IRJSE International Research Journal of Science & Engineering
Int. Res. J. of Science & Engineering, Special Issue A14, June, 2024 SJIF Impact Factor 6.70
ISSN: 2322-0015 https://doi.org/10.5281/zenodo.12702232
RESEARCH ARTICLE OPEN ACCESS

Epilepsy Prediction with Electroencephalogram Using Machine Learning and Deep Learning

Dhanushkumar R[1], Harisudhan S[2] and Pugalenthi R[*]

[1,2]Student, Artificial Intelligence and Data Science, St.Joseph's College of Engineering, Chennai, India
Email: danushidk507@gmail.com[1] | speaktoharisudhan@gmail.com[2]
**Corresponding author:* Dr. Pugalenthi R, Head of Department, Artificial Intelligence and Data Science, St.Joseph's College of Engineering, Chennai, India
Email: rpugalsir@gmail.com

Manuscript Details

Available online on https://www.irjse.in
ISSN: 2322-0015

Editor: Dr. Arvind Chavhan

Cite this article as:
Dhanushkumar R, Harisudhan S and Pugalenthi R. Epilepsy Prediction with Electroencephalogram Using Machine Learning and Deep Learning , *Int. Res. Journal of Science & Engineering*, 2024, Special Issue A14: 141-158. https://doi.org/10.5281/zenodo.12702232

Article published in Special issue of National Conference on Machine Learning and Data Science (NCMLDS-2024)" organized by College of Computer Science and Information Technology (COCSIT) Ambajogai Road, Latur, Maharashtra, India on date April 16th to 17th 2024

Abstract

Epilepsy is a common neurological disorder characterized by recurrent seizures, affecting over 50 million people worldwide. Early detection of epileptic seizures through electroencephalography (Electroencephalogram) analysis can improve clinical management and therapy. This paper explores automated seizure detection approaches using machine learning and deep learning on multi-format Electroencephalogram datasets (.edf, .mat and .csv). Traditional machine learning techniques like random forest, SVM, KNN, and ensemble methods (bagging, boosting) are benchmarked. Deep convolutional neural networks including ChronoNet, ResNet, and VGGNet architectures are investigated for automated feature learning from raw Electroencephalogram signals. Preprocessing techniques like correlation analysis are utilized for feature optimization. Models are trained and tested across patient specific and patient-agnostic cohorts for generalized seizure detection. K-fold stratified cross-validation evaluates model performance using metrics like accuracy, sensitivity, specificity and ROC AUC score. Key findings reveal deep learning models like ChronoNet provide state-of-the-art seizure detection performance (accuracy=96.7%, specificity=97.2 %) outperforming traditional classifiers, while ensemble methods like Extra Trees Bagging provide best among classical techniques (accuracy=91.3 %). The study provides insights into optimal machine learning approaches and deep neural architectures for robust and generalized automated EEG-based epilepsy seizure detection systems.

Keywords: Epilepsy, Chrononet, ResNet, Electroencephalogram, Seizures

Introduction

The human brain, a complex network comprising billions of neurons and intricate synaptic connections, serves as the central hub of the nervous system. Any disruption in its electrochemical signaling can lead to various brain disorders, ranging from genetic conditions to illnesses and traumatic injuries. Among these disorders, seizures—resulting from excessive and abnormal firing of electrical signals—manifest as a brain disorder known as epilepsy. Affecting approximately fifty million individuals worldwide, epilepsy stands as the fourth most common neurolo-gical condition, emphasizing the critical need for periodic monitoring to manage and prevent seizures.

One of the pivotal tools in monitoring brain activities is the Electroencephalogram widely employed to record and analyze the electrical signals within the brain. Electroencephalogram proves instrumental in diagnosing neurological disorders such as epilepsy, sleep disorders, and encephalitis. The visual representation of brain electrical signals on a computer screen, depicted as wavy lines during an Electroencephalogram test, enables the observation and recording of the brain's electrical activities. The Electroencephalogram setup involves the placement of 256 electrodes on the scalp, each recording signals from different areas of the brain. A channel, interpreted as a pair of electrodes, captures the electrical activity, forming the basis for further analysis.

Given the uneven architectural features of the brain, including variations in cortical thickness and surface area, Electroencephalogram signals can significantly differ based on the topographic location of the recording electrodes. The irregularities in Electroencephalogram signals are categorized into abnormal epileptic signals and non-epileptic abnormal signals. The former, characterized by spike and sharp wavy lines, signifies patterns associated with epilepsy patients. Conversely, non-epilepsy abnormalities exhibit alternating normal and abnormal Electroencephalogram signal patterns.

