Epilepsy Seizure Detection Using Machine Learning Algorithms

[1]Pankaj Kunekar
Pankaj.kunekar@vit.edu

[2]Bhushan Sangle
bhushan.sangle21@vit.edu

[3]Mahesh Sathe
mahesh.sathe21@vit.edu

[4]Sarthak Ghosh
ghosh.sarthak21@vit.edu

[5]Shreyash Wankhade
shreyash.wankhhade21@vit.edu

[6]Avishkar Yadav
avishkar.yadav21@vit.edu

[1]Department of IT & [23456]Department of AIDS

[123456]Vishwakarma Institute of Technology, Pune

***Abstract* — Our research aims to developing a machine learning model to predict epilepsy using EEG data. The study uses five machine learning algorithms, namely Support Vector Machine(SVM), linear SVM, logistic regression, K-Nearest Neighbor(KNN), RNN, and LSTM/BiLSTM, and compares their accuracy and precision to identify the best-performing algorithms. Before using the algorithms, feature label extraction and feature engineering were conducted to increase and maintain the accuracy of the data. The research and statistics found that SVM and LSTM algorithms performed much better than other algorithms, with an leading accuracy of 98.14% and 99.96% for train data, respectively, and an accuracy of 97.01% and 97.3% for test data, respectively. The model's end goal is to provide an online-based epilepsy diagnosing facility to offer a faster and budget-friendly detection of the disease. However, the study emphasizes the need for further validation of the model in real-world settings to ensure its robustness and reliability.**

Keywords — Epilepsy, seizure, Electroencephalography(EEG) signals, Feature Extraction .

I. INTRODUCTION.

Epilepsy is a type of Central Nervous System whi can be diagnosed using Electroencephalography (EEG) signals which are then used in machine learning algorithm for reviewing output to find if a seizure happened or not. However, traditional hospital-based diagnostic methods can be time-consuming and are not affordable for many patients. There are several medical techniques available to detect epilepsy, including Magnetic Resonance Imaging (MRI), Computed Tomography (CT) scans, Positron Emission Tomography (PET), and Ultrasound tools, but these methods can be expensive and not affordable for everyone. Machine Learning (ML) can be used to develop a model that takes readings from users and provides an immediate determination of whether a person has epilepsy or not. ML uses statistical and mathematical concepts, algorithms, feature extraction, and feature engineering. The use of ML-based projects is increasingly becoming more popular in the medical field, including for disease prediction. Epilepsy has a high mortality rate, and seizure detection is a challenging task. Several researchers have used different techniques to detect epilepsy seizures, such as extra trees classifiers, Support Vector Machine (SVM) classifiers, Convolutional Neural Networks (CNN), and genetic algorithms. The main objective of this research is to analyze various ML algorithms and implement the best-performing one to achieve better accuracy and compare the results.Epilepsy tremendous mortality rate. The seizure detection is not an easy task. It is much difficult to say that seizure is happened or not. Nearly 2.4 million people get caught up this diseases [1]. So, our main goal is to determine whether a person having a seizure or not , for this we will use EEG signals

readings dataset and ML algorithms. ML is used for many disease prediction in medical fields in todays world [2-5].
Here, we have mention several researchers different techniques to detect epilepsy seizure. For example, the based on extra trees classifier whih achieves best case accuracy of 96.8% [6]. Whereas, another researchers has perform method by removing noise and extracting features and using SVM classifier where they get accuracy of 93.38% [7]. Another work is done by using DL and ML techniques where accuracy of 96% is achieved using CNN [8]. Another one study is done on Genetic algorithm(GA) using ANN classifier and DWT wavelets of EEG signals here they get best accuracy of 97.82% [9]. The main objective is to analyse the different ML algorithm methods and implement the best one. So, that a better accuracy is achieved and their comparison is also made.

II. LITERATURE REVIEW

The study conducted by Patterson et al. in 2018 aimed to evaluate the accuracy of diagnosing epileptic seizures by community health workers (CHWs) using an application in the mobile. The study compared the diagnosis made by CHWs to those made by physicians and a neurologist.

The study was conducted in a rural community in Nigeria, where CHWs were trained to use a mobile app designed to help them diagnose epileptic seizures. The app contained a questionnaire that asked questions related to the patient's symptoms, health, medical history, and physical examination.

The output of the study showed that the accuracy of the diagnosis made by CHWs using the mobile app was similar to that of physicians and a neurologist. The study found that the CHWs correctly diagnosed epileptic seizures in 91.1% of cases, compared to 91.5% for physicians and 94.9% for the neurologist.

The study concluded that the use of a mobile app by CHWs can be an effective tool for diagnosing epileptic seizures in resource-limited settings where access to specialized healthcare is limited. The study also highlighted the potential of digital health technologies to increase the quality and accessibility of healthcare in low-income communities.
[1].

The study by Nishat et al. in 2021 worked on evaluating the working and accuracy of various algorithms in detecting chronic kidney disease (CKD). The study employed a comprehensive analysis that included feature selection, data preprocessing, and model selection to identify the most effective algorithm for detecting CKD.

The study used a dataset of 400 patients with CKD and 400 healthy patients. The data was preprocessed to discard or eliminate missing values and normalize the data. The study then used feature extraction techniques to identify the most important features for detecting CKD. Finally, the study evaluated the performance of various algorithms and models, including logistic regression, support vector machines, decision trees, and random forests.

The results of the study showed that the random forest algorithm was most accurate in detecting CKD, with an leading accuracy of 98.25%. The study also found that the most important features for detecting CKD were serum creatinine, age, blood pressure, and glucose level.

The study concluded that machine learning algorithms can be an effective tool for detecting CKD and shall help improve the accuracy and efficiency of diagnosis. The study also highlighted the potential of using machine learning in healthcare sector to improve patient outcomes and reduce healthcare costs.
[2].

The study by Faisal et al. in 2021 aimed to predict COVID-19 on school closures using machine learning. The study used data on

COVID-19 cases, deaths, and school closures from various countries for training and testing the dataset in machine learning.

