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Seizure Recognition using SVM

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Abstract - This study focuses on using machine learning, specifically Support Vector Machine (SVM) models, for automatic recognition of epileptic seizures from EEG signals. Preprocessed EEG data with relevant features was used to train and evaluate the SVM classifier, achieving promising results in distinguishing between seizure and non-seizure events. The model's effectiveness was demonstrated through performance metrics like accuracy and confusion matrices. This study highlights the potential for traditional machine learning methods in real-time seizure detection, laying the groundwork for future enhancements such as wearable deployment, improved predictive models, and early seizure forecasting.

***Key Words*:** Support Vector Machine (SVM), epileptic seizures, EEG signals, preprocessed EEG data, distinguish seizure and non-seizure events, performance metrics, accuracy, confusion matrices, real-time seizure detection.

1.INTRODUCTION

Epilepsy is one of the most common neurological disorders, characterized by recurrent and unprovoked seizures. Seizures are the result of sudden, abnormal electrical activity in the brain, which can vary in intensity and type. Accurate and timely recognition of these events is crucial for effective management and treatment of epilepsy, helping to prevent potential injury and improve the quality of life for patients.

The Traditional methods of seizure detection often rely on manual observationandanalysis of EEG (electroencephalogram) data by neurologists, a process that is both time-consuming and subject to human error. With the advancements in machine learning, automated systems capable of detecting seizures in EEG data have shown great promise in enhancing diagnostic accuracy and providing real-time monitoring capabilities.

This project, titled **"Seizure Recognition,"** focuses on developing a machine learning-based model to classify EEG signals into seizure and non-seizure events using Support Vector Machine (SVM) techniques. The objective is to design a robust system that can assist healthcare professionals and patients by providing fast and reliable seizure detection. The project utilizes publicly available EEG datasets, employing data preprocessing techniques to prepare the data for training and testing. The model's performance is evaluated through metrics such as accuracy, precision, recall, and F1-score.

By automating seizure detection, this project aims to contribute to the broader field of epilepsy management, paving the way for real-time wearable solutions and enhancing the understanding of seizure patterns. The implementation of such systems could lead to improved patient outcomes, more efficient clinical workflows, and new opportunities for research in epilepsy and other neurological disorders.

The aim is to create a system using Support Vector Machine (SVM) techniques that can process EEG data, learn patterns associated with seizure events, and accurately classify these occurrences, thereby aiding in the early detection and management of epilepsy. This solution could empower clinicians with a supportive diagnostic tool and enable real-time monitoring for patients, ultimately leading to better treatment and prevention strategies.

2. LITERATURE REVIEW

The paper titled "Epileptic Seizures Detection Using Deep Learning Techniques: A Review," published in the International Journal of Environmental Research and Public Health (2021), provides a comprehensive analysis of deep learning (DL) approaches for epileptic seizure detection. The research examines the application of algorithms like Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) on EEG datasets, showcasing the potential of DL in identifying seizures. However, the study emphasizes that the inaccessibility of comprehensive EEG datasets, particularly those with long registration times, poses a significant challenge to real-time detection advancements. Despite promising results, the findings indicate that existing DL models require larger datasets and improved real-time performance for practical implementation. The study underscores the importance of further exploration into DL techniques and their capacity for real-time epileptic seizure detection.

The paper "Brain Connectome Analysis with Machine Learning," published in the IEEE Transactions on Pattern Analysis and Machine Intelligence (2021), explores the use of machine learning techniques for analyzing functional connectivity data in brain networks. The findings demonstrate that machine learning methods significantly enhance the accuracy of brain connectome analysis and improve the prediction of mental health outcomes. Despite these advancements, the study identifies critical challenges, including the limited availability of open-access datasets and the complexities involved in preprocessing and extracting features from fMRI data, which hinder the development of robust models. The research emphasizes the need for improved methods to handle raw neuroimaging data and aims to advance functional brain network analysis through the application of machine learning techniques.

