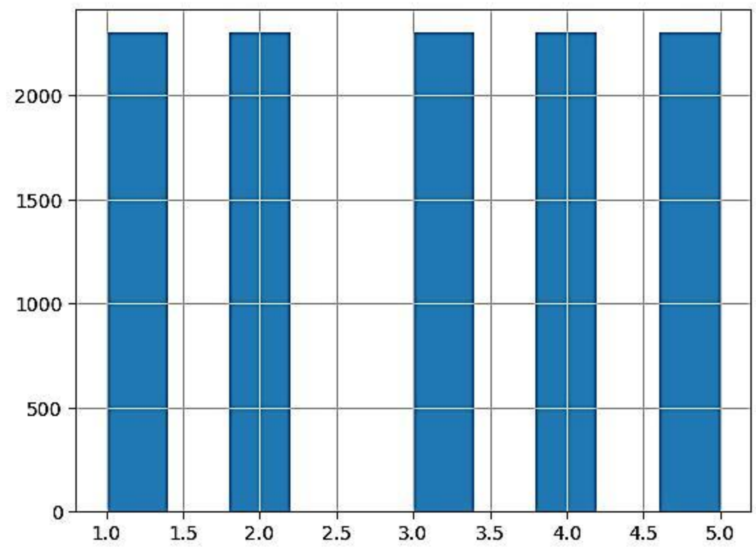

Fig 3: Distribution of EEG Signal Classes (y)

The distribution of EEG signal classes (y), showing a nearly uniform distribution across all five classes shown in Figure 3. Each class has roughly the same number of instances (around 2200), indicating balanced data. This uniformity supports fair training of ML models without class bias.

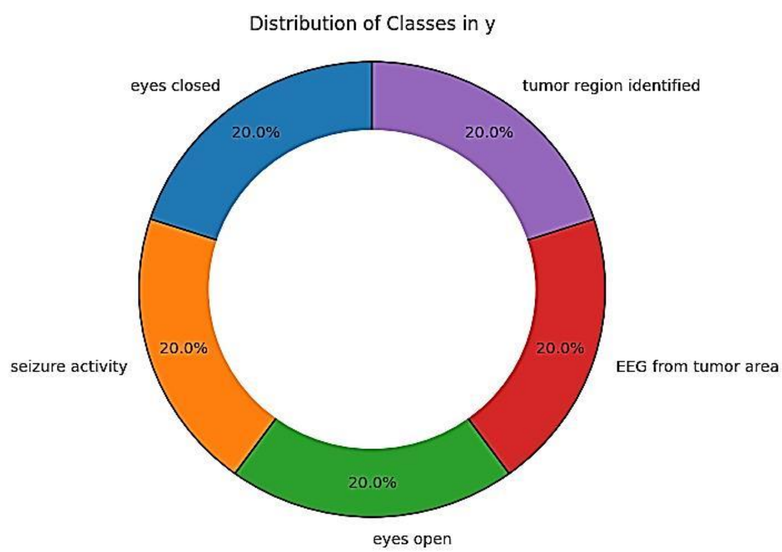

Fig 4: Distribution of Classes in y

Figure 4 shows a donut chart of an equal distribution of EEG signal classes, each representing 20% of the dataset. The classes include eyes closed, eyes open, seizure activity, EEG from the tumor area, and the tumor region identified. This balanced distribution ensures unbiased model training and reliable classification across all EEG conditions.

3.2. Data Preprocessing

The initial stage of preparing EEG signal data for ML is identified as preprocessing. The study required the systematic preprocessing of raw EEG samples to increase data quality, along with the ability to work with learning algorithms. The first step involved the detection and then the removal of outlier measurements that indicated extreme or unnecessary data points. The algorithm applied Min-Max normalization for feature value scaling in order to standardize all data points within a specific range. The following steps of preprocessing are given below:

- **Outlier Detection and Removal:** Finding and removing unusual data points is known as outlier identification and removal, and it guarantees clean, reliable input for model training.

3.3. Data Normalization with Min–Max Scaling

The preprocessing technique known as normalization enables data feature value transformation that produces specific value ranges to achieve better model results and training stability. Through normalization, the larger quantity values remain in check alongside smaller values to achieve an equal input influence from all features. The study utilized Min-Max scaling on EEG signal features to adapt all value ranges from 0 to 1.

The normalization process follows Equation (1) as its definition:

$$x_{normalized} = \frac{(x - x_{min})}{(x_{max} - x_{min})}$$

where X is the data point's initial value and $x_{normalized}$ is its normalised value. x_{min} is the minimum value of the variable, while x_{max} is the maximum value of the variable of the data set.