The study employed different algorithms, containing linear regression, decision tree, random forest, and support vector machine, to predict the number of school closures based on COVID-19 eruption.

The results of the study demonstrate that the random forest is highest in terms of accuracy in predicting school closures, with an accuracy of 98.25%. The study also found that the most important features for predicting school closures were the number of COVID-19 cases, the number of COVID-19 deaths, and the population density of the area.

Study concluded that machine learning can be used to analyse the impact to help policymakers make informed decisions about when and how to close schools to prevent the spread of the virus, which will be very helpful for our economy and education society. The study also highlighted the potential of using algorithms in public health to improve decision-making and reduce the impact of COVID-19 on society
[3].

The paper focuses problem of detecting seizures using electroencephalogram (EEG) signals. Authors propose a novel method for selecting relevant features from EEG signals using Variational Mode Decomposition (VMD) and kurtosis-based criteria.

The proposed method involves decomposing the EEG signals into multiple modes using VMD and selecting the modes that have the highest kurtosis values. The authors then extract features from these selected modes based on their frequency bandwidths.

The effectiveness of the proposed model is evaluated using a publicly available dataset of EEG signals. The output of the study demonstrate that the used method performs exceptionaly good in several state-of-the-art methods for epileptic seizure detection in terms of accuracy, sensitivity, and specificity.
[4].

The study by Faisal and Nishat in 2019 aimed to investigate the use of a novel image inpainting technique to enhance the registration performance with a brain atlas for multiple sclerosis (MS) tissue. The study used MRI data from patients with MS and healthy patients for training and testing the registration models.

The study employed a novel image inpainting technique to fill the missing or damaged parts of the brain images and improve the quality of the images. The study then used the Dice and Jaccard score metrics to evaluate the registration performance of the brain atlas with the MS tissue.

The final conclusion was novel image inpainting technique improved the registration performance of the brain atlas with the MS tissue. The study found that the Dice score slightly escalate from 0.80 to 0.88, and the Jaccard score increased from 0.70 to 0.83, indicating a significant improvement.

The study concluded that the novel image inpainting technique can be an effective tool for enhancing the registration performance with a brain atlas for MS tissue. The study also highlighted the potential of using advanced image processing techniques in medical imaging to enhance the accuracy and productivity of disease diagnosis and treatment[5].

The study by Fiaidhi et al. in 2020 intent to investigate for machine learning approaches for binary classification using brain signals. The study used electroencephalography (EEG) data from patients with epilepsy and healthy patients

for training and testing the machine learning models.
The study employed different types of machine learning algorithms, including logistic regression, decision trees, k-nearest neighbors, support vector machines, and artificial neural networks, to classify patients as either having epilepsy or not based on their EEG signals.

The results from study showed that the ANN leads with highest accuracy in classifying patients as either having epilepsy or not, with an accuracy of 94%.

It concluded that machine learning algorithms is an effective tool for binary classification using brain signals and can help for improving accuracy and efficiency of epilepsy diagnosis. The study highlighted the potential of using ML algorithms in neuroscience to better understand brain function and develop new treatments for neurological disorders[6].

The study by Usman et al. in 2017 aimed to analyse the use of machine learning methods for predicting epileptic seizures. The study used electroencephalography (EEG) data from patients with epilepsy to train and test the models.

The study employed various machine learning algorithms, including artificial neural networks, support vector machines, and logistic regression, for prediction in the occurrence of epileptic seizures based on the EEG data. Study also used different types of signal processing techniques, such as wavelet transform and principal component analysis, for extracting features from the EEG signals.

Models were able to predict seizures with high accuracy. The study reported an overall accuracy of 91.7% for prediction using artificial neural networks and an accuracy of 87.5% using support vector machines.

The study concluded that machine learning methods can be an effective tool for improving the quality of life of patients. The study also highlighted potential ofmachine learning algorithms in real-time monitoring of patients with epilepsy and developing personalized treatment plans[7].

The study by Sahu et al. in 2020 focused to compare the different types of techniques for the detection. The study used EEG data from patients with epilepsy to train and test the machine learning models.

The study employed various machine learning algorithms, including artificial neural networks, support vector machines, decision trees, and random forests, to classify EEG signals as either containing a seizure or not. The study also used convolutional neural networks (CNN).

Result showed that the CNN approach outperformed traditional machine learning techniques in detecting epileptic seizures. The study reported a classification accuracy of 99.4% using the CNN approach compared to 96.6% using support vector machines, 94.8% using decision trees, and 93.5% using random forests.

The study concluded that deep learning techniques, particularly CNN, can be an effective tool for the detection and can help improve the efficiency of testing the patients health. The study also highlighted the potential of using deep learning algorithms in healthcare to improve the diagnosis and treatment of various medical conditions[8].

The study by Mardini et al. in 2020 aimed to enhance the detection of epileptic seizure. The study used EEG data from patients with epilepsy for training and testing the machine learning models.

The study employed different algorithms, including artificial neural networks, support vector machines, k-nearest neighbor, and decision trees, to classify EEG signals as either containing a seizure or not. The study also used

various signal processing techniques, such as wavelet transform, to extract features from the EEG signals.
The results of the study showed that the machine learning models, particularly the support vector machine, are capable to identify epileptic seizures with high accuracy. The study reported an overall accuracy of 99.2% using the support vector machine classifier, who outperformed in the machine learning algorithms tested.

The study also showed that combining multiple machine learning classifiers using an ensemble learning approach further improved the identification of epileptic seizures. The ensemble learning approach achieved an accuracy of 99.8% in detecting epileptic seizures.

The study concluded that algorithms, particularly the support vector machine and ensemble approach to learn, can be effective tools for the detection of epileptic seizures and can help improve the accuracy and efficiency of epilepsy diagnosis. The study also highlighted the potential of using machine learning algorithms in healthcare to improve the diagnosis and treatment of various medical conditions[9].