The paper "The Combination of a Graph Neural Network Technique and Brain Imaging to Diagnose Neurological Disorders," published in Brain Sciences (2023), reviews the application of Graph Neural Networks (GNNs) in brain imaging for diagnosing neurological disorders such as Alzheimer's, Parkinson's, and ADHD. The study highlights the effectiveness of GNNs in leveraging the complex structural and functional relationships within neuroimaging data to improve diagnostic accuracy. However, it identifies key challenges, including small sample sizes, individual heterogeneity, domain generalization, and the integration of multimodal data, which hinder the broader application of GNNs in clinical practice. Utilizing datasets such as ADHD-200, PPMI for Parkinson's, ABIDE for Autism, and proprietary in-house data, the study underscores the need for advancements in data availability and methodological approaches to enhance the utility of GNNs in neurological disorder diagnosis.

The study "Automated Recognition of Epilepsy from EEG Signals Using a Combining Space–Time Algorithm of CNN-LSTM," published in Scientific Reports (2023), introduces a hybrid CNN-LSTM approach for the automated classification of epileptic EEG signals. This method achieves state-of-the-art performance in both binary and ternary classification tasks, showcasing its effectiveness in epilepsy diagnosis. Using Bonn University's public epilepsy EEG dataset, the study highlights the model's ability to capture both spatial and temporal patterns in EEG data. Despite these advancements, the research identifies challenges related to model interpretability, real-time application, and computational efficiency. The study emphasizes the need for further development to enhance the practical applicability of CNN-LSTM models in clinical epilepsy diagnosis.

The paper "Epileptic Seizure Detection Using Machine Learning," published in Diagnostics (2023), provides a systematic review of various machine learning models, including Artificial Neural Networks (ANN), Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Random Forests (RF), for epileptic seizure detection. The study achieved a notable accuracy of 95.14% using ANN, with other models demonstrating comparable performance. Leveraging datasets such as CHB-MIT and Bonn University, the research underscores the potential of machine learning in seizure detection. However, it identifies the need for further studies focusing on real-time implementation to ensure the practical utility of these models in clinical settings.

The paper "Detection of Epileptic Seizure in EEG Signals Using Machine Learning and Deep Learning Techniques," published in the Journal of Engineering and Applied Science (2024), evaluates various machine learning and deep learning approaches, including Long-Short Term Memory (LSTM), logistic regression, K-Nearest Neighbors (KNN), Support Vector Machines (SVM), and Artificial Neural Networks (ANN), for automated seizure detection. Among these, LSTM demonstrated superior accuracy in analyzing EEG signals. Using the UCI-Epileptic Seizure Recognition dataset, the study highlights the effectiveness of these models in detecting seizures. However, it points out the limitations in dataset size and diversity, which restrict the generalizability of the models. The research emphasizes the importance of diverse and comprehensive datasets to enhance model performance and reliability in clinical applications.

The study "BrainGB: A Benchmark for Brain Network Analysis with Graph Neural Networks," published in IEEE Transactions on Medical Imaging (2022), introduces BrainGB, a standardized framework for brain network analysis using Graph Neural Networks (GNNs). The framework is designed to facilitate reproducibility and modularity in research, addressing the lack of systematic benchmarks in the field. The study conducts extensive experiments across functional MRI (fMRI) and Diffusion Tensor Imaging (DTI) datasets, proposing effective GNN designs for brain network analysis. Despite its contributions, the research highlights challenges such as the limited availability of published datasets and detailed model descriptions, which hinder result evaluation and reproducibility. BrainGB aims to fill this gap by providing a comprehensive platform for advancing GNN-based brain network analysis.

The paper "Interpretable Sparsification of Brain Graphs: Better Practices and Effective Designs for Graph Neural Networks," presented at ACM SIGKDD in 2022, introduces Interpretable Graph Sparsification (IGS), a novel method for improving the efficiency and interpretability of brain graph classification. IGS reduces noisy edges in functional MRI (fMRI) brain graphs, achieving up to a 5.1% improvement in classification performance while retaining only 55.0% of the original edges. This approach addresses a key limitation of prior methods, which prioritized explainability at the cost of degraded Graph Neural Network (GNN) performance. Furthermore, it optimizes edge selection across multiple graphs, a challenge overlooked by earlier sparsification techniques. The study highlights the potential of IGS for enhancing both the interpretability and computational efficiency of GNN-based models in brain graph analysis.