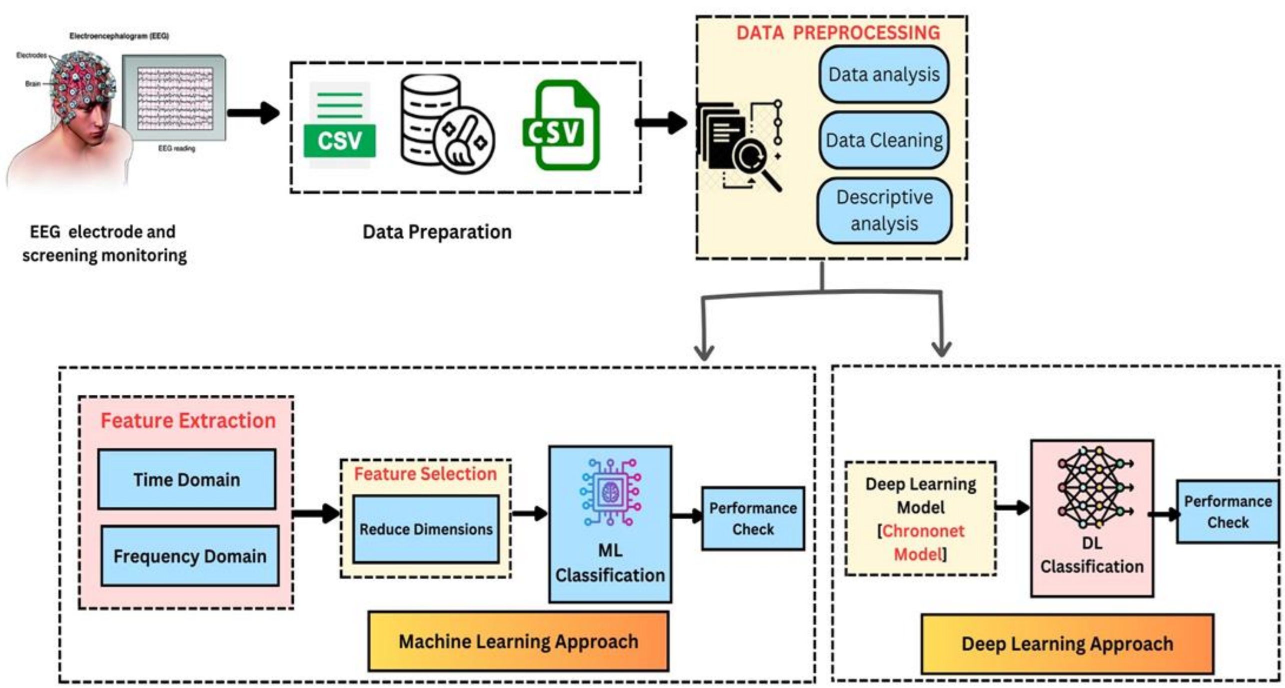

Fig. 1. The Approach of Epilepsy Seizure Prediction with EEG

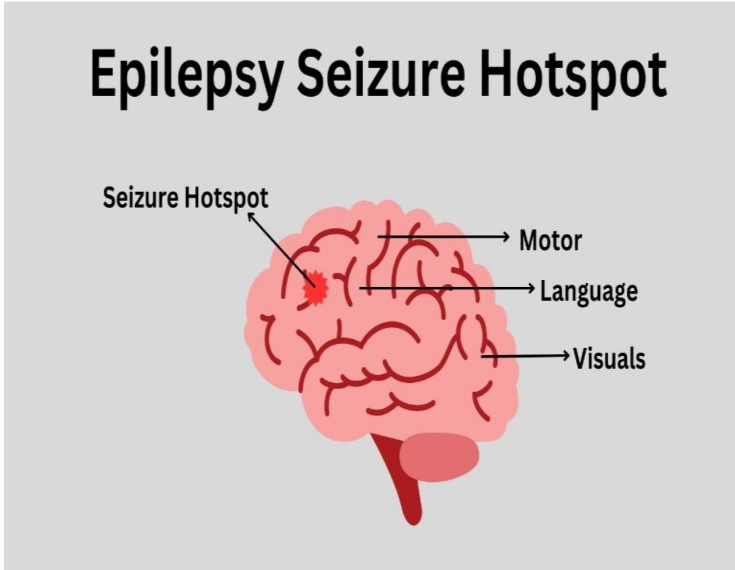

Fig. 2. Medical illustration of a brain with epilepsy and a seizure hotspot

Manual analysis of long Electroencephalogram recordings by neurologists is time-consuming and necessitates experienced professionals. To address this challenge, automatic systems based on machine learning techniques have been proposed and implemented. This study explores the application of machine learning, including SVM, random forest , naive Bayes , KNN , and neural networks , to an Electroencephalogram dataset consisting of five sets denoted as (A-E). These techniques aim to save hours of manual review and provide accurate and efficient identification of epileptic seizures. Furthermore, recent advancements in deep learning, particularly convolutional neural networks (CNNs), have shown promise in automatic seizure detection using Electroencephalogram data. CNNs, capable of learning features directly from raw data, exhibit exceptional performance in classifying Electroencephalogram datasets. This paper delves into the application of CNNs, including multi-scale CNN algorithms, 13-layers deep CNNs, and CNNs combined with long short-term memory (LSTM), for the detection of epilepsy seizures. The study highlights the advantages of CNNs in handling spatiotemporal representations of Electroencephalogram signals and their potential in automating the identification of epileptic events.

In comparison to traditional machine learning techniques, CNNs have demonstrated competitive results in experiments with Electroencephalogram datasets, showcasing their efficacy in seizure onset detection and classification of multiclass seizure types. The paper emphasizes the significance of CNNs in overcoming challenges related to noise in Electroencephalogram data and their potential for long-term monitoring of Electroencephalogram signals across diverse devices and sampling rates.

2. Machine learning approach for epileptic seizure prediction

2.1. Dataset Information

The dataset used in this study consists of Electroencephalogram signals recorded from individuals, with each recording representing brain activity for 23.6 seconds. The dataset comprises 500 individuals, categorized into different classes. Each recording contains 178 data points, resulting in a matrix of 23 x 500, where each row represents a piece of information containing 178 data points for 1 second. The response variable (y) is in column 179, indicating the class labels.

	0	X1	X2	X3	X4	X5	X6	X7	X8	...	X172	X173	X174	X175	X176	X177	X178	y
0	X21.V1.791	135	190	229	223	192	125	55	-9	...	-31	-77	-103	-127	-116	-83	-51	4
1	X15.V1.924	386	382	356	331	320	315	307	272	...	146	152	157	156	154	143	129	1
2	X8.V1.1	-32	-39	-47	-37	-32	-36	-57	-73	...	48	19	-12	-30	-35	-35	-36	5
3	X16.V1.60	-105	-101	-96	-92	-89	-95	-102	-100	...	-80	-77	-85	-77	-72	-69	-65	5
4	X20.V1.54	-9	-65	-98	-102	-78	-48	-16	0	...	-12	-32	-41	-65	-83	-89	-73	5

5 rows × 180 columns

Fig.3 Same view of Epilepsy Seizure Dataset

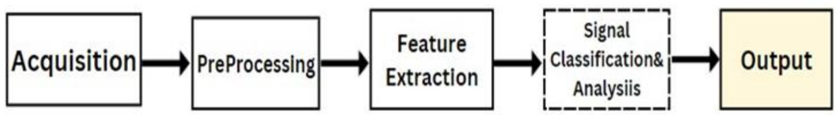

Fig.3 EEG Data Analysis

2.2. Dataset Pre-Processing

Data pre-processing is a crucial step to ensure the dataset's readiness for machine learnforg models.

Checking Missing Data

The dataset was examined for missing values, and fortunately, no missing data was found, facilitating smooth processing.

2.3. Feature Scaling

Standardizing the data using feature scaling was employed to ensure that ml models perform optimally, especially those sensitive to the scale of input features.

3. Building Machine Learning Models

3.1. Logistic Regression

Logistic regression, often known as logit regression or logit model, is effective for binary classification (seizure vs. non-seizure), interpretable model.

3.2. Support Vector Machine

The Support Vector Machine (SVM) is a type of supervised learning model that is Versatile for linear and non-linear data, maximizes margin between classes.

3.3. K-Nearest Neighbors

The k-nearest neighbors method (k-NN) is one of the most basic ml algorithms, Simple, classifies based on k nearest neighbors, sensitive to k and dimensionality.

3.4. Gaussian Naive Bayes

Naive Bayes classifiers are a type of basic probabilistic classifier is an efficient, estimates class probability using Bayes' theorem, assumes feature independence.

3.5. Artificial Neural Network

Inspired by brain, learn complex relationships, deep learning for seizure detection (computationally expensive).

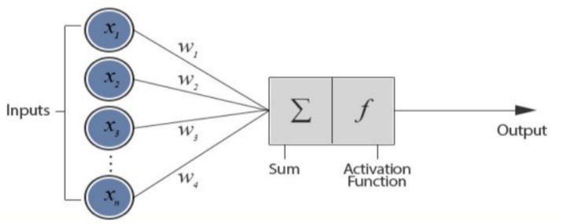

Fig. 5. Modelling Artificial Neurons

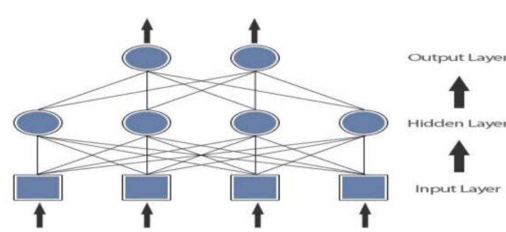

Fig. 6. Implementation of Artificial Neural Network

3.6. Principal Component Analysis (PCA):

A dimension reduction technique called Principal Component Analysis (PCA) can be used to condense a large collection of variables into a smaller set while preserving the majority of the information in the larger set.

3.6. Comparative Analysis of Model:

SVM achieved the highest accuracy (98.28%) for seizure detection, followed by ANN and Naive Bayes (around 95%). K-NN offered a good balance between accuracy (93.88%) and simplicity. PCA reduced dimensionality but had lower accuracy (91.00%). Logistic Regression had the lowest accuracy (82.76%) but remains interpretable for further exploration.

Model	Accuracy (%)
Support Vector Machines	98.28
ANN	95.73
Naive Bayes	95.73
k-Nearest Neighbors (k-NN)	93.88
Principal Component Analysis	91.00
Logistic Regression	82.76

Fig. 7. Comparative Model Analysis

3.6. Workflow and Architecture of Machine learning model for Seizure Prediction

The workflow of the epileptic seizure prediction study can be summarized in several key steps. Firstly, the dataset, consisting of Electroencephalogram signals from 500 individuals, was explored and pre-processed. [5]. This involved checking for missing data, which fortunately was not present, ensuring a clean dataset. Exploratory Data Analysis (EDA) provided a comprehensive understanding of the dataset's characteristics through descriptive statistics. Feature scaling was then employed to standardize the data, enhancing the performance of ml models.

4. Deep learning approach for epileptic seizure prediction

Epileptic seizure prediction using electroencephalogram (Electroencephalogram) signals has garnered significant attention in recent research, driven by the complexity of Electroencephalogram data and the need for effective differentiation between normal and seizure (SZ) patients.