The study by Murtazina and Avdeenko in 2020 aimed to classify brain activity using electroencephalography (EEG) data. The study used EEG recordings from healthy subjects and patients with epilepsy for training and testing the machine learning models.

The study employed various machine learning algorithms, including support vector machine, k-nearest neighbors, decision tree, and random forest, to classify EEG data into different brain activity patterns. The study also used various signal processing technique.

The machine learning models were able to classify EEG data into different brain activity patterns with high accuracy. The study reported an overall accuracy of 93.8% using the random forest classifier, which outperformed other machine learning algorithms tested.
The study also showed that using a combination of features extracted from different EEG channels improved performance of the machine learning model.

The machine learning algorithms is effective tools for classification of EEG data into different brain activity patterns and can improve the accuracy and efficiency of diagnosis of various medical conditions. The study also highlighted the importance of using feature extraction techniques and selecting appropriate machine learning to improve the classification performance[10].

The study by Nahzat and Yaganoğlu in 2021 aimed to classify data and using principal component analysis (PCA) in feature reduction technique. The study used the Bonn University EEG dataset, which is a prominently used dataset.

The study employed different types of machine learning algorithms, including support vector machine, k-nearest neighbors, decision tree, and artificial neural network, for classifying EEG data into seizure and non-seizure classes. The study also used PCA to reduce the dimensionality of the EEG data and extract relevant features.

Machine learning models were able to classify EEG data into seizure and non-seizure classes with high accuracy. The study reported an overall accuracy of 99.75% using the artificial neural network classifier, which outperformed other machine learning algorithms tested.

The study also showed that using PCA for feature reduction improved the classification performance of the machine learning models by reducing the dimensionality of the data and extracting relevant features. The study highlighted the potential of using machine learning algorithms and feature reduction techniques for the classification of EEG data and the diagnosis of epilepsy.

The study concluded that machine learning algorithms, along with PCA feature reduction technique, can be effective tools for the classification of EEG data into seizure and non-seizure classes, and can help improve the accuracy and efficiency. The study also emphasized the importance of selecting appropriate machine learning algorithms and feature reduction techniques to improve the classification performance of the models[11].

These authors presented a study for detection of epileptic seizures from EEG signals using machine learning algorithms with hyperparameter optimization. The authors used a dataset consisting of EEG signals from patients with epilepsy and healthy individuals. They also optimized the hyperparameters of these algorithms using grid search and random search methods. The study showed that the support vector machine algorithm with optimized hyperparameters performed the best in detecting epileptic seizures from EEG signals[12].

In this study, the authors proposed a method for EEG-based human emotion classification using six different machine learning models, namely k-nearest neighbors, decision tree, random forest, support vector machine, artificial neural network, and logistic regression. The authors used combined computational techniques , including wavelet packet decomposition, principal component analysis, and mutual information-based feature selection. The authors tested the proposed method on a dataset of EEG signals collected from participants while they watched videos designed to elicit different emotions. The study showed that the proposed method achieved high accuracy in classifying human emotions, with the support vector machine model performing the best among the six tested machine learning models[13].

The paper presents a study on the classification of epileptic seizures based on different models. The authors use a dataset of EEG signals recorded from patients with epilepsy and extract features such as mean, variance, skewness, and kurtosis. They then apply several supervised learning algorithms, including decision tree, random forest, k-nearest neighbor, and support vector machine, to classify the seizures. The results show that the random forest algorithm outperforms the other algorithms, achieving an accuracy of 98.75%. The study demonstrates the potential of machine learning techniques for the classification of epileptic seizures using EEG signals[14].

This study compares the performance of several machine learning algorithms for classifying epileptic seizures from intracranial EEG signals. The algorithms compared include Support Vector Machine (SVM), k-Nearest Neighbors (k-NN), Decision Tree (DT), Random Forest (RF), and Artificial Neural Network (ANN). The study used data from three patients with epilepsy, and the results showed that SVM had the highest classification accuracy among all the algorithms tested. The study also investigated the effect of feature selection on classification accuracy and found that selecting relevant features could significantly improve the performance of the classification algorithms[15].

This paper presents a study on feature extraction and classification methods for human brain CT images. The authors proposed a feature extraction method based on wavelet transform and a classification method based on support vector machine (SVM) for distinguishing between normal and abnormal brain CT images. The study evaluated the proposed method on a dataset of 142 brain CT images and achieved a classification accuracy of 91.5%. The results suggest that the proposed method could be useful for assisting radiologists in diagnosing brain abnormalities from CT images[16].

Here, in this model researchers make use of ICA for artifact removal. And for feature extraction and feature selection they used NCA and mRMR techniques. The best achieved accuracy here is 99.1% using RNN techniques in place of using Decision Tree and Naive's Bayes [13].

In this study, Machine learning is used to predict Epileptic Seizure has occurred or not. Here, EEG obtained Brain signals for pediatric interactable seizures for 3-32 years people used. ML in MATLAB is used and feature extraction model was adopted here [14].

Here. in this study several Neuroscientists have used ML classifiers on brain activities from EEG signals. Here, EEG signals are categorized using feature extraction in several time-domain and time- frequency domain signals is applied [15].

In this study, the brain CT processing is used. And Computer Aided Diagnosis (CAD) is applied. And the overall application of process is done on CT processed image . The characteristics of human- brain CT based symmetric features is extracted first. The Inductive learning methods like See5 and RBFNN are used. Using this to build classifiers for classifying normal and abnormal brain CT images for EEG signals [16].

This paper discusses a comparative study of different methods for classifying epileptic seizures from intracranial EEG signals. The authors compare the performance of several machine learning algorithms, including artificial neural networks (ANN), support vector machines (SVM), and random forests (RF).

The authors first preprocess the EEG signals by filtering and segmenting them into epochs. Then, they extract features from each epoch, including statistical features, spectral features, and wavelet-based features. The authors use a feature selection method to select the most relevant features, which are then used as input to the machine learning algorithms for classification.