3.4. Feature Extraction

In order to fulfil user intent, feature extraction is the process of extracting task-specific information from the signal. Each data instance comprises 178 raw EEG signal values, representing brain electrical activity recorded over a 1-second interval. These time-series values were directly utilized as input features without additional manual feature engineering. Prior to model training, the signals were preprocessed and normalized to ensure consistency across samples, facilitating effective learning of temporal dynamics by both ML and DL models.

3.5. Data Splitting

The process of dividing a dataset into discrete subsets for model training and assessment is known as data splitting. To ensure accurate model learning and unbiased evaluation, the dataset utilized in their work 80% training and 20% validation sets in this work.

3.6. Classification with Convolutional Neural Network (CNN) Model

CNN, a DL subtype, has garnered significant interest recently and is employed in image-related applications. recognition, which includes computed tomography analysis, histopathology, fundus, magnetic resonance, and x-ray medical pictures. However, the application of CNN with physiological signals has received very little attention. Therefore, CNN was applied to ECG data in the authors' earlier publications in order to examine how well the CNN algorithm performed signal analysis [16]. Recently, CNN was utilized to automatically identify myocardial infraction and coronary artery disease based on ECG data. The CNN model uses the weights and biases of the network structure's preceding layers to determine its final output, just like the ANN does. As a result, each layer's weights and biases are adjusted using Equations (2) and (3), respectively.

$$\vartriangle w_l(t+1) = -\frac{x\lambda}{r} w_l - \frac{x}{n}\frac{\partial C}{\partial w_l} + m \vartriangle w_l(t)$$

$$\vartriangle w_l(t+1) = -\frac{x}{n}\frac{\partial C}{\partial B_l} + m \vartriangle B_l(t)$$

The individual letters represent weight, bias, regularization parameter, layer number, learning rate, total training sample count, momentum, update step, and cost function, in that order. Figure 5 below depicts the CNN model architecture proposed in this study.

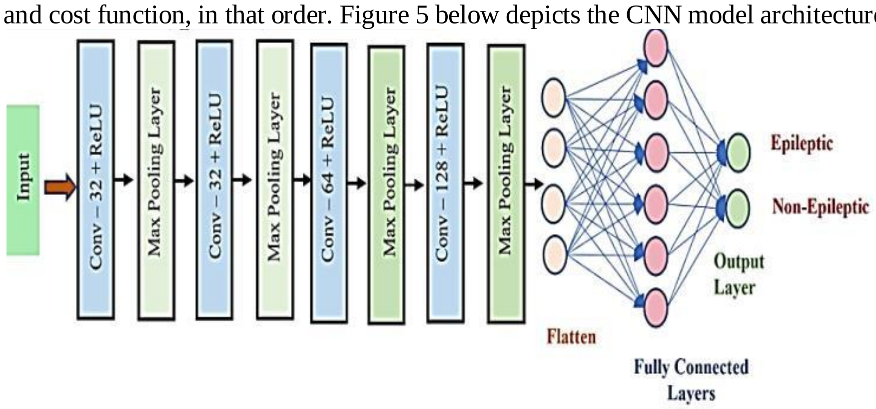

Fig 5: CNN Architecture of the Proposed Method

Three distinct layers make up the CNN architecture three layers: convolutional, pooling, and fully linked.

3.6.1. Convolutional Layer:

The EEG signal is traversed by kernels, also known as filters. Stride determines how much the matrix that will convolve with the EEG signal is called a kernel, and the input signal is convoluted by the filter. As Equation (4), it appears:

$$y_k = \sum_{n=0}^{N-1} x_n h_{k-n}$$

3.6.2. Pooling Layer:

This layer is sometimes referred to as the down-sampling layer. The convolutional layer's output neurons are shrunk in size using the pooling technique to avoid overfitting and save processing power.

3.6.3. Fully Connected Layer:

This layer is completely linked to all of the activations in the layer above it.

3.7. Performance Matrix

Several common assessment indicators were used to gauge how well the seizure prediction models performed. A thorough understanding of these measures provide ability of the model to distinguish between EEG data from epileptic and non-epileptic subjects. By comparing the actual and anticipated labels, a confusion matrix was utilized to assess the categorization results. The results are divided into four main groups: TP, TN, FP, and FN. To make it easier to comprehend the model's efficacy, these categories serve as the foundation for computing performance indicators recall, F1-score, accuracy, and precision. These are briefly explained below.

The fundamental parameters are:

- **True Negative (TN):** The quantity of executables with incorrect diagnoses of epilepsy and non-epilepsy.
- **True Positive (TP):** The quantity of executables with mild epilepsy and properly diagnosed.
- **False Negative (FN):** The quantity of executables with epilepsy that are classified as non-epilepsy.
- **False Positive (FP):** The quantity of executables that are considered to be epileptic but are actually innocuous.

