Deep Learning Approaches for Seizure Detection and Prediction Using EEG Signals: A Comprehensive Review and Proposed CNN Framework

C V Keerthi Latha [1*], M Kezia Joseph [1*]

Abstract

Background: Epilepsy, a neurological disorder characterized by recurring seizures, affects millions globally and presents significant medical challenges. The unpredictable nature of seizures necessitates advancements in their detection and prediction. This study introduces a novel approach for classifying and identifying epileptic seizures through the analysis of EEG (Electroencephalogram) data using Convolutional Neural Networks (CNNs). Methods: We employed CNNs to analyze EEG signals, identifying recognizable patterns in temporal and spatial information, thereby enhancing the accuracy of seizure detection. Our proposed CNN framework incorporates Batch Normalization (BN), dropout layers, and dense layers specifically designed for EEG signal analysis. This novel approach improves the model's capacity for extracting and detecting complex spatial-temporal patterns in EEG data, supporting effective seizure prediction and detection. The implementation of this Deep Learning (DL) methodology allows for continuous epilepsy monitoring, significantly advancing seizure prediction accuracy. Results: Extensive validation of the framework on a publicly accessible dataset demonstrated its superiority over traditional Machine Learning (ML) techniques, achieving an accuracy rate of 98.52%. This CNN-based approach successfully distinguished between abnormal brain activity due to seizures and normal brain function. Conclusion: The developed DL framework represents a significant advancement in epileptic seizure detection and prediction. By leveraging CNNs for EEG signal analysis, this study provides a robust and accurate tool for continuous epilepsy monitoring, offering improved patient outcomes and contributing to the broader field of neurological disorder management.

Keywords: Epilepsy Seizure Detection (ESD), Convolutional Neural Networks (CNNs), EEG Signal Analysis, (DL) Deep Learning, (SD)Seizure Detection, Epilepsy Detection, SP (Seizure Prediction).

Significance | Early seizure prediction via EEG signals might enable timely intervention, potentially improving patient outcomes and reducing clinical risks.

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1. Introduction

Epilepsy is a chronic neurological disorder, characterized by recurring seizures, and is considered to be one of the major risks in the clinical field (Milligan, 2021). Seizures are becoming a widespread clinical issue as they affect many people, occurring with various signs and symptoms. They affect people of all ages, irrespective of socioeconomic backgrounds (Sen et al., 2020). The seizures are unpredictable and often detectable only with signs and symptoms, which makes them a significant risk in this clinical field in terms of saving patients' lives. Consequently, several researchers have employed EEG signals for seizure prediction (SP) as well as seizure detection (SD) (Aslam et al., 2022; Roy et al., 2019). EEG data is a crucial tool for effective SD and SP because it records the

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electrical impulses of the brain (Benbadis et al., 2020; Kuhlmann et al., 2018). Through this approach, identifying EEG signals might support effective seizure detection and prediction. The significance of utilizing EEG signals cannot be overstated, as they are employed for both SD and SP. Early identification of seizures may help reduce the effects and assist in detection (Wanleenuwat et al., 2020; Tzallas et al., 2012). Through rapid detection, clinical experts may lessen the severity of seizures. Proper medical care for persons with seizures can improve their features, thereby minimizing risk (Kudlacek et al., 2021).Analyzing EEG data presents a risk factor in classifying SD schemes (Chaddad et al., 2023; Acharya et al., 2018). Among various individuals, the complex structure of EEG data varies across time. Differentiating brain function with seizures is a major challenge due to noise in EEG recordings. Minor but significant features, including the early detection of seizures, are often undetected by conventional approaches, leading to false alarms or missing data. Reliable and robust techniques that effectively process the complex nature of EEG data and pre-seizure detection signals are crucial for dealing with these risks.There is enormous potential for modernizing SD and SP by utilizing deep learning (DL) frameworks for EEG signal analysis. Particularly, the abilities of Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs) in processing and interpreting complex EEG data are notable (Gao et al., 2021; Zhou et al., 2020). The ability of CNNs to extract spatial features from complex multidimensional data permits the detection of intricate patterns in EEG signals. RNNs are particularly beneficial for identifying temporal connections. However, detecting patterns in the time-series data structure of EEG data is important. The integration of multiple models offers a comprehensive framework, significantly improving the accuracy and precision of identification and seizure prediction (Singh & Malhotra, 2021; Usman et al., 2021; Hussein et al., 2019).