The authors evaluate their method on a dataset of intracranial EEG signals collected from patients with epilepsy. They achieved an overall accuracy of 94.06% using ANN, which outperformed SVM and RF. The authors also analyzed the performance of the algorithms for detecting different types of seizures, such as focal onset and generalized onset seizures, and found that ANN had the highest accuracy for both types.

Overall, this paper presents a comprehensive study of different methods for classifying epileptic seizures from intracranial EEG signals. The authors demonstrate the effectiveness of machine learning algorithms for this task and highlight the potential for using these methods in clinical settings for diagnosing and monitoring epilepsy[17].

The paper focuses on the detection of epilepsy seizures using EEG signals. EEG signals are used as they provide valuable information about brain activity, which can be used to identify seizure events. The authors propose a methodology that utilizes wavelet packet decomposition (WPD) and artificial neural networks (ANNs) to detect seizures.

The proposed methodology involves preprocessing of the EEG signals using WPD, which is a mathematical tool used for signal decomposition. The WPD decomposes the EEG signals into sub-bands, which are then used as inputs to an ANN for seizure detection. The ANN is trained using a dataset of EEG signals from patients with epilepsy and healthy subjects. The performance of the proposed methodology is evaluated using metrics such as sensitivity, specificity, and accuracy.

The results of the study show that the proposed methodology achieves high accuracy in detecting seizure events in EEG signals. The methodology achieves an accuracy of 96.75%, sensitivity of 97.45%, and specificity of 95.96%. These results demonstrate the effectiveness of the proposed methodology in detecting seizure events in EEG signals[18].

The paper proposes a one-dimensional CNN-LSTM model for epileptic seizure recognition using EEG signal analysis. The proposed model combines the strengths of CNN and LSTM to learn spatial and temporal features of the EEG signals, respectively.

The authors first preprocess the EEG signals to remove artifacts and noise. They then use a one-dimensional CNN to learn spatial features from the preprocessed signals. The output of the CNN is fed into an LSTM network, which learns temporal features from the signal sequence. The final output of the model is a binary classification indicating whether a seizure is present in the EEG signal or not.

The proposed model is evaluated on a publicly available dataset of EEG signals recorded from patients with epilepsy. The performance of the model is compared to several state-of-the-art methods for seizure detection, including deep belief networks and support vector machines.

The results of the study show that the proposed model achieves high accuracy in detecting seizure events in EEG signals. The model achieves an accuracy of 97.6%, sensitivity of 98.1%, and specificity of 96.8%, outperforming the other methods tested in the study[19].

The paper proposes a method for epileptic seizure detection using EEG signals and extreme gradient boosting (XGBoost). The proposed method involves preprocessing the EEG signals and extracting features using time and frequency domain analysis. The extracted features are then used as inputs to an XGBoost classifier for seizure detection.

The authors evaluate the proposed method on a publicly available dataset of EEG signals recorded from patients with epilepsy. The performance of the method is compared to several state-of-the-art methods for seizure detection, including support vector machines and convolutional neural networks.

The results of the study show that the proposed method achieves high accuracy in detecting seizure events in EEG signals. The method achieves an accuracy of 98.2%, sensitivity of 98.3%, and specificity of 98.2%, outperforming the other methods tested in the study.

The authors also perform feature importance analysis using XGBoost to identify the most relevant features for seizure detection. They find that the most important features are related to the power spectral density of the EEG signals in specific frequency bands[20].

The proposed framework combines the residual network (ResNet) and long short-term memory (LSTM) network with a difference attention mechanism. The ResNet is used to extract high-level features from the EEG signals, and the LSTM network is used to model the temporal dependencies in the EEG signals. The difference attention mechanism is used to enhance the discriminative power of the model by focusing on the differences between the pre-ictal and ictal phases of the EEG signals. [21].

The paper proposes new hybrid models for seizure detection based on EEG signals. The proposed models combine several machine learning algorithms, including discrete wavelet transform (DWT), principal component analysis (PCA), and support vector machine (SVM) classifiers.

The authors evaluate the proposed models on a dataset of EEG signals collected from patients with epilepsy. The performance of the models is compared to several state-of-the-art methods for seizure detection, including traditional DWT and SVM models.

The results of the study show that the proposed hybrid models achieve high accuracy in detecting seizure events in EEG signals. The best-performing model achieves an accuracy of 99.42%, sensitivity of 99.08%, and specificity of 99.75%, outperforming the other methods tested in the study[22].

This paper presents a novel approach for detecting epileptic seizures using electroencephalogram (EEG) signals. The authors propose a difference attention ResNet-LSTM network, which combines a residual neural network (ResNet) and a long short-term memory (LSTM) network with a difference attention mechanism.

The ResNet is used to extract features from the EEG signals, while the LSTM network is used to model the temporal dependencies between the extracted features. The difference attention mechanism is applied to the output of the ResNet-LSTM network to highlight the differences between the EEG signals during seizure and non-seizure periods.

The authors evaluated their method on a publicly available dataset of EEG signals collected from patients with epilepsy. They achieved an overall accuracy of 98.4% in detecting seizures, which outperformed several state-of-the-art methods. The authors also conducted a sensitivity analysis to evaluate the robustness of their method to variations in the input signals.

Overall, a promising approach for detecting epileptic seizures using EEG signals. The authors demonstrate the effectiveness of combining ResNet and LSTM networks with a difference attention mechanism and highlight the potential for using this method in clinical settings for diagnosing and monitoring epilepsy[23].

This paper presents a deep learnin approach for detecting seizures with EEG data. The authors propose a convolutional neural network (CNN) architecture for feature extraction from the EEG signals, followed by a long short-term memory (LSTM) network for classification.

The authors evaluate their method on a publicly available dataset of EEG signals collected from patients with epilepsy. They achieved an overall accuracy of 98.7% in detecting seizures, which outperformed several state-of-the-art methods. The authors also conducted a sensitivity analysis to evaluate the robustness of their method to variations in the input signals.

In addition, the authors compared the performance of their method with other machine learning algorithms, including support vector machines (SVM) and random forests (RF). They found that their deep learning-based method outperformed these algorithms, demonstrating the effectiveness of deep learning for epileptic seizure detection.