3.7.1. Accuracy

Accuracy is by far the most used performance statistic. The computation and identification process are easy and convenient, as shown in Equation (5).

$$\text{Accuracy} = \frac{\text{TN} + \text{TP}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$

3.7.2. Precision

The precision shows how accurate the classification is. Both high precision and poor accuracy lead to fewer false positives and lower accuracy. It is calculated using the Equation (6):

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

3.7.3. Recall

Recall shows the proportion of actual positive cases that the model accurately forecasted. When there is a chance of FN, it is beneficial, it is given blow Equation (7).

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

3.7.4. F1-Score

F1-Measure combines accuracy and sensitivity. This is the weighted harmonic approach for sensitivity, accuracy, and precision. It has been demonstrated that the F1 measurement is just as accurate as the F1 rating is derived from the following Equation (8):

$$\text{F1} = \frac{2 * (\text{precision} * \text{recall})}{\text{precision} + \text{recall}}$$

3.7.5. ROC

The connection between the percentage of TP and FP classifications that arise from each potential decision threshold value in a two-class classification problem is shown by an ROC curve.

These performance matrices are utilized for comparative analysis and to evaluate the model performance for the UCI Epileptic Seizure Recognition dataset.

4. Result Analysis And Discussion

The experimental analysis was performed on a high-performance computing system to ensure efficient handling of the EEG dataset and precise evaluation of model performance. The machine, running Windows 11 Pro, has an Intel Core i9-13900K CPU (3.0 GHz), 64 GB of DDR5 RAM and a 24 GB VRAM-equipped NVIDIA RTX 4090 GPU. According to Table II's assessment results, the suggested CNN-based method for real-time epileptic seizure prediction is robust and successful, which supports its possible incorporation into intelligent healthcare applications.

Table 2: Performance matrix for Convolutional Neural Networks (CNN) model

Matrix	CNN Model (%)
Accuracy	99
Precision	99
Recall	99
F1-Score	99

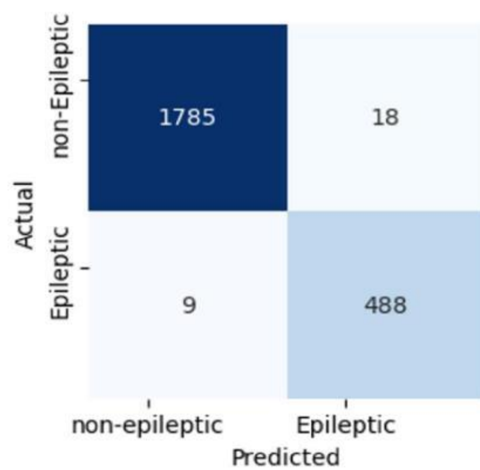

Fig 6: Confusion Matrix of CNN Model

Figure 6 shows the CNN model's confusion matrix. With 18 FP and 9 FN, it accurately diagnoses 488 instances of epilepsy and 1,785 non-epileptic cases. When separating epileptic from non-epileptic cases, the model performs exceptionally well and with high accuracy.

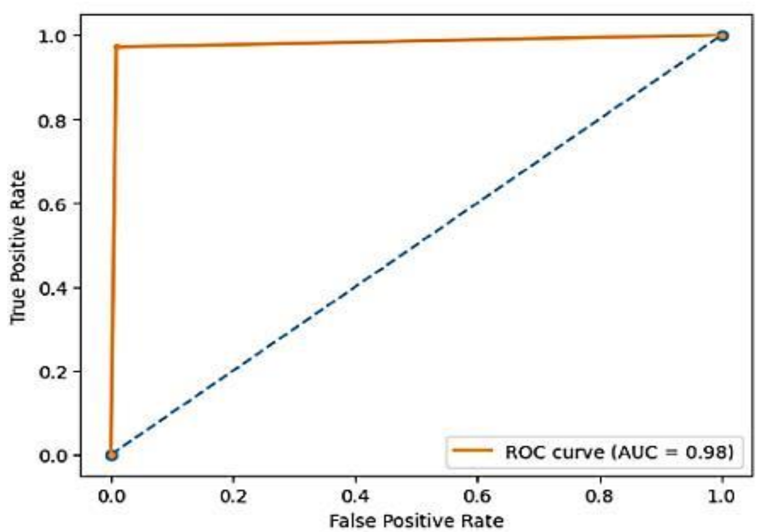

Fig 7: ROC-AUC Curve of CNN Model

Figure 7 displays the ROC-AUC curve for the CNN model. Strong classification capacity is indicated by the curve's high true positive rate and low FPR. With an AUC of 0.98, it is clear that people with epilepsy may be distinguished from those without.