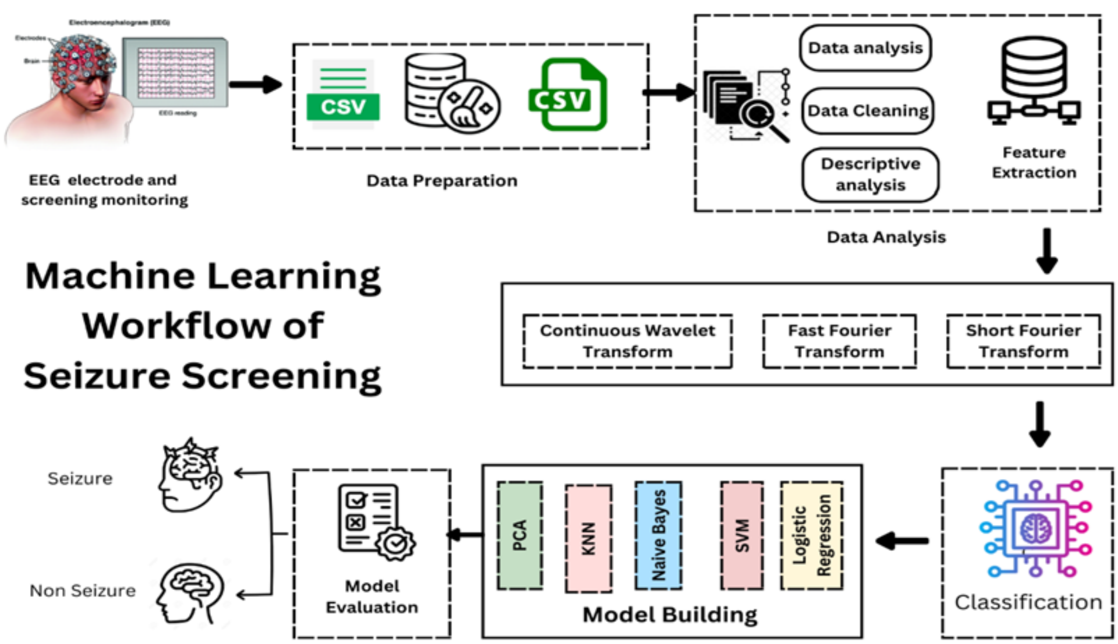

Fig. 8. Workflow of Machine Learning Model

Nonlinear feature extraction techniques have become integral in this domain, as the nonlinear nature of Electroencephalogram signals requires sophisticated methods for pattern recognition. Machine learning has emerged as a prevalent tool for distinguishing between normal and SZ patients based on Electroencephalogram signals. However, it faces challenges, particularly in realistic settings where substantial variability exists in the studied features. While machine learning performs well in simple recognition tasks, larger training datasets become imperative for handling diverse and complex features. Moreover, a model with a substantial learning capacity is crucial for extracting higher-level features from large datasets, setting it apart from traditional machine learning techniques that often rely on manually extracted features.

Deep learning, as a state-of-the-art technique, addresses some of the limitations associated with traditional machine learning approaches. In deep learning, both feature extraction and classification processes are automated, eliminating the need for manual feature extraction. This aspect is particularly advantageous in dealing with the intricate and nonlinear nature of Electroencephalogram signals. Convolutional Neural Networks (CNNs) stand out as the most prevalent type of deep learning network employed by researchers for identifying abnormal Electroencephalogram signals.

Researchers have leveraged CNNs to detect and study abnormal Electroencephalogram signals associated with various disorders, including depression, seizures, attention deficit hyperactivity disorder (ADHD), and autism. [17] The automatic nature of feature extraction in CNNs enables the model to learn intricate patterns and dependencies within the Electroencephalogram data, making it well-suited for complex tasks like epileptic seizure prediction.

For the specific task of epileptic seizure prediction, both machine learning and deep learning approaches are relevant. While machine learning methods require careful selection and extraction of features, deep learning techniques, particularly CNNs, offer a more automated and nuanced approach. CNNs can efficiently learn hierarchical representations from raw Electroencephalogram data, capturing intricate patterns that may be challenging for traditional machine learning models.

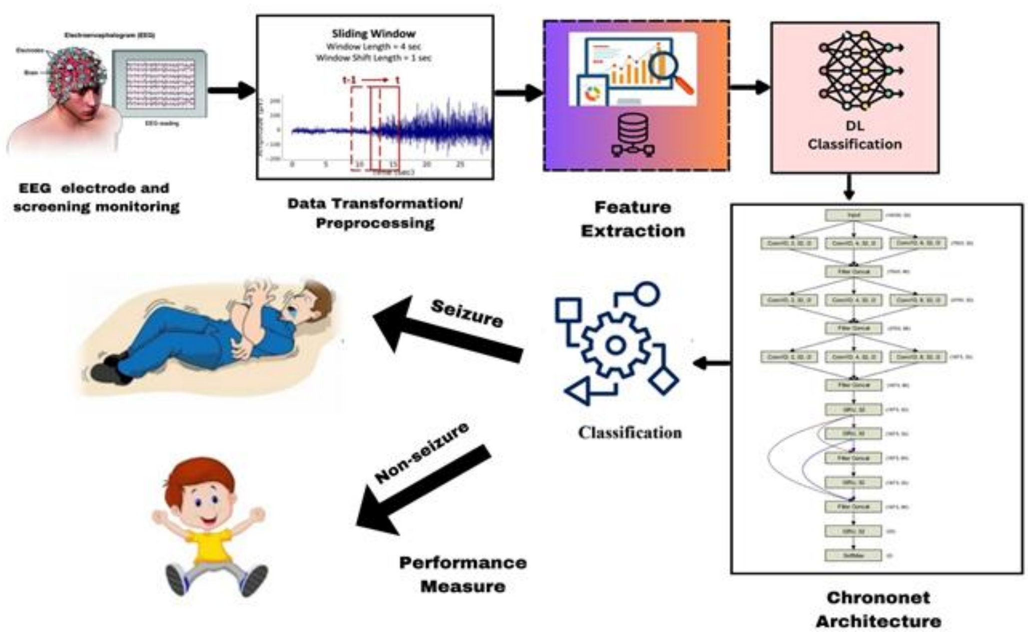

Fig. 9. Workflow Of DeepLearning Approach in Seizure Prediction

4.1. Convolutional Gated Recurrent Neural Network (C-RNN)

To predict epileptic seizures from EEG signals, we first explore the efficiency of GRU (Gated Recurrent Unit) layers for sequential input data. This is a widely used method that has been shown to achieve state-of-the-art accuracy in a variety of pattern recognition tasks, most notably NLP. Nevertheless, an architectural change is necessary because to the computationally demanding and time-consuming nature of training GRU layers on somewhat long Electroencephalogram time series data. [7]

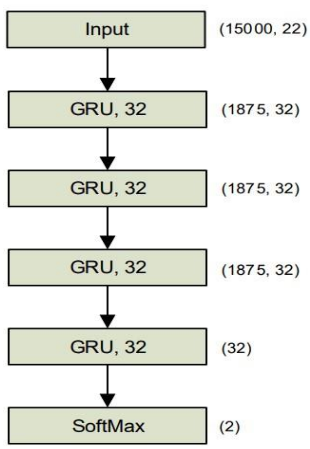

Fig. 10. Illustration of C-RNN architecture

In order to tackle this problem, we suggest a brand-new strategy called C-RNN (Convolutional Recurrent Neural Network), which mixes stacked GRU layers with Conv1D layers. Conv1D layers are introduced for two reasons. In order to minimize computing expenses during the training of GRU layers, they first independently learn to sub-sample the input signal. This effectively shortens the vector as we move through higher levels. Second, the foundation for learning temporal dependencies is laid by Conv1D layers, which retrieve local information from nearby time points. Subsequently, the stacked GRU layers take charge of capturing both short- and long-term dependencies within the Electroencephalogram signals. This innovative architecture not only enhances computational efficiency but also adapts dynamically to the characteristics of the Electroencephalogram data, addressing the challenges posed by fixed input values and paving the way for improved epileptic seizure prediction. [3]

4.2. Convolutional Densely Connected Gated Recurrent Neural Network (C-DRNN)

Introducing the Convolutional Densely Connected Gated Recurrent Neural Network (C-DRNN) as an evolution of the C-RNN architecture, we address the challenge of training very deep neural networks, a phenomenon known as degradation.