2. **Literature Survey**

For the purpose of monitoring one's health, an innovative approach that aims for detecting SP was suggested by Kuldeep Singh et al. (2022). Through deep learning by applying spectrum analysis for EEG data, the approach has been accomplished. By implementing such filters, signals are segmented into smaller time chunks, also transferring those signals into the spectroscopic domain are some of the procedures that constitute this approach (Li et al., 2021). Further, the signals are split into multiple spectral bands, with alpha, beta, delta, theta, and gamma subsets for conducting spectral analysis (Zhang et al., 2022). Statistical measurements are created from each spectral band, like average spectral amplitude, for the further classification of different seizure conditions. Thus, these features are detected and employed as inputs via the suggested CNN and Long Short-Term Memory (LSTM) networks.A novel ensemble learning methodology utilizing deep learning techniques was established by Syed Muhammad Usman et al. (2021) for ESD. It pre-processes EEG signals through empirical mode decomposition and noise reduction through bandpass filtering (Qin et al., 2020). Generative adversarial networks can be used to generate fake preictal segments as a solution to the issue of class imbalance (Huang et al., 2020). The preprocessed EEG data is recommended to be fed into a customized three-layer CNN to automatically extract key properties (Xu et al., 2021). To generate a complete set of features, these automated features are combined with features that were created by humans. Utilizing Model Agnostic Meta Learning, the feature set serves as the foundation for training an ensemble classifier that incorporates the outputs of LSTM, CNN, and Support Vector Machines (SVM).EEG data can be effectively classified into three categories using methods outlined by Fatma E. Ibrahim et al. (2022): normal, pre-ictal, and ictal activities (Kim et al., 2022). It offers three models designed especially for this classification task: two models adapted to specific patients and one model intended for broader classification. In order to detect SP and SD, the procedure of classification involves distinguishing between pre-ictal and usual behaviors as well as between ictal and usual behaviors (Chen et al., 2020). To detect all activity in EEG signals, an extended three-class classification system is employed. Four residual learning blocks make up the thirteen-layer CNN used in the first model. EEG data segment spectrograms are used by this framework to operate. By comparison, the second system utilizes a CNN with three layers that function by analyzing spectrograms. On the other hand, the limitations observed in the spectrograms of the preceding systems are addressed by the third approach through the application of PSR (Phase Space Reconstruction). This technique uses a five-layer CNN with Projection onto Convex Sets Reconstruction (PSR) to preserve the important patterns of various signal activities while instantly converting signals from the temporal domain. The third approach, which was evaluated on every patient in the CHB-MIT dataset, takes into account all signal activity. Because this model can manage a larger spectrum of signal activity with greater effectiveness than the original models, it performs better than the SOTA (State-Of-The-Art) models currently in practice.In order to examine iEEG (intracranial electroencephalogram) datasets and SP occurrences separately, Omaima Ouichka et al. (2022) presented five DL models. The algorithms include the CNN framework, two CNNs combined (2-CNN), three CNNs combined (3-CNN), four CNNs combined (4-CNN), and the usage of ResNet50 for TL (Transfer Learning). An overview of the research outcomes indicated that the suggested approaches, depending on the 3-CNN and 4-CNN architectures, produced the most effective outcomes (Zhou et al., 2022).A novel technique for Epileptic EEG Signal Classification (EESC) was introduced by Yunyuan Gao et al. (2020). It transforms EES into PSDEDs (Power Spectrum Density Energy Diagrams), and features are detected from the PSDED through the utilization of Deep CNNs (DCNNs) and TL. The classification of four different epileptic conditions, including the interictal period up to 30 minutes preictal step, 10-minute