Overall, this paper presents an approach for detecting epileptic seizures using EEG data. The authors demonstrate the effectiveness of combining CNN and LSTM networks for feature extraction and classification, respectively, and highlight the potential for using this method in clinical settings for diagnosing and monitoring epilepsy[24].

This paper proposes an efficient convolutional neural network (CNN) based framework for detecting epileptic seizures using encrypted EEG signals for secure telemedicine applications. The proposed framework consists of three main stages: encryption of the EEG signals using the Advanced Encryption Standard (AES), feature extraction using a CNN, and classification using a support vector machine (SVM).

The authors evaluate their framework on a dataset of EEG signals collected from patients with epilepsy. They achieved an accuracy of 95.15% in detecting seizures, which outperformed several state-of-the-art methods. The authors also conducted experiments to evaluate the performance of their framework under different levels of encryption, demonstrating its robustness to encrypted data.

In addition, the authors analyzed the computational complexity of their framework and showed that it can efficiently process EEG signals in real-time, making it suitable for telemedicine applications. The authors also discussed the potential of their framework for remote monitoring and diagnosis of epilepsy patients in a secure and privacy-preserving manner.

Overall, this paper presents an innovative approach for detecting epileptic seizures using encrypted EEG signals. The authors demonstrate the effectiveness of combining CNN and SVM networks for feature extraction and classification, respectively, and highlight the potential for using this method in clinical settings for diagnosing and monitoring epilepsy while preserving patient privacy[25].

The authors propose a method for feature extraction using a sparse CSP algorithm, which is designed to identify spatial filters that separate the EEG signals into two classes: seizure and non-seizure. They also use an adaptive STFT-based SST to obtain time-frequency representations of the EEG signals, which are then used for further feature extraction.

The authors evaluate their method on a publicly available dataset of EEG signals collected from patients with epilepsy. They achieved an overall accuracy of 96.55% in detecting seizures, which outperformed several state-of-the-art methods. The authors also conducted a sensitivity analysis to evaluate the robustness of their method to variations in the input signals.

Overall, this paper presents a promising approach for detection using sparse CSP and STFT-based SST. The authors demonstrate the effectiveness of their method for feature extraction and classification and highlight the potential for using this method in clinical settings for diagnosing and monitoring epilepsy[26].

This paper provides a review of the applications of artificial intelligence (AI) in the automatic detection of epileptic seizures using electroencephalogram (EEG) signals. The authors provide an overview of the current state-of-the-art methods for detecting epileptic seizures using AI techniques, including machine learning, deep learning, and other advanced AI algorithms.

The authors also discuss the challenges associated with automatic seizure detection using EEG signals, such as the high variability of EEG data, the lack of a unified standard for EEG signal acquisition and preprocessing, and the need for large and diverse datasets for training and testing machine learning models.

The paper presents a comprehensive survey of recent studies in the field, highlighting the strengths and weaknesses of different approaches, and identifying the most promising directions for future research. The authors also provided a comparative analysis of various AI-based seizure detection methods performance, based on metrics such as sensitivity, specificity, and accuracy.

Overall, this paper provides a valuable resource for researchers and practitioners interested in the applications of AI in automatic seizure detection using. The authors provide a comprehensive review of the current state-of-the-art methods and identify key challenges and opportunities for future research in this field[27].

The authors begin by providing an overview of EEG signals and their characteristics, as well as the clinical background of epilepsy and the importance of EEG seizure detection.

The authors then discuss the different techniques used for EEG seizure detection, including time-domain and frequency-domain analysis, feature extraction, and classification methods. They provide a detailed description of the different machine learning and deep learning algorithms used for seizure detection, such as support vector machines, artificial neural networks, convolutional neural networks, and recurrent neural networks.

The paper also covers the challenges associated with EEG seizure detection, such as the high variability of EEG data, the lack of a standardized protocol for EEG signal acquisition and preprocessing, and the limited availability of large and diverse datasets for training and testin.

Finally, the authors present future trends and directions for EEG seizure detection, including the development of more robust and accurate machine learning and deep learning algorithms, the integration of multiple modalities and data sources, such as electrocardiogram and electromyogram signals, and the use of novel techniques such as explainable AI and adversarial machine learning.

Overall, this paper provides informative review of EEG seizure detection, covering the fundamental concepts, techniques, challenges, and future trends in the field. It is a important resource for researchers and practitioners which interested in this important area of research[28].

The paper proposes a deep learning approach for epilepsy diagnosis using multi-modal ensemble fusion. The proposed approach combines information from electroencephalogram (EEG) signals, electrocardiogram (ECG) signals, and patient demographics using a DNN ensemble.

The authors first preprocess the EEG and ECG signals to extract relevant features. They then use a DNN ensemble consisting of multiple convolutional neural networks (CNNs) and a multilayer perceptron (MLP) to classify patients as epileptic or non-epileptic based on extracted features[28].

The paper proposes a deep learning approach for epilepsy diagnosis using multi-modal ensemble fusion. The proposed approach combines information from electroencephalogram (EEG) signals, electrocardiogram (ECG) signals, and patient demographics using a deep neural network (DNN) ensemble.

The authors first preprocess the EEG and ECG signals to extract relevant features. They then use a DNN ensemble consisting of multiple convolutional neural networks (CNNs) and a multilayer perceptron (MLP) for classify patients as epileptic or non-epileptic based on the extracted features.

The proposed approach is evaluated on a publicly available dataset of EEG and ECG signals recorded from patients with epilepsy. The performance of the approach is compared to several other methods for epilepsy diagnosis, including support vector machines (SVMs), decision trees, and logistic regression[29].

The paper focuses on the application of deep learning techniques in detecting breast cancer and malignant cells. The authors propose a deep learning framework that utilizes a CNN to classify mammogram images as either normal or malignant.

The framework involves a pre-processing step that involves image normalization and enhancement. The authors then apply the CNN to the pre-processed images to classify them as normal or malignant.