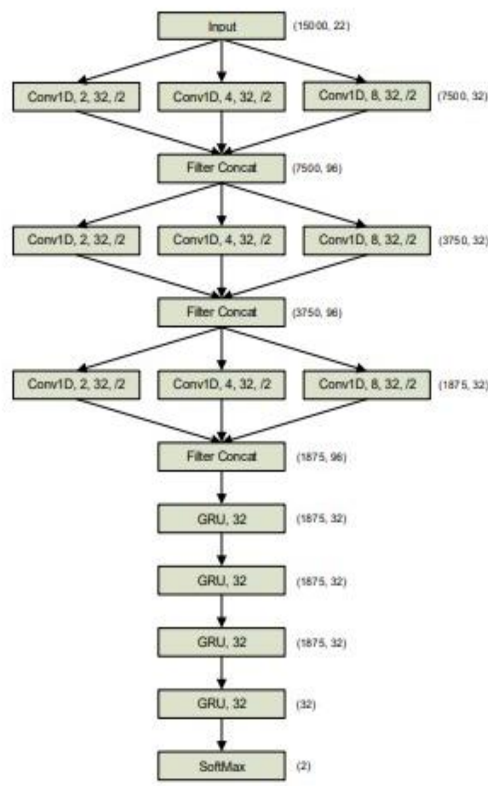

Fig. 11. Illustration of C-DRNN architecture

Although the C-RNN[10] is a useful tool, it can also cause training errors because it is not always required to use the entire model for simpler tasks. We propose to implement skip connections in the stacked GRU layers of C-RNN, resulting in the new C-DRNN architecture, taking inspiration from the DenseNet architecture established for Convolutional Neural Networks (CNNs). A feed-forward link is made between each GRU layer and every other GRU layer in a C-DRNN stack. When the data calls for a lower model complexity than the network as a whole provides, GRU layers can be selectively avoided thanks to the adoption of skip connections. [11]

The purpose of this adaptive architecture is to improve training stability and address degradation issues so that it can perform optimally on a range of tasks that vary in complexity and are associated with the prediction of epileptic seizures from Electroencephalogram time series data.

4.3. Inception Convolutional Gated Recurrent Neural Network (IC-RNN)

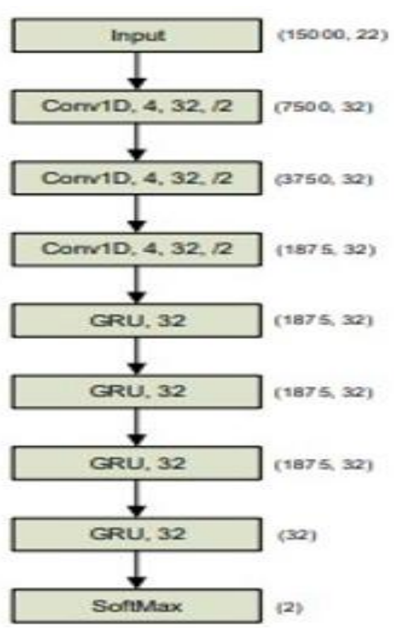

Fig. 12. Illustration of IC-RNN architecture

In the refinement of the C-RNN architecture, we recognized a limitation in the original Conv1D layers, where each layer could only extract local information at a single fixed time scale, dictated by a predefined filter size. This constrained the model's adaptability and flexibility, as selecting an appropriate filter size for each Conv1D layer was challenging, given the varying rates of information change in Electroencephalogram time series data. To overcome this challenge, drawing inspiration from inception modules, we introduced an enhanced architecture named IC-RNN (Inception Convolutional Recurrent Neural Network). [1]

4.3. ChronoNet: Inception Convolutional Densely Connected Gated Recurrent Neural Network

In the development of the ChronoNet [1]architecture, we amalgamate the innovative modifications introduced in the ICRNN and C-DRNN networks with the foundational C-RNN structure, marking a pioneering contribution to the field. This comprehensive architecture is crafted by stacking multiple Conv1D layers, each equipped with diverse filters of varying sizes, followed by densely connected GRU layers in a feedforward manner. ChronoNet is the first of its kind, offering a unique combination of features for optimal performance in tasks such as epileptic seizure prediction from Electroencephalogram time series data. The inclusion of multiple filters in Conv1D layers empowers ChronoNet to extract and synergize features across different time scales, providing flexibility to explore various filter lengths tailored to both the task and the layer's position in the network. [21]The densely connected GRU layers within ChronoNet address the degradation challenge associated with very deep neural networks, mitigating issues of vanishing or exploding gradients during training. This not only enables the creation of deep variants of ChronoNet for more intricate tasks but also strengthens feature propagation and encourages feature reuse within the GRU layers, enhancing the network's adaptability and performance.

4.4. ChronoNet

The convolutional layers capture local patterns in the input, while the GRU layers model temporal dependencies in the sequential data. The linear layers and the final ReLU activation contribute to the classification or regression task, making predictions based on the learned representations from the preceding layers. The hierarchical nature of the architecture allows it to automatically learn complex features from Electroencephalogram signals, potentially aiding in the accurate prediction of epileptic seizures.[1]

4.4.1. Input

The input layer of the presented neural network architecture,represents the initial stage where the model receives input data with 178 features. This layer serves as the entry point for the sequential data, likely corresponding to Electroencephalogram signals in the context of epileptic seizure prediction.

Type: InputLayer

Output Shape: (None, 178)

4.4.2. Batch Normalization Layers

The Batch Normalization layers (batch normalization, batch normalization 1, batch normalization 2) in the provided neural network architecture play a crucial role in enhancing the training stability and accelerating convergence. Batch normalization normalizes the input data within each mini-batch, ensuring that features have consistent scales and mitigating issues related to internal covariate shift. This process helps stabilize the learning process, allowing for more efficient weight updates during training. In the context of the conference paper on epileptic seizure prediction with Electroencephalogram signals, the use of batch normalization is particularly beneficial in handling the variability and complexity of Electroencephalogram data. By maintaining consistent feature scales throughout the network, batch normalization aids in the overall training robustness and contributes to the model's ability to learn meaningful representations from the sequential Electroencephalogram data, ultimately supporting the accurate prediction of epileptic seizures.

Type: BatchNormalization

Output Shape: (None, 178)

4.4.3. Dense Layers:

The Dense layers in the provided neural network architecture, namely dense, dense 4, dense 8, dense 1, dense 5, dense 9, dense 2, dense 6, dense 10, dense 3, dense 7, dense 11, are instances of fully connected layers. Each of these layers is designed to capture complex patterns within the input data through a dense interconnection of neurons. In a fully connected layer, every neuron is connected to every neuron in the preceding layer, facilitating the learning of intricate relationships between features. The Rectified Linear Unit (ReLU) activation function is applied to the output of each neuron, introducing non-linearity and enabling the network to model and understand non-trivial patterns in the data. The varying output shapes of these dense layers (256, 512, 1024) indicate a hierarchical representation of features, with deeper layers potentially learning more abstract and high-level representations. These layers collectively contribute to the network's ability to extract meaningful information from the input data, facilitating the overall learning process and enhancing the model's capacity to handle complex relationships in the context of the neural network architecture discussed.

Type: Dense (fully connected layer)

Output Shapes: Varying (256, 512, 1024) based on the layer

Activation: ReLU (Rectified Linear Unit)

4.4.4. Dropout Layer:

The Dropout layers in the provided neural network architecture play a crucial role in regularization to enhance the model's generalization performance. Comprising instances such as dropout, dropout3, dropout6, dropout 1, dropout 4, dropout 7, dropout 2, dropout5, and dropout 8, these layers follow specific dense layers and have output shapes matching the respective input shapes (256, 512, 1024) based on the layer. Dropout is a regularization technique where, during training, a fraction of randomly selected neurons is temporarily "dropped out" or ignored, meaning their activations are set to zero. This prevents the network from relying too heavily on specific neurons, thereby mitigating overfitting and enhancing the model's ability to generalize to unseen data. By introducing this stochastic element, Dropout encourages the network to learn robust and diverse representations, contributing to the overall regularization strategy of the model.