preictal period, and seizure, was considered the main goal. When compared to other epileptic classification techniques, the suggested technique provides better accuracy (Wang et al., 2021).A simple technique for SP was suggested by Ranjan Jana and Imon Mukherjee (2021), utilizing CNN with fewer channels. For automatically extracting features from epilepsy-affected persons and the different condition classifications, CNNs are employed (Sun et al., 2020). Thus, CNN is capable of attaining a mean accuracy in classification.A novel neurocare approach that integrates cloud and fog computing for unprocessed EEG data estimation and DP techniques was implemented for SD by Kuldeep Singh and Jyoteesh Malhotra (2022). It requires no specific data from patients, and prompt diagnosis and computational efficiency on fog layer devices were accomplished by single-channel EEG inputs. This technique employs maximum variance-based channel selection for selecting one channel from the original scalp EEG data. Those signals are then filtered and segmented into smaller temporal bits. These are then sent into suggested techniques like CNN, RNN, and stacked AE (AutoEncoder) DL classifiers for EEG pattern analysis (Zheng et al., 2021). The study, which makes use of simulation information, demonstrates clearly the extent to which the suggested CNN-based temporal analysis approach performs better than alternative methods.Deep learning is a unique technique that Anand Shankar et al. (2021) demonstrated for identifying epileptic seizures. The method uses EEG data that captures various brain rhythms to create 2D Recurrence Plot (RP) images. Unlike traditional methods that depend on human feature engineering, DL automatically extracts features from input photographs and has demonstrated impressive results across a variety of classification tasks (Liu et al., 2020). Nevertheless, the issue of producing superior 2D pictures from 1D EEG data for deep learning (DL) applications has not been sufficiently resolved. This is a critical matter since the performance of DL greatly relies on the quality of the input. Furthermore, the investigation into the identification of suitable brain rhythms for the study of seizures is still lacking in thorough exploration. Therefore, this work aims to create two-dimensional input pictures using the RP approach from EEG data that accurately represent distinct brain rhythms while maintaining the nonlinear properties of the EEG. The research used a well-recognized DL model, namely the convolutional neural network (CNN). Experimental validation entails using two well-known EEG datasets, namely the Bonn University and CHB-MIT (PhysioNet) databases, for the purpose of analyzing seizures. The study thoroughly examines and analyzes three crucial parameters—recurrence threshold, time delay, and embedding dimension—that are necessary for producing RP pictures.Ahmed Abdelhameed et al. (2021) proposed a novel deep-learning approach that aims to identify seizures in pediatric patients by categorizing minimally processed raw multichannel EEG signal recordings. The unique method utilizes a 2D deep convolution autoencoder (2D-DCAE) that has automated feature learning capability, along with a neural network-based classifier. The unified system is trained using supervised learning to obtain the highest possible accuracy in classifying brain signals as either ictal or interictal. Two models were created and evaluated utilizing three different EEG data segment lengths and a 10-fold cross-validation (CV) approach in order to investigate the proposed method. A supervised deep convolutional autoencoder (SDCAE) approach that makes use of Bi-LSTM (Bidirectional-LSTM) classifier was determined to be the most effective approach after five metrics were assessed. Four-second EEG segments are used in this framework (Chen et al., 2021).A hybrid framework was created by Muhammet Varlı and Hakan Yılmaz (2023) that integrates the time-frequency-image transformations of time-varying EEG signals with the temporal sequence of EEG data. The data was transformed into images utilizing the CWT (Continuous Wavelet Transform) and STFT (Short-Time Fourier Transform) approaches (Tan et al., 2022). Subsequently, the utilized images provided through the CWT and STFT approaches led to the creation of two separate models.