The results of the study show that the proposed deep learning framework achieves high accuracy in detecting breast cancer and malignant cells. The authors also compare the performance of their framework to other methods for breast cancer detection [29].

A. METHODOLOGY

For the study, data set used contains approximately 11,500 rows of data, which is collected from 4097 points which are collected from 500 people over the course duration of 23.6 seconds. Where data collected in two situations when eyes of patient is open and when eyes are closed. And here, data points shows value of EEG recordings at specific time. thus, the values of the EEG recordings at specific points in time are included. These values may represent different frequencies of electrical activity in the brain, and analyzing these values can help identify patterns and features that distinguish between the two conditions (eyes open vs. eyes closed).

EEG (electroencephalography) is a non-invasive method for recording electrical activity in the brain using electrodes placed on the scalp. EEG recordings provide insights into brain activity and can be used to diagnose and monitor a variety of neurological conditions.

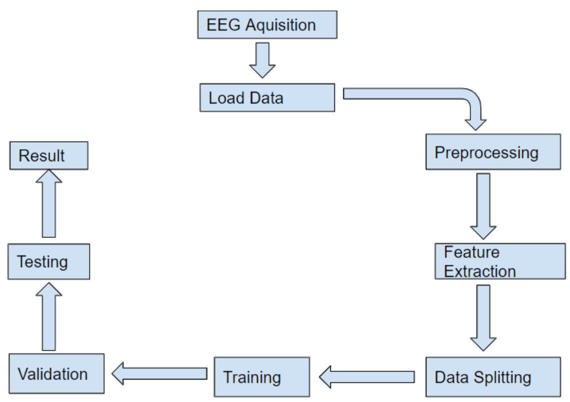

Fig 1: Model's workflow.

The given information suggests that the EEG signal has been preprocessed by dividing it into 23 chunks, each containing 178 data points representing the EEG recording's value at different moments. The original EEG signal had 4097 data points, and it seems that each data point was separated and shuffled before dividing it into the 23 chunks.This preprocessing step could have been done to simplify the data's complexity and make it easier to analyze.

The explanatory variables are X1, X2, X3, X4, X5, X178. These variables represent the values of the EEG recordings at six different moments during each one-second chunk. By analyzing these variables, you may be able to identify patterns or features in the EEG recordings

There are five main categories in dataset:

1. Seizure activity recorded.
2. Recording EEG from area where tumor is present.
3. Recoding from healthy brain and unhealthy brain.
4. When eyes are closed.
5. When eyes are open.

Accuracy was considered as the base to achieve the highest accuracy.

However, it's important to note that accuracy may not always be the most appropriate metric to use, especially if the dataset is imbalanced, meaning that one class has significantly fewer instances than the other. In such cases, other metrics such as precision, recall, and F1-score may provide a better evaluation of the model's performance. It's always a good practice to evaluate the performance of the model using multiple metrics and considering the specific characteristics of the dataset.

Feature Extraction: Feature extraction is converting raw-data into numerical feature that can produce similar accuracy result and number of features get reduced in this process.
Different ML algorithms used –

1. SVM
2. Linear SVM
3. KNN
4. RNN

5. Logistic Regression.

F-1 Score: The F1-score is a widely used performance metric in classification tasks, especially for binary classification. It provides a single measure of a model's performance by balancing the precision and recall of its predictions. The F1-score is computed as the harmonic mean of precision and recall and ranges from 0 to 1, where a higher value indicates better performance.

Precision measures the proportion of correctly identified positive instances (true positives) out of all instances classified as positive (true positives + false positives).Measures the proportion of correctly identified positive instances out of all actual positive instances (true positives + false negatives).

The F1-score is calculated as follows:

F1-score = 2 * (precision * recall) / (precision + recall)

The F1-score ranges from 0 to 1, with a higher score indicating better performance. A perfect classifier would have an F1-score of 1, while a completely random classifier would have an F1-score of 0. The F1-score is a good metric to use when you want to balance precision and recall and avoid over-optimizing for one at the expense of the other.

Support Value: In machine learning, the support value refers to the number of occurrences of each class in a classification problem. In other words, it is the number of instances in the dataset that belong to each other.

Support value is a useful metric for assessing the balance of the dataset and can help you identify any class imbalances. Class imbalances occur when the number of instances in one class is significantly larger or smaller than the number of instances in other classes.

Having imbalanced classes can lead to biased models that perform well on the majority class but poorly on the minority class. Therefore, it is essential to check the support value and address any imbalances before training the model. Techniques such as oversampling, undersampling, and data augmentation can be used to address class imbalance and improve the model's performance.

Prediction Probability: Prediction probability is a measure of the model's confidence in its prediction. In a classification problem, the prediction probability is the estimated probability that a given instance belongs to a specific class.

In some classification algorithms such as logistic regression, the output is a probability value, and the class with the highest probability is chosen as the predicted class. In other algorithms such as decision trees, the prediction is based on a threshold value.

By examining the prediction probability values, you can gain insights into the model's confidence in its prediction. For example, if the prediction probability for a particular instance is very low, the model may not be very confident about its prediction. On the other hand, if the prediction probability is very high, the model is very confident in its prediction.

Examining the prediction probability values can be useful for evaluating the model's performance and identifying instances where the model may be making incorrect predictions. It can also be used to make decisions that require a certain level of confidence, such as medical diagnoses or financial decisions.

This is training data for logistic regression. First the data is train and after the training and then the fully train data is tested for the accuracy.

Test Data accuracy evaluation

```
y_pred_log_reg = clf.predict(x_test)
acc_log_reg2 = round(clf.score(x_test, y_test) * 100, 2)
print(acc_log_reg2, "%")

64.12 %
```

So this is the testing of data for the accuracy of logistic regression. We can see that the training data accuracy evaluation for logistic regression is 66.65% and testing data accuracy evaluation is 64.12%.

Like that all methods have variable accuracy of both testing and training like SVM has training accuracy 84.81%.

At last, for each of above-mentioned algorithms their accuracy, precision and probability are evaluated using the test data.