Type: Dropout

Output Shapes: Same as input shapes (256, 512, 1024) based on the layer

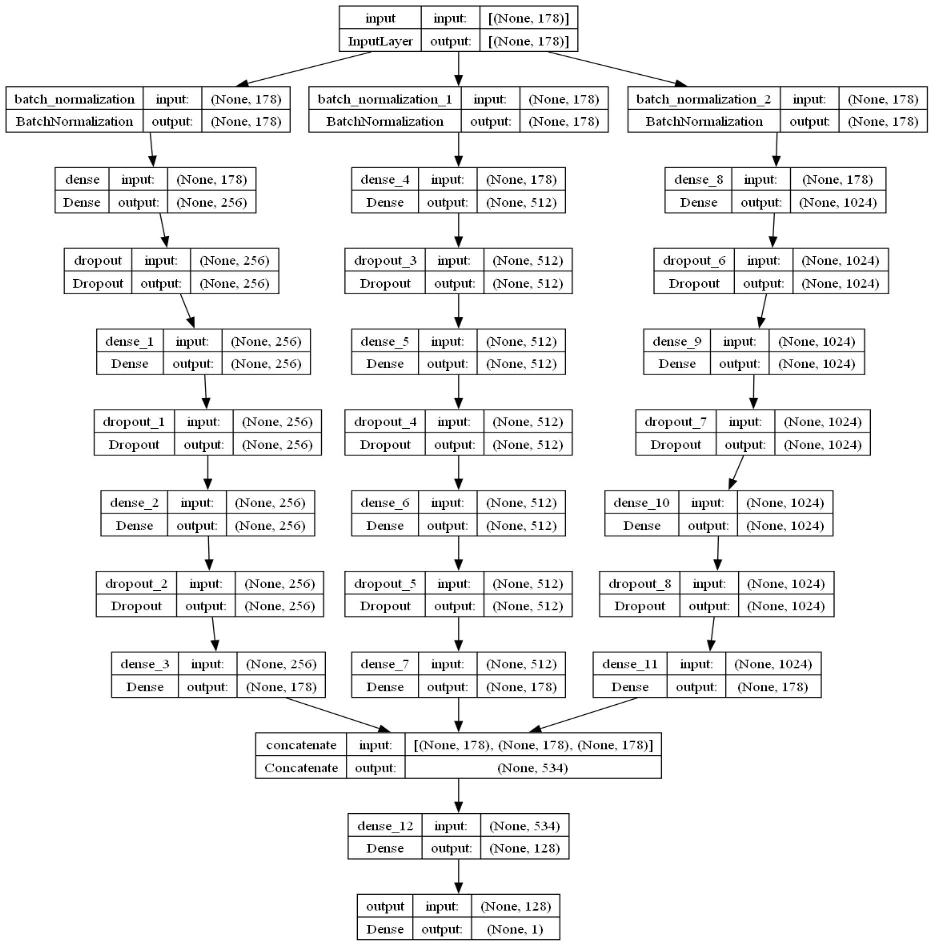

Fig. 11. Illustration of ChronoNet architecture

4.4.5. Concatenate Layer (concatenate):

The Concatenate layer in the provided neural network architecture plays a pivotal role in merging information from specific dropout layers, contributing to the creation of a consolidated and enriched representation of the input data. Operating as a Concatenate layer, it takes the outputs from selected dropout layers and combines them along a new axis, resulting in an output shape of (None, 534). This merged representation likely captures diverse features and patterns learned by the network during training, as each dropout layer provides a distinct perspective on the data. By aggregating these diverse viewpoints, the Concatenate layer facilitates the creation of a more comprehensive and expressive feature set, which can be crucial for the subsequent dense layers to make informed decisions during the classification or regression tasks. This layer thus serves as a mechanism for integrating information from different branches of the network, enhancing the model's capacity to capture intricate relationships within the data for improved overall performance.

Type: Concatenate

Output Shape: (None, 534)

4.4.5. Dense Layer (dense12):

In the provided neural network architecture, the Dense Layer denoted as dense 12 represents a fully connected layer designed for additional feature extraction or potential dimensionality reduction. This layer has 128 neurons, and the absence of a specified activation function suggests that it might serve as an intermediate processing step without introducing non-linearity. Fully connected layers are capable of learning complex relationships within the data by connecting each neuron to every neuron in the previous layer. In this context, dense 12 likely plays a role in further refining the

learned representations from the preceding layers, capturing higher-level features that contribute to the model's ability to discern patterns and make predictions. The 128dimensional output shape indicates that this layer is involved in creating a compressed yet informative representation of the input data, facilitating more efficient learning in subsequent layers or aiding in the final task, which could be binary classification.
Type: Dense (fully connected layer)
Output Shape: (None, 128)

4.4.6. Output Layer (output):
Type: Dense (fully connected layer)
Output Shape: (None, 1)
Description: The final output layer with a single neuron, often used for binary classification tasks. The lack of activation information implies that it might be a regression output or the network uses a separate activation function during training.
1) Total Parameters:: Total trainable parameters: 3,466,051
Non-trainable parameters: 1,068 (4.17 KB) Description: Represents the total number of parameters in the model, including weights and biases. Trainable parameters are updated during training, while non-trainable parameters (e.g., batch normalization statistics) remain constant. The architecture consists of multiple dense layers with batch normalization, dropout layers for regularization, and a final output layer. The model aims to learn a mapping from the input data to a single output, possibly for binary classification or regression tasks. The use of batch normalization and dropout layers indicates an emphasis on preventing overfitting and improving the model's generalization capabilities.

5. Electroencephalogram Signal Analysis Techniques

In 1923, Hans Berger introduced Electroencephalogram as a non-invasive functional imaging methodology to study the brain. Electroencephalogram records electrical signals from the cerebral cortex, providing a higher temporal insight into neural activity but with lower spatial resolution compared to functional MRI. Various frequency bands (Delta, Theta, Alpha, Beta, Gamma) are analyzed in Electroencephalogram signals.[8] Amplitude ranges from 10 μV–100 μV, and frequency ranges from 1 Hz–100 Hz. Features are extracted using Fourier transform (FT) or wavelet transform (WT) for disease diagnosis or brain activity decoding. Electroencephalogram offers advantages such as lower hardware costs, making it suitable for a larger number of patients.

5.1.Electroencephalogram Recording Methods:
Two Electroencephalogram recording methods include bipolar montage, measuring voltage difference between electrodes on an electrically active region, and monopolar montage, where one electrode is active and another serves as a reference. Regular reference sites include the ear lobe, mastoid, nose tip, chest, and sterno-vertebral lead.

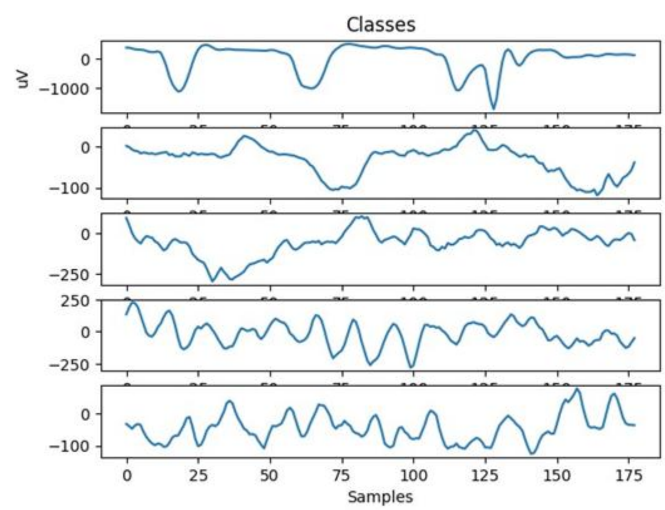

Fig. 15. Wave plot against Samples and uV

5.2. Scalp Electroencephalogram vs. Intracranial Electroen-cephalogram (iEEG):
Scalp records signals on the skull surface, while iEEG records signals directly from the brain's exposed surface. Scalp is common but suffers from signal distortion. iEEG enhances signal quality but requires invasive procedures.