3. **Proposed Method**

According to this study, the suggested CNNs framework for the ESD. A robust automatic technique for the effective SP and SD are considered to be the main objective. For image classification and image recognition, DL NN's common type CNN is employed. It employs the ability for extracting complex spatial and temporal patterns for classifying the seizures and SD effectively. It offers great potential for the prediction and it leads to the appropriate medical care in diagnosing epilepsy.

The EEG's complicated patterns and spatial correlations are analyzed by CNNs as it automatically extracting hierarchical features from raw data effectively. It is capable for differentiating seizure abnormalities from normal cerebral functions in EEG recordings. Through the implementation of spatial correlations among various sensor locations, evaluating multi-channel EEG data promptly done by CNN algorithms. By learning unique properties from different brain regions, the network is able for enhancing the SP and SD accuracy. Additionally, CNN models are improved for attaining superior effectiveness in differentiating various kinds of seizures, aiding patients for the prompt diagnosis and care.The suggested model for structure is depicted in Figure 1.

The proposed model for epileptic seizure recognition incorporates a flowchart that illustrates the sequential processing steps required to convert electroencephalogram (EEG) data, which consists of recordings of electrical brain activity, into a format that is appropriate for seizure detection using a Convolutional Neural Network (CNN).

Below is an elaboration of the steps shown in the flowchart (Figure 1) :

Input Layer: The input layer functions as the first access point to a NN and has a crucial function in the processing and management of the incoming data. Within the framework of ESD using EEG data, the first phase, similar to the input layer, involves the ingestion of unprocessed EEG data into the neural network. EEG data comprises electrical impulses that are captured from electrodes positioned on the scalp. The electrodes are capable of detecting the electrical activity generated by neurons in the brain. Unprocessed EEG readings show how electrical potential varies over time, offering information on the way the brain functions. The raw EEG data serves as the basic data for the NN's input layer, which is responsible for PS. Each electrode records the electrical potentials at specific scalp regions, producing a series of voltage values that vary with time. After that, the voltage values are entered into the network as the initial data input.

The electrodes record EEG data, which is frequently shown as a dataset with multiple channels, each of which corresponds to an electrode. This dataset's measurement order represents the temporal variations in brain function. In order to prepare these signals for later analysis by layers in the NN structure, the input layer uses many channels to arrange and analyze them. This input layer's primary goal is to streamline the preliminary processing and setup of raw EEG data so that the network may examine and learn from the spatial connections and time-based patterns found in the electrical signals generated by the brain. Epileptic seizure activity is subsequently detected and classified by employing subsequent layers, like convolutional and pooling layers, to extract unique features and patterns from the raw EEG data.

Dense: The next layer is a crucial preparation step specific to EEG data, related to the "Dense (Word Embedding)" level in text processing. Its goal is to get the data ready for the NN's of ESD. Word embeddings can be used to turn text into numerical vectors, but other transformation algorithms are required for EEG data. In this case, the temporal EEG data are converted into numerical representations using methods like DWT (Discrete Wavelet Transform) or various FE (Feature Extraction) strategies. In signal processing, WTs are frequently employed to separate data into discrete frequency components. Because WT can separate the complex temporal signals into distinct frequency bands, they are helpful for studying EEG data. This makes it possible to identify both broad low-frequency patterns in brain function and detailed high-frequency data. The translation process makes it easier to organize the information from the EEG into a numerical format that NNs can use. This makes it possible for the network to examine and learn from these altered images. FE approaches are employed for capturing EEG inputs are considered as an alternative, it may include extracting pertinent information, such as frequency content, spectrum power, statistical features, or time-frequency representations.

For preparing inputs for the NN's final layer analysis, the features are gathered and it serve as the numerical representations of the significant data in the EEG signals. Pre-processing layer is vital for the converting the EEG data's complex temporal patterns into predictable numerical representations. Also, it has the tendency for the identification of ESD patterns and effective extraction. The Convolutional layers are considered as the main structural component and active element also known as Dense 55, 56, 57, and 58.

Through the implementation of learning filters to the data, EEG signals are analyzed by those layers and helps in detecting such patterns in the impulses of the brain. Convolution layers are crucial for the identification as well as learning different aspects related to the seizures. By combining EEG data, it enables to differentiate such patterns from the normal ones. It aims for enhancing the ESC and SD accuracy for extracting and focussing those distinctive features. Since the model permits automatically differentiate such patterns in EEG singals. Thus convolutional layers are essential to SD NNs.

Batch Normalization (BN): For ESD, the BN in the CNN framework comprises the intermediate layers output normalization throughout the training. The consistency of stimulation level across EEG data batches are verified by this procedure. It supports in enhancing the gradient's smoothness, reducing internal variable shift and maintains the learning procedure. In future, it also supports in enhancing NN ability for detecting such complex from normal features in EEG signals.

The present architecture for the ESD contains deliberate augmentation of BN, BN 31, 32, 33, and 34 among convolutional layers. Through normalizing input data, these layers serve as a crucial part in enhancing the NN's process of learning. Batch Normalization layers standardize the output of the convolutional layers. Following every convolution operation, the data undergoes scaling and shifting to maintain stable distributions of the activations throughout the network's training phase. Normalization helps to stabilize and speed up the training process by reducing problems such as internal covariate shift. This enables quicker convergence and better gradient flow.

The Activation Layers, namely Leaky ReLU 55, 56, 57, 58, are deliberately placed between the convolutional layers in the intended architecture of the convolutional neural network for epileptic seizure identification. The Activation Layers play a crucial role in injecting non-linearities into the network by applying the Leaky ReLU (Rectified Linear Unit) activation function. Leaky ReLU, in contrast to classic ReLU, permits a tiny gradient for negative inputs, so averting the entire inactivity of neurons and resolving the issue of "dying ReLU". The little negative gradient of this slope guarantees that neurons consistently contribute to the network's learning process, hence boosting the network's ability to learn complex patterns within EEG data linked to epileptic seizure activity.

Activation layer: An activation layer in a neural network applies an activation function to the output of the preceding layer to induce non-linearities. It helps the network understand and solve complicated issues by learning complex data patterns and correlations.