	precision	recall	f1-score	support
0	0.99	0.99	0.99	1803
1	0.96	0.98	0.97	497
accuracy			0.99	2300
macro avg	0.98	0.99	0.98	2300
weighted avg	0.99	0.99	0.99	2300

Fig 8: Classification Report of CNN Model

Figure 8, the CNN model's categorization report. Recall, F1-score, and class 0 precision are all 0.99 with 1803 samples. For class 1, these metrics are 0.96, 0.98, and 0.97 with 497 samples. The weighted and macro F1-score averages were 0.98 and 0.99 for accuracy, recall, and F1-score and 0.99/0.99, respectively, for a total of 2300 samples, yielding an overall accuracy of 0.99.

4.1. Comparative Analysis

In this section, the baseline models and the suggested CNN model are compared. FCNN [17], RF [18], and SVC [19] applied to predicting epileptic seizures using EEG data. Table III summarizes the classification accuracy of different models, demonstrating their exceptional capacity to detect patterns in EEG data over time and differentiate between seizure and non-seizure episodes.

Table 3: Comparative Analysis Between Base And Proposed Model Performance On Epileptic Seizures Disease Detection

Matrix	FCNN	RF	SVC	CNN
Accuracy (%)	97	96	97.1	99

The dataset analysis for seizure detection presented in Table III demonstrates which model shows the highest accuracy among various baseline models. The suggested CNN model outperformed all baseline models on the dataset, achieving 99% accuracy. In contrast, the baseline models FCNN, RF, and SVC achieved accuracies of 97%, 96%, and 97.1%, in turn. The suggested CNN model performs exceptionally well in detecting seizure events from EEG data, according to research findings.

The suggested approach offers several benefits for epileptic seizure warnings derived from the analysis of EEG signal data. The implementation of CNN leads to a high accuracy rate of 99%, surpassing traditional ML approaches for seizure identification. The automatic extraction of features eliminates manual engineering work, which reduces preprocessing complexity while improving model operational speed. The performance stability of the system improves while its precision remains high because of data normalization with the integration of outlier removal and noise filtering processes. The CNN model performs precise and dependable predictions because it successfully detects temporal relationships in EEG signal data. The model's capability enables real-time seizure detection to generalize while maintaining low overfitting rates, which brings enhanced patient healthcare solutions to clinical settings.

5. Conclusion And Future Scope

Hospital systems implementing modern healthcare require predictions about seizures because they advance safety measures and improve treatment response. ML-based approaches implementing CNN represent robust systems for identifying early signs of epileptic seizures. The CNN model operates with performance metrics for training-validation that yield 99% accuracy for identifying epileptic and non-epileptic signals. The analysis demonstrates that CNN produces better results than RF and SVC when detecting complex temporal patterns in EEG signals. The model exhibits high performance but has shown minor errors when detecting unusual seizure occurrences. Future research will concentrate on enhancing the model's generalization, incorporating multimodal data, and enhancing real-time monitoring capabilities for broader clinical applications.

References

[1] V. Kolluri, "Machine Learning in Managing Healthcare Supply Chains: How Machine Learning," *J. Emerg. Technol. Innov. Res.*, vol. 3, no. 6, 2016.