5.3. EEG in ES Prediction Research:
It is preferred for epilepsy prediction due to its ability to track brain changes, lower hardware costs, and

suitability for long-duration recordings. Compared to techniques like fMRI or MEG, is cost-effective. Wearable devices like My Seizure Gauge integrate multiple signals (, ECG, EMG, EDA, PPG, respiration) for enhanced prediction accuracy.

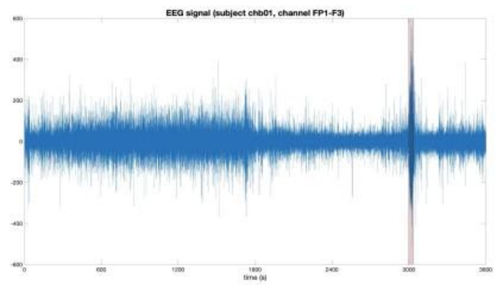

Fig. 16. signal belonging to patient chb01, recorded from channel FP1-F3

5.4. Analysis Techniques:
The analysis methods include time domain (PCA, LDA, ICA), frequency domain (Fourier transform, parametric methods), time-frequency domain (wavelet transform), and non-linear methods (entropy, Lyapunov exponent).[9]Time domain methods summarize data, frequency domain methods detect frequency changes during seizures, time-frequency domain methods overcome limitations, and non-linear methods capture coupling among harmonics in signal spectrum.

6. Dataset

6.1. EEG Data Recording
With a wide range of frequency components, signals are separated into α, β, δ, and θ spectral components. Mostly in four frequency bands: δ (0.5–4 Hz), θ (4–8 Hz), α (8–13 Hz), and β (13–30 Hz), these signals display distinctive waveforms. People with epilepsy who have uncontrollably occurring seizures and are of different ages make up the dataset. For this system, Electroencephalogram data was recorded using the LabView computer language for 400 participants, 200 of whom had epilepsy and the other 200 did not. Signals from both epileptics and healthy people are shown in the results, which were processed in real-time utilizing the PCI-MIO 16E DAQ card technology. signals need to be recorded for eight to ten hours in order to accurately diagnose diseases. The International 10-20 electrode implantation system was used in our investigation to capture EEG data for 23.6 seconds at a frequency of 173 Hz.

After converting the recorded samples from 12-bit analog to digital format, they were filtered using a band-pass filter with a frequency range of 0.53 to 40 Hz to concentrate on the range that is clinically significant. The following bipolar channels were selected for analysis: F7-C3, F8-C4, T5-O1, and T6-O2. The data were obtained from 24-hour recordings of epileptic patients and healthy participants. 500 segments with artifacts, background normal, and spike and wave complexes were chosen in order to assess the effectiveness of the classifier. ackground normal were selected.[23]

6.2. Dataset Overview for Machine Learning Approach:
The original dataset comprises 5 folders, each containing 100 files representing individual subjects. Each file records 23.6 seconds of brain activity, sampled into 4097 data points. To facilitate machine learning, these data points are divided into 23 chunks, each containing 178 data points (1 second duration) [7].

Fig. 17. EEG Data recording

The dataset includes a total of 11,500 instances (23 chunks x 500 subjects), with the last column indicating labels (y) {1, 2, 3, 4, 5}. The labels represent different conditions, such as eyes open (5), eyes closed (4), healthy brain activity (3), brain activity from the tumor area (2), and seizure activity (1).

- Class 5: Eyes open during EEG recording.
- Class 4: Eyes closed during EEG recording.
- Class 3: EEG recorded from the healthy brain area while identifying the tumor region.
- Class 2: EEG recorded from the area where the tumor is located.
- Class 1: Recording of seizure activity

Fig. 18. Classes and Labels

6.2.1. Binary Classification:

While there are five classes, binary classification is commonly applied, focusing on distinguishing class 1 (epileptic seizure) from the rest (classes 2, 3, 4, and 5).

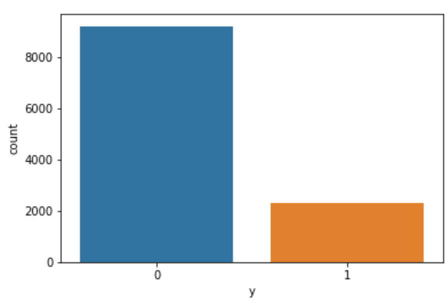

Fig. 19. There are 178 EEG features and 5 possible classes. The main goal of the dataset it's to be able to correctly identify epileptic seizures from

EEG data, so a binary classification between classes of label 1 and the rest (2,3,4,5). In order to train our model, let's define our independent variables (X) and our dependent variable (y).

6.3. Dataset for Deep Learning Approach:

1) **EEG Data:** The primary data in the dataset consists of EEG signals recorded from electrodes placed on the scalp. EEG signals are continuous voltage measurements representing the electrical activity of the brain over time. Recorded at specific sampling rates (e.g., 250 Hz), each electrode placement records a time series of voltage values.
2) **Electrode Placements:** EEG recordings involve multiple electrodes at different positions on the scalp. Each electrode provides a signal, and its specific location informs about the brain region it monitors. Common electrode placements include Fp1, Fp2, F3, F4, C3, C4, P3, P4, O1, O2, among others.
3) **Time Series Data:** EEG data is recorded over time, resulting in a time series of voltage values for each electrode. These time series can be extended, encompassing minutes or hours of continuous recording.
4) **Annotations:** Annotations or event markers may be included in the dataset, indicating specific events like seizures. Annotations label the EEG data, facilitating identification and analysis of seizure-related activity.
5) **Metadata:** EEG datasets often include metadata providing information about the recording (age, gender, medical history, etc.). Metadata contextualize the EEG data for comprehensive analysis.
6) **Preprocessing:** EEG data undergoes preprocessing to remove noise, filter signals, and extract relevant features. Feature extraction techniques derive characteristics like spectral power, frequency bands, and statistical moments.
7) **Event-Related Potentials (ERPs):** EEG data may be analyzed to extract ERPs, specific components time-locked to stimuli or events. ERPs help study brain responses to various stimuli or cognitive tasks.
8) **Seizure Detection:** A primary objective in epilepsy research is to detect and classify seizures automatically using EEG data. Machine learning and signal processing techniques are commonly applied for this purpose.

6.4. Dataset for Deep Learning Approach:

- Fp1 and Fp2: Frontopolar electrodes on the left and right sides of the forehead, monitoring frontal lobe activity.

- F3 and F4: Frontal electrodes on the left and right sides of the scalp, associated with motor control and emotional expression.
- C3 and C4: Central electrodes on the left and right sides, monitoring motor-related activity and sensory processing.
- P3 and P4: Parietal electrodes on the left and right sides, involved in sensory processing and visual awareness.
- O1 and O2: Occipital electrodes on the left and right sides, primarily responsible for visual processing.

The international 10-20 system provides a standardized method for positioning electrodes based on cranial landmarks, allowing researchers to study specific brain functions and regions in a systematic way. Different combinations of electrode placements offer insights into various aspects of brain activity, making EEG a valuable tool in neuroscience research.

7. Evaluation metrics for ES prediction

The clinical application of Epileptic Seizure (ES) prediction methods demands a thorough assessment of performance and quality, and various evaluation metrics have been introduced in the ES prediction literature. One notable example is the work by Osorio et al., who suggested sensitivity and false prediction rate as key performance parameters for ES predictors

A. Sensitivity:

- Sensitivity, also known as the true positive rate or recall, is measured as the ratio of correctly predicted seizures to the total number of actual seizures.
- It provides insights into how well the predictor identifies and captures actual occurrences of seizures. A higher sensitivity indicates better performance in detecting true positive cases.