Leaky ReLU: To overcome few drawbacks in the traditional ReLU (Rectified Linear Unit) activation function, NNs employ the Leaky ReLU. It deactivates or "kills" a neuron if produces continually negative outputs throughout training by limiting its negative values to 0. For negative inputs, Leaky ReLU offers a small gradient. It integrates a tiny bias (usually a minor positive number, like 0.01) so that neurons remained active regardless of the presence of negative values, instead of assigning a value of 0 to negative inputs. This slight inclination minimizes the risk of death of neurons and promotes smooth gradient progression. Also permitting constant learning thereby avoiding overload throughout training.

Leaky ReLU facilitates better gradient propagation throughout (Back Propagation) BP, thereby assisting to solve the disappearing gradient issue. By maintaining non-zero gradients for negative inputs, Leaky ReLU keeps neurons from going into a state of inaction and enables them to continue to engage in the procedure of learning. The diagnosis of epileptic seizures is made easier by the application of this activation function, which promotes the existence of a few activated neurons and improves DNNs' capacity to learn intricate patterns and representations in EEG data.

The framework is more robust and successful at identifying important patterns, which are necessary for accurately SD in EEG recordings, when these layers are included.

Dropout Layer: In order to lessen neuron interdependencies and promote the network's acquisition of stronger features throughout training, CNN Dropout Layers randomly deactivate a portion of neurons at each iteration. By reducing the framework's dependency on certain attributes, this regularization technique enhances the model's ability to identify and extrapolate data patterns. The current architecture, which uses NNs to ESD, relies heavily on Dropout Layers more precisely, the ones designated as "Dropout 45, 46, 47, 48" to minimize overfitting. Overfitting occurs if a technique takes excess information in the training set, particularly minor details and unique features, rather than learning common techniques and it can be employed with fresh, unproved information. This problem is addressed with a normalization approach termed dropout, which avoids an excessive dependence on specific neurons or features. Drop out layers randomly deactivate a fraction of neurons in each stage of training iterations (often indicated by a predetermined probability rates, such as 0.2 or 0.5). In an identical NN, facilitating ensemble learning with it, the distinctive randomly chosen sub-networks are performed at every stage of training. It reduces the neural functions and its connections with others. This prevents the neurons from adjusting to one another and compels the network to acquire robust and varied representations of the attributes detected in the EEG data. As an outcome, the network has the tendency to adapt the data shifts and delays so as to enhance the production of the undetected EEG samples with more accurate accuracy. It also supports in creating further data about patients. It may result in detecting ESD and thus improved algorithm executes effective through the untested data.

Concatenate Layer: The Concatenate Layer of NNs combines the outputs of many layers along a designated axis and occasionally adds qualities obtained through different methods. This is employed for ESD, that integrates information retrieved across multiple convolutional paths to understand EEG spatial correlations. This might improve the network's ability to identify complicated data structures.

Concatenate Layer, also called "Concatenate 7," plays a crucial role in combining generated data from different EEG channels or electrode placements in the specific example of NN developed to identify ESD with EEG data. To capture EEG signals, many electrodes are attached to the scalp, each of which recognizes a distinct impulse in the brain. By combining or merging the feature maps created from many convolutional pathways, it effectively integrates the data collected from numerous electrode sites or EEG channels. Because of the technique of fusion, the structure can provide an improved representation of the spatial connections among the electroencephalogram (EEG) signals. Through the integration of acquired characteristics from several channels, the network acquires a thorough understanding of the interplay and correlation across distinct areas of the brain undergoing seizures. Combined variables from different electrode locations permit the structure to identify more subtleties in the spatial patterns and correlations identified in the EEG data. This comprehensive perspective facilitates the SD-related patterns, as it improves the model's ability to recognize complex spatial arrangements and distinguish between different EEG patterns linked to ESD. Ultimately, the Concatenate Layer enhances the network's capacity to identify significant spatial information, which is necessary for precise SD.

The dense layers form an interpretive layer termed as "Dense 128" after the FE stages. To identify the complex patterns, this NN layers analyses the gathered features obtained from the previous layers. It permits for analysing the representations from the previous layers, also for such patterns linked with SD's and without SD's differentiation.