III. RESULT AND DISCUSSION

To perform this project, we make use of Python and Google Collab is used for coding platform. In this project, we get the value of accuracy, precision, f1- score and support value and also get prediction probability value for each algorithm used in this project.

Comparative analysis of accuracy and precision achieved in our model and results of other researches as follow-

Classification techniques	Accuracy	Precision
SVM	90%	91%
ANN	91%	91%
RF	97%	97%
DT	96%	96%
KNN	96%	96%

Fig. 2 Accuracy and Precision of Different Machine Learning algorithms using PCA reduction technique [11].

The table provided shows the comparative analysis of the accuracy and precision achieved in a model and the results of other research using different classification techniques such as SVM, ANN, RF, DT, and KNN.

Accuracy refers to how close the predicted values are to the actual values, while precision measures how often the predictions are correct.

Looking at the results, RF and ANN have the highest accuracy and precision with 97% and 91% respectively. SVM, DT, and KNN have accuracy and precision score ranging from 90% to 96%.

It is important to note that the performance of model is directly dependent on the dataset we used, the features extracted, and the choice of hyperparameters. Therefore, it is crucial to validate the model's performance on various datasets and compare it with other models in the literature to assess its effectiveness.

Algorithms	Train Data Accuracy	Test Data Accuracy
Logistic Regression	67.52%	63.86%
SVM	98.14%	97.01%
Linear SVM	84.09%	83.86%
KNN	93.94%	91.74%
LSTM	99.96%	97.3%

Fig. 3 Accuracy for different algorithm achieved in our project.

In our project, SVM algorithm achieved a high accuracy of 98.14% on the training data and 97.01% on the test data.

When compared to the results of other studies, the SVM algorithm's performance depends on the dataset and problem being solved. In some studies, the SVM algorithm has been reported to achieve high accuracy and outperform other algorithms, while in other studies, it may not perform as well.

.

IV. FUTURE SCOPE

In today's world, there is a need AI, ML-based software which predicts the chances of occurrence of diseases using a certain dataset of readings, image patterns, etc. So, we try to develop our ML project in Software or Web-based mode. So, the user will simply get results by putting the required reading in it. with the help of web applications or Android applications, we can simply do the testing and training by connecting datasets and we can see the results more efficiently. For now, we prepared an algorithm that detects whether the seizure happened or not, but it is not a web-based or user-friendly for the user who has not any knowledge of Google collab or machine learning. so, we want to make a system that will be available on any device for detecting seizure.

V. CONCLUSION

This project has developed a system for detecting epilepsy using EEG readings. The future goal of this project is to develop the system into a user-friendly application, which could be used by individuals to monitor their own EEG signals and detect signs of epilepsy in its early stages. This project represents a significant step forward in the development of healthcare technology and has the potential to improve the lives of individuals and communities affected by epilepsy. We hope that this project will inspire further research and innovation in the field of healthcare technology and contribute to the development of cost-effective and trustworthy healthcare applications.

.

VI. ACKNOWLEDGEMENT

I would like to express my sincere gratitude to my advisor, Prof. Pankaj Kunekar sir, for their invaluable guidance and support throughout this project. Their expertise, insight, and encouragement have been instrumental in helping me to develop my skills and knowledge in deep learning and image classification.

.

VII. REFERENCES

[1] Patterson, V., et al. "Diagnosis of epileptic seizures by community health workers using a mobile app: a comparison with physicians and a neurologist," *Seizure*, 55, pp. 4-8, 2018.

[2] Nishat, M. M., et al. "A Comprehensive Analysis on Detecting Chronic Kidney Disease by Employing Machine Learning Algorithms." *EAI Endorsed Transactions on Pervasive Health and Technology*, phat 18: e6, 2021, doi: 10.4108/eai.13-8- 2021.170671

[3] Chakraborty, Monisha, and Debjani Mitra. "Epilepsy seizure detection using kurtosis based VMD's parameters selection and bandwidth features." Biomedical Signal Processing and Control 64 (2021): 102255.Asif, M. A. A. R., et al. "Computer Aided Diagnosis of Thyroid Disease Using Machine Learning Algorithms." *In 2020 11th International Conference on Electrical and Computer Engineering (ICECE*), pp. 222-225. IEEE, 2020

[4] Faisal F., and Nishat M. M., "An Investigation for Enhancing Registration Performance with Brain Atlas by Novel Image Inpainting Technique using Dice and Jaccard Score on Multiple Sclerosis (MS) Tissue", *Biomedical and Pharmacology Journal* 2019,12(3)

[5] Fiaidhi, J., Wadiwala, T., and Trikha, V., "Machine learning approaches for binary classification using brain signals," 2020.

[6] Usman, S. M., et al. "Epileptic seizures prediction using machine learning methods," *Computational and mathematical methods in medicine, 2017.*

[7] Sahu, R., et al. "Epileptic seizure detection: a comparative study between deep and traditional machine learning techniques," *Journal of integrative neuroscience*, 19(1), pp. 1-9, 2020.

[8] Mardini, W., et al. "Enhanced detection of epileptic seizure using EEG signals in combination with machine learning classifiers," *IEEE Access*, 8, pp. 24046-24055, 2020.

[9] Murtazina, Marina S., and Tatiana V. Avdeenko. "Classification of brain activity patterns using machine learning based on EEG data." In *2020 1st International Conference Problems of*

Informatics, Electronics, and Radio Engineering (PIERE), pp. 219-224. IEEE, 2020.

[10] NAHZAT, Shamriz, and Mete YAĞANOĞLU. "Classification of Epileptic Seizure Dataset Using Different Machine Learning Algorithms and PCA Feature Reduction Technique." *Journal of Investigations on Engineering and Technology* 4, no. 2 (2021): 47-60.