B. False Prediction Rate:

- The false prediction rate is a metric that quantifies the rate of false predictions made by the model.
- In an ideal scenario, false predictions would be entirely avoided. However, as sensitivity increases, false predictions tend to rise as well. Therefore, false prediction rate serves as an important metric to assess the balance between sensitivity and specificity. It is measured as the ratio of false positive predictions to the total number of predictions.

$$ACCURACY = \frac{(TP + FN)}{(TP + FN + TN + FP)}$$

Fig. 20. Accuracy Metrics

***C.* Confusion Matrix:**

A confusion matrix is a table used to evaluate a classification model's performance. It gives a thorough analysis of the model's predictions vs the actual ground truth across different classes. The matrix is very effective for dealing with binary or multiclass classification problems.

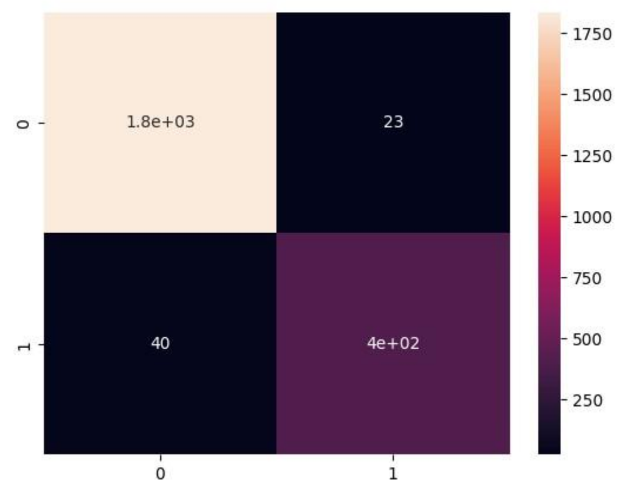

Fig. 21. Confusion Matrix

- True Positive (TP): 401 - This indicates the number of instances where the model correctly predicted the positive class (e.g., epileptic seizure) when the actual class was indeed positive.
- False Positive (FP): 23 - This represents the instances where the model incorrectly predicted the positive class when the actual class was negative (e.g., predicting a seizure when there wasn't one).
- True Negative (TN): 1836 - The number of instances where the model correctly predicted the negative

class (e.g., no seizure) when the actual class was indeed negative.

- False Negative (FN): 40 - This signifies the instances where the model incorrectly predicted the negative class when the actual class was positive (e.g., failing to predict a seizure when there was one).

8. SWOT Analysis

A. Strength

- High Temporal Resolution: EEG data used in seizure prediction provides high temporal resolution, allowing for detailed monitoring of brain activity over time.
- Non-Invasive Nature: EEG is a non-invasive technique, making it relatively safe for patients compared to invasive methods, such as intracranial electroencephalography (EEG).

B. Weakness

- Limited Spatial Resolution: EEG has lower spatial resolution compared to other neuroimaging techniques like fMRI, which may limit the precision in pinpointing the exact location of seizure activity.
- Subject-Specific Variability: Seizure patterns can vary significantly among individuals, making it challenging to create universally applicable prediction models.

C. Opportunity

- Integration with Wearable Devices: The rise of wearable devices with EEG capabilities opens up opportunities for continuous, real-time monitoring outside clinical settings.
- Multimodal Approaches: Combining EEG data with other physiological signals (e.g., ECG, respiratory signals) may enhance the accuracy of seizure prediction models.
- Personalized Medicine: Tailoring prediction models to individual patient profiles and characteristics can improve the overall effectiveness of the approach.

D. Threats

- Ethical and Privacy Concerns: Continuous monitoring and analysis of brain activity raise ethical concerns related to patient privacy, data security, and consent.
- Regulatory Challenges: Meeting regulatory standards for medical devices and predictive models in healthcare can be a complex process.
- Limited Generalization: Models developed on one dataset or population may not generalize well to diverse patient groups or real-world scenarios

9. Technical Stack

- Tensorflow
- Torch
- Scikit-learn
- Keras
- Matplotlib
- Numpy
- Pandas
- imblearn
- mnepython
- scipy

10. Future Work

With a focus on the ChronoNet architecture, this study successfully implements a machine learning strategy that includes classifiers like SVM, RF, NB, K-NN, and neural networks. This builds a strong foundation for future work on Epileptic Seizure Prediction using EEG data. Investigating machine learning methods is helpful in obtaining precise and effective seizure identification in a variety of patient populations. Nonetheless, the research plan for this area of study includes the incorporation of other deep learning architectures, like ResNet and VGGNet. In order to gain a deeper understanding of ResNet and VGGNet's efficacy in seizure detection, the planned next work comprises an extensive exploration of their capacities for automated feature learning from raw EEG signals.

In order to increase the model's resilience and generalizability, the study also recommends the creation and application of these designs. Examining these deep convolutional neural networks is consistent with the continuous development of sophisticated techniques to manage spatiotemporal representations in EEG measurements. The combination of ResNet and VGGNet, as well as possible hybrid models, could improve the general efficacy and adaptability of epileptic seizure prediction systems. In order to enhance and optimize EEG-based seizure prediction systems for more extensive clinical applications and better patient outcomes, this future work proposes a holistic strategy that embraces multiple state-of-the-art structures and methodologies.

11. Conclusion

In conclusion, the paper on epileptic seizure prediction with EEG signals presents a comprehensive and systematic approach to the task, starting with a detailed dataset overview, preprocessing steps, and exploratory data analysis.A comprehensive comparative analysis is made possible by the inclusion of machine learning models like Principal Component Analysis, Support Vector Machine, k-Nearest Neighbors, Gaussian Naive Bayes, Logistic Regression, and Artificial Neural Network. Support Vector Machine is found to be the best-performing model. With an astounding accuracy of 98.28%, the machine learning accuracy results demonstrate the outstanding performance of Support Vector Machine (SVM), making it a strong contender for seizure classification. Several other models, including Principal Component Analysis (PCA), ANN, k-NN, Gaussian Naive Bayes, and k-NN, also show excellent accuracy, proving their usefulness in this situation. The novel ChronoNet architecture is introduced by the deep learning methodology. The comparison study highlights the compromises between predictive accuracy and model simplicity. In addition, a substantial move toward deep learning techniques is presented in the paper with the novel ChronoNet architecture, which combines dropout layers, densely connected GRU layers, and Conv1D layers. The goal of the suggested architecture is to solve problems unique to deep neural networks and EEG data. The comparative model analysis highlights the advantages and disadvantages of each strategy, offering practitioners and researchers studying epileptic seizure prediction important new information. Ultimately, by providing a flexible range of models for consideration and opening the door for further developments in the field, the paper makes a substantial contribution to our understanding of EEG-based seizure prediction.