Prior to reaching the final output layer, the attributes that have been processed through the Dense Layer are further optimized through the BN, Activation, and Dropout Layers. BN guarantees consistent activations, activation layers (such ReLU or Leaky ReLU) introduce non-linear alterations to information, and dropout layers disable neurons at randomly for avoiding overfitting. The incorporation of these layer works to improve and optimize the acquired features, enabling reliability and persistence in the model's predictions. For extracting features from the EEG signals, those layers are built. As those features are properly decoded and augmented already when it reaches the output layer. This progressive manner will lead to the precise predictions with the presence or absence of ESD in EEG data. It further enhancing the SD technique more precise.

Output Layer: The final stage, known as the output layer, is responsible for producing predictions based on the EEG data that has been processed. The next layer, which is typically another Dense Layer, predicts whether the EEG data represents seizure activity or normal brain function by using the features that have been processed and interpreted from previous levels. In order to distinguish among patterns associated with epileptic seizures and those suggesting normal brain function, the Dense Output Layer uses learned patterns and representations to classify the EEG signals.

The early ESD prediction and diagnosis are considered to be the main objective of the study. The network predicts if there is ESD in the input data through learnt features and patterns. Thus proper immediate care is given to the patients, thereby identify ESD in EEG recordings for efficient medical treatment and care management by converting the learned representations into predictions.

Detecting patterns in EEG data may be employed for CNN model training thereby estimating ESD. Layers of convolution, pooling, normalization, and dense interpretation are implemented to raw EEG data. For such differentiation among normal and abnormal activities obtained by the collected data. This final layer allows for such variations. Also it classifies the processed EEG data as either SD or normal brain function.

For ESD, the CNN models advances the diagnosis and immediate medical care facilities. Through early SD, experts are able to reduce those risks also providing immediate care to the patients. Thus continuous monitoring and real-time seizure diagnosis may improve the quality of life of patients. Based on the SP and early diagnosis, that supports experts for detection and immediate therapy.

4. **Experimental Results**

The outcomes of the simulations that were conducted utilizing the recommended approach are examined in detail in this section. The open-source Kaggle platform was employed for obtaining the dataset for the purpose of the research. The dataset was processed with the suggested methods. Each of the 5 folders in the original dataset from the study has 100 files, each of which represents an issue or individual. Every file contains a 23.6-second recording of brain activity. Data points totaling 4097 are collected from the related time-series. The value of the EEG recording at a particular moment in time is represented by each data point. There are 500 people in all, and each of them has 4097 data points for 23.5 seconds. Every 4097 data points were split and scrambled into 23 chunks, each of which has 178 data points for a single second. The values of the EEG recordings at each distinct time are represented by the data points. We now have 23 x 500 = 11500 informational rows, with each row containing 178 data points for a single second (column), and the last column displaying the label y {1,2,3,4,5}.In column 179, the response variable is y, and the explanatory variables are X1, X2,..., X178. The category of the 178-dimensional input vector is included in y. To be more precise, y in {1, 2, 3, 4, 5}: 5-eyes open, which indicates that the patient's eyes were open throughout the recording of the brain's EEG data. 4-eyes closed, indicating that the patient's eyes were closed throughout the EEG signal recording. 3-The location of the tumor in the brain was determined, and the EEG activity from the healthy brain region was recorded. 1-Capturing information about seizures,2-The EEG from the region where the tumor was placed was recorded.

A thorough examination of the efficacy and precision of the suggested CNN algorithm for ESD can be found in the section that follows, intends to further explain and evaluate the outcomes attained by the application of the CNN structure to EEG data. It will contain comprehensive data on the algorithm's assessment measures, such as accuracy, sensitivity, and specificity. The results of the clinical study indicate that it has the ability to provide accurate and timely seizure activity detection. The information and analysis in this section are crucial for validating the suitability and effectiveness of the CNN model in supporting medical professionals with automated seizure recognition, hence advancing the diagnosis and treatment of epilepsy.

Important metrics utilized in SL (Supervised Learning) tasks like regression or classification are training loss and validation loss. The difference among the target values in the training dataset and the model's predictions is measured by the training loss. As training goes on, it evaluates the extent to which the model fits the training set. Reducing this loss indicates that the algorithm is getting better at making accurate predictions on the training dataset, thereby achieving the goal.