[2] M. A. Sayeed, S. P. Mohanty, E. Kougianos, and H. P. Zaveri, "eSeiz: An Edge-Device for Accurate Seizure Detection for Smart Healthcare," *IEEE Trans. Consum. Electron.*, vol. 65, no. 3, pp. 379–387, 2019, doi: 10.1109/TCE.2019.2920068.
[3] R. B. Pachori and V. Bajaj, "Analysis of normal and epileptic seizure EEG signals using empirical mode decomposition," *Comput. Methods Programs Biomed.*, vol. 104, no. 3, pp. 373–381, 2011, doi: https://doi.org/10.1016/j.cmpb.2011.03.009.
[4] K. Tsiouris, V. C. Pezoulas, M. Zervakis, S. Konitsiotis, D. D. Koutsouris, and D. I. Fotiadis, "A Long Short-Term Memory deep learning network for the prediction of epileptic seizures using EEG signals," *Comput. Biol. Med.*, 2018, doi: 10.1016/j.compbiomed.2018.05.019.
[5] V. Kolluri, "An Innovative Study Exploring Revolutionizing Healthcare with AI: Personalized Medicine: Predictive Diagnostic Techniques and Individualized Treatment," *J. Emerg. Technol. Innov. Res.*, vol. 3, no. 11, 2016.
[6] A. K. Jaiswal and H. Banka, "Epileptic seizure detection in EEG signal using machine learning techniques," *Australas. Phys. Eng. Sci. Med.*, vol. 41, no. 1, pp. 81–94, 2018, doi: 10.1007/s13246-017-0610-y.
[7] A. Pumsirirat and L. Yan, "Credit Card Fraud Detection using Deep Learning based on Auto-Encoder and Restricted Boltzmann Machine," *Int. J. Adv. Comput. Sci. Appl.*, vol. 9, no. 1, 2018, doi: 10.14569/IJACSA.2018.090103.
[8] V. Kolluri, "A Pioneering Approach To Forensic Insights: Utilization AI for Cybersecurity Incident Investigations," *Int. J. Res. Anal. Rev.*, vol. 3, no. 3, 2016.
[9] N. Ahammad, T. Fathima, and P. Joseph, "Detection of Epileptic Seizure Event and Onset Using EEG," *Biomed Res. Int.*, vol. 2014, pp. 1–7, 2014, doi: 10.1155/2014/450573.
[10] G. Xun, X. Jia, and A. Zhang, "Detecting epileptic seizures with electroencephalogram via a context-learning model," *BMC Med. Inform. Decis. Mak.*, vol. 16, no. S2, p. 70, Jul. 2016, doi: 10.1186/s12911-016-0310-7.
[11] S. A. Grabat, A. S. Ashour, M. M. A. Elnaby, and F. E. A. El-Samie, "S-Transform-Based Electroencephalography Seizure Detection and Prediction," in *2019 7th International Japan-Africa Conference on Electronics, Communications, and Computations, (JAC-ECC)*, 2019, pp. 111–115. doi: 10.1109/JAC-ECC48896.2019.9051320.
[12] L. Billeci, A. Tonacci, M. Varanini, P. Detti, G. Z. M. de Lara, and G. Vatti, "Epileptic seizures prediction based on the combination of EEG and ECG for the application in a wearable device," in *2019 IEEE 23rd International Symposium on Consumer Technologies (ISCT)*, 2019, pp. 28–33. doi: 10.1109/ISCE.2019.8900998.
[13] A. A. Gaho, M. A. Jatoi, S. H. A. Musavi, and M. Shafiq, "Brain Mapping of Cortical Epileptogenic Zones and Their EEG Source Localization," in *2019 2nd International Conference on Computing, Mathematics and Engineering Technologies (iCoMET)*, IEEE, Jan. 2019, pp. 1–6. doi: 10.1109/ICOMET.2019.8673488.
[14] V. Rajendran and S. Kumar, "Performance Analysis of Epileptic Seizure Detection System Using Neural Network Approach," in *2019 International Conference on Computational Intelligence in Data Science (ICCIDS)*, IEEE, Feb. 2019, pp. 1–5. doi: 10.1109/ICCIDS.2019.8862158.
[15] U. R. Acharya, S. L. Oh, Y. Hagiwara, J. H. Tan, and H. Adeli, "Deep convolutional neural network for the automated detection and diagnosis of seizure using EEG signals," *Comput. Biol. Med.*, vol. 100, pp. 270–278, Sep. 2018, doi: 10.1016/j.compbiomed.2017.09.017.
[16] M. Zhou *et al.*, "Epileptic Seizure Detection Based on EEG Signals and CNN," *Front. Neuroinform.*, vol. 12, Dec. 2018, doi: 10.3389/fninf.2018.00095.
[17] G. A. Maggiotti, "EEG-Based Brain Disorders Diagnosis through Deep Neural Networks," *KDD Conf.*, 2019.
[18] A. H. Osman and A. A. Alzahrani, "New Approach for Automated Epileptic Disease Diagnosis Using an Integrated Self-Organization Map and Radial Basis Function Neural Network Algorithm," *IEEE Access*, vol. 7, pp. 4741–4747, 2019, doi: 10.1109/ACCESS.2018.2886608.
[19] A. Bhowmick, T. Abdou, and A. Bener, "Predictive Analytics in Healthcare Epileptic Seizure Recognition," in *CASCON '18: Proceedings of the 28th Annual International Conference on Computer Science and Software Engineering*, 2018, pp. 323–330.
[20] Kalla, D., & Samiuddin, V. (2020). Chatbot for medical treatment using NLTK Lib. *IOSR J. Comput. Eng*, *22*, 12.
[21] Kuraku, S., & Kalla, D. (2020). Emotet malware a banking credentials stealer. *Iosr J. Comput. Eng*, *22*, 31-41.