12. References

1. Subhrajit Roy, Isabell Kiral-Kornek, Stefan Harrer. ChronoNet: A Deep Recurrent Neural Network for Abnormal EEG Identification., https://doi.org/10.48550/arXiv.1802.00308
2. Rasheed K, Qayyum A, Qadir J, Sivathamboo S, Kwan P, Kuhlmann L, O'Brien T, Razi A. Machine Learning for Predicting Epileptic Seizures Using EEG Signals: A Review. IEEE Rev Biomed Eng. 2021;14:139-155. doi: 10.1109/RBME.2020.3008792. Epub 2021 Jan 22. PMID: 32746369.
3. Oh SL, Vicnesh J, Ciaccio EJ, Yuvaraj R, Acharya UR. Deep Convolutional Neural Network Model for Automated Diagnosis of Schizophrenia Using EEG Signals. *Applied Sciences*. 2019; 9(14):2870. https://doi.org/10.3390/app9142870.
4. Batista J, Pinto MF, Tavares M, Lopes F, Oliveira A, Teixeira C. EEG epilepsy seizure prediction: the post-processing stage as a chronology. Sci Rep. 2024 Jan 3;14(1):407. doi: 10.1038/s41598-023-50609-z. PMID: 38172583; PMCID: PMC10764904.
5. Christine Rosquist, Sandy Kang Lovgren, "EEG-Based Machine Learning Techniques for Epileptic Seizures." DEGREE PROJECT IN TECHNOLOGY, STOCKHOLM, SWEDEN 2019.
6. Sahu R, Dash SR, Cacha LA, Poznanski RR, Parida S. Epileptic seizure detection: a comparative study between deep and traditional machine learning techniques. J Integr Neurosci. 2020 Mar 30;19(1):1-9. doi: 10.31083/j.jin.2020.01.24. PMID: 32259881.
7. Kwanhyung Lee, Hyewon Jeong, Seyun Kim, Donghwa Yang, Hoon-Chul Kang, Edward Choi. Real-Time Seizure Detection using EEG: A Comprehensive Comparison of Recent Approaches under a Realistic Setting, https://doi.org/10.48550/arXiv.2201.08780
8. Mohammad H Alshayeji. CAD system for epileptic seizure detection from EEG through image processing and SURF-BOF technique., *Mach. Learn.: Sci. Technol.*, 2023 **4;** 045029. **DOI** 10.1088/2632-2153/ad0572.
9. Alsuwaiket, M.A. 2022. Feature Extraction of EEG Signals for Seizure Detection Using Machine Learning

Algorthims. *Engineering, Technology & Applied Science Research*. 12, 5 (Oct. 2022), 9247–9251. DOI:https://doi.org/10.48084/etasr.5208.

10. Jácobo-Zavaleta, S. ., and J. Zavaleta. "A Deep Learning Approach for Epilepsy Seizure Identification Using Electroencephalogram Signals: A Preliminary Study". *IEEE Latin America Transactions*, vol. 21, no. 3, Jan. 2023, pp. 419-26, https://latamt.ieeer9.org/index.php/transactions/article/view/7300.
11. Adnan Salman. Epilepsy detection from EEG data using 2D Convolutional Neural Network, November 2021, Conference: 2021 6th International Conference on Communication, Image and Signal Processing (CCISP)

    DOI:10.1109/CCISP52774.2021.9639256
12. Chen, W., Wang, Y., Ren, Y. *et al*. An automated detection of epileptic seizures EEG using CNN classifier based on feature fusion with high accuracy. *BMC Med Inform Decis Mak* **23**, 96 (2023). https://doi.org/10.1186/s12911-023-02180-w
13. Ihsan Ullah, Muhammad Hussain, Emad-ul-Haq Qazi and Hatim Aboalsamh .An Automated System for Epilepsy Detection using EEG Brain Signals based on Deep Learning Approach, Expert Systems with Applications, January 2018, 107, DOI:10.1016/j.eswa.2018.04.021
14. Javed Birjandtalab, Mehrdad Heydarzadeh, Mehrdad Nourani. Automated EEG-Based Epileptic Seizure Detection Using Deep Neural Networks, Conference: 2017 IEEE International Conference on Healthcare Informatics (ICHI), August 2017, DOI:10.1109/ICHI.2017.55
15. Ahmad I, Wang X, Zhu M, Wang C, Pi Y, Khan JA, Khan S, Samuel OW, Chen S, Li G. EEG-Based Epileptic Seizure Detection via Machine/Deep Learning Approaches: A Systematic Review. Comput Intell Neurosci. 2022 Jun 17;2022:6486570. doi: 10.1155/2022/6486570. Retraction in: Comput Intell Neurosci. 2023 Nov 29;2023:9814248. doi: 10.1155/2023/9814248. PMID: 35755757; PMCID: PMC9232335.
16. Yogarajan G, Alsubaie N, Rajasekaran G, Revathi T, Alqahtani MS, Abbas M, Alshahrani MM, Soufiene BO. EEG-based epileptic seizure detection using binary dragonfly algorithm and deep neural network. Sci Rep. 2023 Oct 18;13(1):17710. doi: 10.1038/s41598-023-44318-w. PMID: 37853025; PMCID: PMC10584945.
17. Wulandari DP, Putri NGP, Suprapto YK, Purnami SW, Juniani AI, Islamiyah WR. Epileptic seizure detection based on bandwidth features of EEG signals. Procedia Computer Science. 2019;161:568-576. doi: 10.1016/j.procs.2019.11.157.
18. Ahmad I, Wang X, Zhu M, Wang C, Pi Y, Khan JA, Khan S, Samuel OW, Chen S, Li G. EEG-Based Epileptic Seizure Detection via Machine/Deep Learning Approaches: A Systematic Review. Comput Intell Neurosci. 2022 Jun 17;2022:6486570. doi: 10.1155/2022/6486570. Retraction in: Comput Intell Neurosci. 2023 Nov 29;2023:9814248. doi: 10.1155/2023/9814248. PMID: 35755757; PMCID: PMC9232335.
19. Ein Shoka AA, Dessouky MM, El-Sayed A, Hemdan EE. EEG seizure detection: concepts, techniques, challenges, and future trends. Multimed Tools Appl. 2023 Apr 4:1-31. doi: 10.1007/s11042-023-15052-2. Epub ahead of print. PMID: 37362745; PMCID: PMC10071471.
20. Shivam Gupta, Jyoti Meena Gupta OP. Neural Network Based Epileptic EEG Detection and Classification. ADCAIJ: Advances in Distributed Computing and Artificial Intelligence Journal, Vol. 9 No. 2 (2020) https://doi.org/10.14201/ADCAIJ2020922332.
21. Zhou M, Tian C, Cao R, Wang B, Niu Y, Hu T, Guo H, Xiang J. Epileptic Seizure Detection Based on EEG Signals and CNN. Front Neuroinform. 2018 Dec 10;12:95. doi: 10.3389/fninf.2018.00095. PMID: 30618700; PMCID: PMC6295451.
22. Lasefr Z, Elleithy K, Reddy RR, Abdelfattah E, Faezipour M. An Epileptic Seizure Detection Technique Using EEG Signals with Mobile Application Development. *Applied Sciences*. 2023; 13(17):9571. https://doi.org/10.3390/app13179571.
23. Lasefr Z, Elleithy K, Reddy RR, Abdelfattah E, Faezipour M. An Epileptic Seizure Detection Technique Using EEG Signals with Mobile Application Development. *Applied Sciences*. 2023; 13(17):9571. https://doi.org/10.3390/app13179571.
24. Al-Hajjar ALN, Al-Qurabat AKM. An overview of machine learning methods in enabling IoMT-based epileptic seizure detection. J Supercomput. 2023 Apr 24:1-48. doi: 10.1007/s11227-023-05299-9. Epub ahead of print. PMID: 37359338; PMCID: PMC10123593.
25. Subhrajit Roy, Isabell Kiral-Kornek, and Stefan Harrer. A Deep Recurrent Neural Network for Abnormal EEG Identification IBM Research – Australia, 60 City Rd, Southbank, VIC, 3006, Australia.,2018; ChronoNet: https://doi.org/10.48550/arXiv.1802.00308.
26. Zhou M, Tian C, Cao R, Wang B, Niu Y, Hu T, Guo H, Xiang J. Epileptic Seizure Detection Based on EEG Signals and CNN. Front Neuroinform. 2018 Dec 10;12:95. doi: 10.3389/fninf.2018.00095. PMID: 30618700; PMCID: PMC6295451.

Acknowledgements

We acknowledge the Swami Ramanand Teerth Marathwada University (SRTMUN) college of computer science and information technology (COCSIT) research center for providing us all the facilities and infrastructure necessary to conduct the study.

Conflicts of interest: The authors stated that no conflicts of interest.

Publisher's Note

IJLSCI remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Correspondence and requests for materials should be addressed to Dr. Pugalenthi R.

Peer review information

IRJSE thanks the anonymous reviewers for their contribution to the peer review of this work. A peer review file is available.

Reprints and permissions information is available at https://www.irjse.in/reprints