The difference among the model's predictions and the actual target values on a different validation dataset is known as validation loss. This dataset is not used during the training process; rather, it is set aside for evaluating the effectiveness of the model on fresh data. The

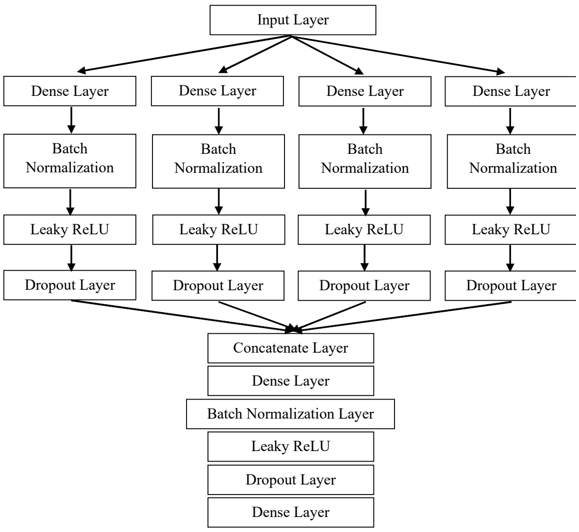

Figure 1. Proposed model architecture

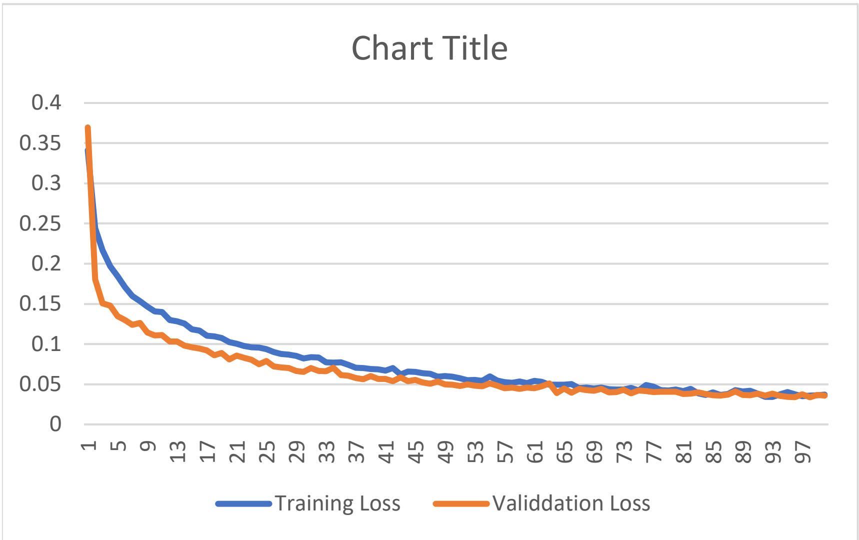

Figure 2. Training and Validation Loss

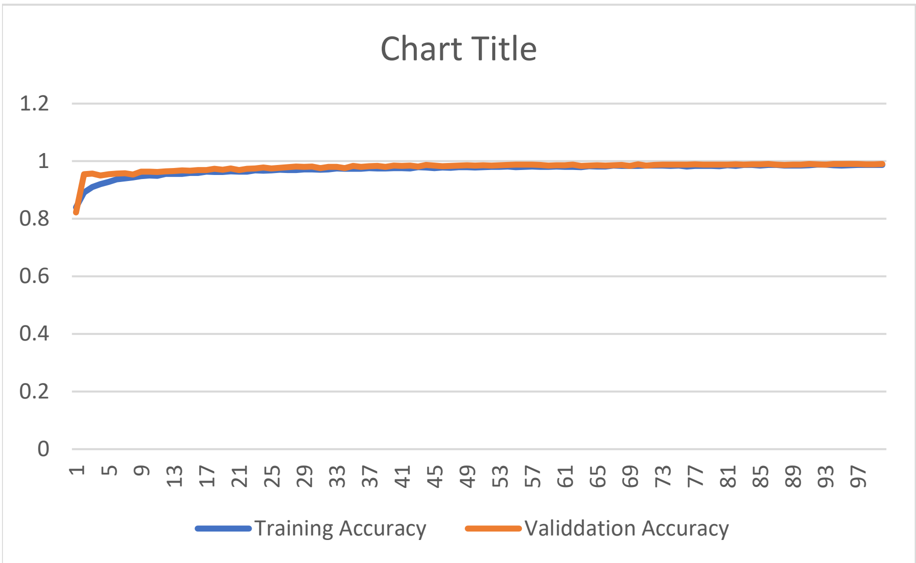

Figure 3. Training and Validation Loss

Table 1. Metrics Evaluated

Metric	**Value**
Accuracy	0.985217
Precision	0.985217
Recall	0.985217
F1 score	0.985217
Cohens kappa	0.970433

Table 2. Classification Report

	Precision	**Recall**	**F1-Score**
0	0.99	0.99	0.99
1	0.99	0.99	0.99

Figure 4. Confusion Matrix

Table 3. Comparative Analysis

Method	**Accuracy**
Logistic Regression	82.59
Principle Component Analysis	90.00
Naïve Bayes	95.78
KNN	93.96
Proposed Model	98.52

validation loss assesses the manner in which the model generalizes to fresh, untested data. As with training loss, the objective is to minimize validation loss in order to demonstrate that the algorithm can produce accurate predictions on fresh data.