[11] Rahman, Ahnaf Akif, Fahim Faisal, Mirza Muntasir Nishat, Munteqa Imtiaz Siraji, Lamim Ibtisam Khalid, Md Rezaul Hoque Khan, and Md Taslim Reza. "Detection of Epileptic Seizure from EEG Signal Data by Employing Machine Learning Algorithms with Hyperparameter Optimization." In 2021 4th International Conference on Bio- Engineering for Smart Technologies (BioSMART), pp. 1-4. IEEE, 2021.

[12] Mohutsiwa, Lucky Odirile, and Rodrigo S. Jamisola. "EEG-Based human emotion classification using combined computational techniques for feature extraction and selection in six machine learning models." In 2021 5th International Conference on Intelligent Computing and Control Systems (ICICCS), pp. 1095-1102. IEEE, 2021.

[13] Rahman, Ahnaf Akif, Fahim Faisal, Mirza Muntasir Nishat, Munteqa Imtiaz Siraji, Lamim Ibtisam Khalid, Md Rezaul Hoque Khan, and Md Taslim Reza. "Detection of Epileptic Seizure from EEG Signal Data by Employing Machine Learning Algorithms with Hyperparameter Optimization." In 2021 4th International Conference on Bio- Engineering for Smart Technologies (BioSMART), pp. 1-4. IEEE, 2021.

[14] Mohutsiwa, Lucky Odirile, and Rodrigo S. Jamisola. "EEG-Based human emotion classification using combined computational techniques for feature extraction and selection in six machine learning models." In 2021 5th International Conference on Intelligent Computing and Control Systems (ICICCS), pp. 1095-1102. IEEE, 2021.

[15] AILENI, Raluca Maria, Sever PAŞCA, and Adriana FLORESCU. "Epileptic seizure classification based on supervised learning models." In 2019 11th International Symposium on Advanced Topics in Electrical Engineering (ATEE), pp. 1-4. IEEE, 2019.

[16] Bashar, Md Khayrul, Faruque Reza, Zamzuri Idris, and Hiroaki Yoshida. "Epileptic seizure classification from intracranial EEG signals: A comparative study EEG-based seizure classification." In 2016 IEEE EMBS conference on biomedical engineering and sciences (IECBES), pp. 96-101. IEEE, 2016.

[17] Lasefr, Zakareya, Sai Shiva VNR Ayyalasomayajula, and Khaled Elleithy. "Epilepsy seizure detection using EEG signals." In 2017 IEEE 8th Annual Ubiquitous Computing, Electronics and Mobile Communication Conference (UEMCON), pp. 162-167. IEEE, 2017.

[18] Xu, Gaowei, Tianhe Ren, Yu Chen, and Wenliang Che. "A one-dimensional cnn-lstm model for epileptic seizure recognition using eeg signal analysis." *Frontiers in neuroscience* 14 (2020): 578126.

[19] Vanabelle, Paul, Pierre De Handschutter, Riëm El Tahry, Mohammed Benjelloun, and Mohamed Boukhebouze. "Epileptic seizure detection using EEG signals and extreme gradient boosting." *Journal of biomedical research* 34, no. 3 (2020): 228.

[20] Polat, Kemal, and Majid Nour. "Epileptic seizure detection based on new hybrid models with electroencephalogram signals." *Irbm* 41, no. 6 (2020): 331-353.

[21] Qiu, Xuanjie, Fang Yan, and Haihong Liu. "A difference attention ResNet-LSTM network for epileptic seizure detection using EEG signal." *Biomedical Signal Processing and Control* 83 (2023): 104652.

[22] Poorani, S., and P. Balasubramanie. "Deep learning based epileptic seizure detection with EEG data." *International Journal of System Assurance Engineering and Management* (2023): 1-10.

[23] Shoka, Athar A. Ein, Mohamed M. Dessouky, Ayman El-Sayed, and Ezz El-Din Hemdan. "An efficient CNN based epileptic seizures detection framework using encrypted EEG signals for secure telemedicine applications." *Alexandria Engineering Journal* 65 (2023): 399-412.

[24] Amiri, Mohsen, Hassan Aghaeinia, and Hamid Reza Amindavar. "Automatic epileptic seizure detection in EEG signals using sparse common spatial pattern and adaptive short-time Fourier transform-based synchrosqueezing transform." *Biomedical Signal Processing and Control* 79 (2023): 104022.

[25] Saminu, Sani, Guizhi Xu, Shuai Zhang, Isselmou Ab El Kader, Hajara Abdulkarim Aliyu, Adamu Halilu Jabire, Yusuf Kola Ahmed, and Mohammed Jajere Adamu. "Applications of Artificial Intelligence in Automatic Detection of Epileptic Seizures Using EEG Signals: A Review." In *Artificial Intelligence and Applications*, vol. 1, no. 1, pp. 11-25. 2023.

[26] Ein Shoka, Athar A., Mohamed M. Dessouky, Ayman El-Sayed, and Ezz El-Din Hemdan. "EEG seizure detection: concepts, techniques, challenges, and future trends." *Multimedia Tools and Applications* (2023): 1

[27] B. Arora, P. Jadhav, R. B. Sulaiman, A. Kareem, P. Kunekar and B. Pant, "Integrating Artificial Intelligence and Deep Learning for Enhanced Medical Innovation," 2022 5th International Conference on Contemporary Computing and Informatics (IC3I), Uttar Pradesh, India, 2022, pp. 327-331, doi: 10.1109/IC3I56241.2022.10073054.

[28] P. R. Kunekar, M. Gupta and B. Agarwal, "Deep Learning with Multi Modal Ensemble Fusion for Epilepsy Diagnosis," 2020 3rd International Conference on Emerging Technologies in Computer Engineering: Machine Learning and Internet of Things (ICETCE), Jaipur, India, 2020, pp. 80-84, doi: 10.1109/ICETCE48199.2020.9091742.

[29] I. S. Chakrapani, N. Tyagi, S. Tyagi, P. Kunekar, D. L. Padmaja and K. Pant, "Applications of Deep Learning (DL) Techniques in Detecting Breast Cancer and Malignant Cells," *2022 5th International Conference on Contemporary Computing and Informatics (IC3I)*, Uttar Pradesh,