Measures that support training and validation loss, respectively, are training accuracy and validation accuracy. The proportion of correctly classified samples in the training dataset is known as training accuracy. It displays the effectiveness of the model using the training set of data. The proportion of correctly detected instances in the validation dataset is known as validation accuracy, and it provides insight into how well the model performs when applied to fresh data. In order to make sure the algorithm can accurately predict on both sets and show that it can generalize well to new data, the objective is to maximize the training as well as validation accuracy.

The effectiveness of a classification model is evaluated using several metrics shown in Table 1. With an accuracy of 98.52%, the model's total prediction accuracy is quite high. The identical outcome, 98.52%, is obtained for both precision and recall, showing high levels of both. Whereas recall is the proportion of accurately anticipated positive instances among all real positive cases, precision quantifies the % of properly predicted positive cases among all predicted positive cases. The model's strong performance is corroborated by its F1 score of 98.52%, which accounts for the model's accuracy and recall. Additionally, the Cohen's kappa coefficient, a statistic that evaluates the agreement among predicted and actual classifications while accounting for the probability that agreement would occur by chance, indicates a very high similarity level of 97.04%.

A classification report that summarizes a binary classification model's performance metrics is shown in the table. For the two classes, F1-score, recall, and precision are given (0 and 1). By expressing the percentage of TP (True Positive) predictions among all positive predictions, precision quantifies the accuracy of positive predictions. Recall, which serves as a equivalent for sensitivity, expresses the percentage of TPs that are successfully detected and evaluates the model's capacity to detect each relevant cases. The F1-score, which represents the overall accuracy of the model, is the harmonic mean of precision and recall. It provides a balanced measure of both precision and recall. In this case, both classes show strong performance by the precision, recall, and F1-score values, which are around 0.99.

Figure 4's confusion matrix illustrates the effectiveness of a model for classification with two classes labelled as 0 and 1. The matrix's columns each indicate the quantity of samples that fall into a particular category. As per the values in this particular context, 2248 instances are accurately classified as TNs (True Negatives), 34 instances are incorrectly classified as class 1 when they are actually class 0 FP (False Positives), 34 instances are incorrectly classified as class 0 when they are actually class 1 FNs (False Negatives), and 2284 instances are correctly classified as TPs.

Table 3 displays a comparative analysis of various machine learning algorithms based on their respective levels of accuracy for a specific job or dataset. Among the methods evaluated are a suggested framework, NB (Naïve Bayes), KNN (K-Nearest Neighbors), PCA (Principle Component Analysis), and LR (Logistic Regression). The accuracy values illustrate the degree of effectiveness of each predictive modelling approach has the highest accuracy at 95.78%, with the Suggested framework coming in second at 98.52%. These results suggest that the Suggested Approach outperforms the other methods, which include more complex algorithms like KNN and tried-and-true methods like PCA and LR. This suggests that the Suggested Approach may determine the application in tasks or datasets of similar types.

5. Conclusion

CNN combination makes it possible to analyze complex EEG data automatically, which can help identify seizures promptly and improve the standard of life for those who have epilepsy. The development and application of an CNN algorithm for the analysis of EEG data represents a significant advancement in SD and epilepsy monitoring. The sophisticated design of the model, which includes dropout layers to prevent overfitting, BN for stability, and dense layers for FE, effectively detects and classifies epileptic seizures. With an accuracy of 98.52%, the model's exceptional performance shows how much better it is than both present algorithms and traditional techniques. This strategy's effectiveness has been further confirmed by comparison analysis, where the model outperformed well-known algorithms including LR, PCA, NB, and KNN.

Author contributions

C.V.K.L. formulated the study objectives, designed the methodology, and revised the manuscript. M.K.J. conducted the data collection, performed the data analysis, and contributed to the manuscript revision. Both authors reviewed and approved the final manuscript.

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