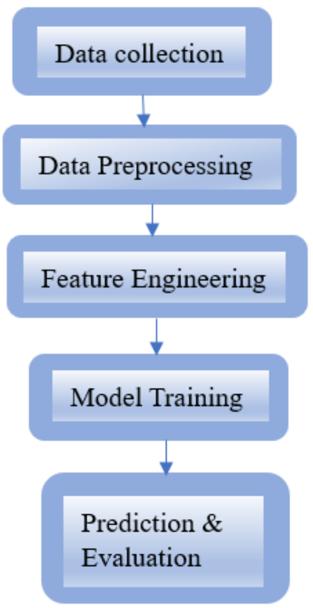
The paper "SeizFt: Interpretable Machine Learning for Seizure Detection Using Wearables," published in Bioengineering (2023), presents SeizFt, a novel model combining feature extraction, Fourier Transform (FT) surrogates, and CatBoost decision trees for real-time seizure detection. This method demonstrated a 30% improvement in detection accuracy, with enhanced sensitivity and reduced false alarm rates compared to existing approaches. Key features such as delta waves, theta waves, and signal complexity significantly contributed to its performance. Utilizing the SeizeIT1 dataset for training and SeizeIT2 for validation and testing, the study addresses the challenge of achieving both high accuracy and interpretability in seizure detection models. However, it highlights the ongoing need for deep learning approaches that balance interpretability with robust performance, particularly for wearable EEG devices.

After referring several other similar papers this study underscores the effectiveness of traditional machine learning models, like SVM, in applications involving biomedical signal analysis, particularly in seizure detection. It reinforces the importance of feature engineering and preprocessing in boosting model performance and reliability. Overall, the integration of EEG data with machine learning techniques such as SVM holds promise for improving the early diagnosis and management of epilepsy.

3. METHODOLOGY

To develop a seizure recognition model using the Support Vector Machine (SVM) algorithm, we first need to input the EEG data into the dataset. This involves cleaning and preprocessing the data to ensure it is in a format that the model can understand. The preprocessing step includes removing irrelevant columns, handling class labels, and applying feature scaling to standardize the data. The SVM model is then trained on this dataset using the input features and corresponding labels to learn patterns and make accurate classifications.

After training the SVM model, we evaluate its performance by calculating metrics such as accuracy, precision, recall, F1-score, and the Confusion Matrix (CF). Accuracy measures the overall correctness of the model, while precision and recall provide insights into the model's performance in identifying seizure events. The F1-score is a balance between precision and recall, giving a single performance metric. The CF provides a breakdown of true positives, true negatives, false positives, and false negatives, helping to visualize the model's predictive performance. These metrics help assess the model's reliability and determine its effectiveness in distinguishing between seizure and non-seizure events.



3.1 DATASET

The original dataset from the reference consists of 5 different folders, each with 100 files, with each file representing a single subject/person. Each file is a recording of brain activity for 23.6 seconds. The corresponding time-series is sampled into 4097 data points. Each data point is the value of the EEG recording at a different point in time. So we have total 500 individuals with each has 4097 data points for 23.5 seconds.

We divided and shuffled every 4097 data points into 23 chunks, each chunk contains 178 data points for 1 second, and each data point is the value of the EEG recording at a different point in time. So now we have 23 x 500 = 11500 pieces of information(row), each information contains 178 data points for 1 second(column), the last column represents the label y {1,2,3,4,5}. The response variable is y in column 179, the Explanatory variables X1, X2, …, X178.
Specifically y in {1, 2, 3, 4, 5}:

5	eyes open, means when they were recording the EEG signal of the brain the patient had their eyes open
4	eyes closed, means when they were recording the EEG signal the patient had their eyes closed
3	Yes they identify where the region of the tumor was in the brain and recording the EEG activity from the healthy brain area
2	They recorder the EEG from the area where the tumor was located
1	Recording of seizure activity

Fig -1:Dataset Description

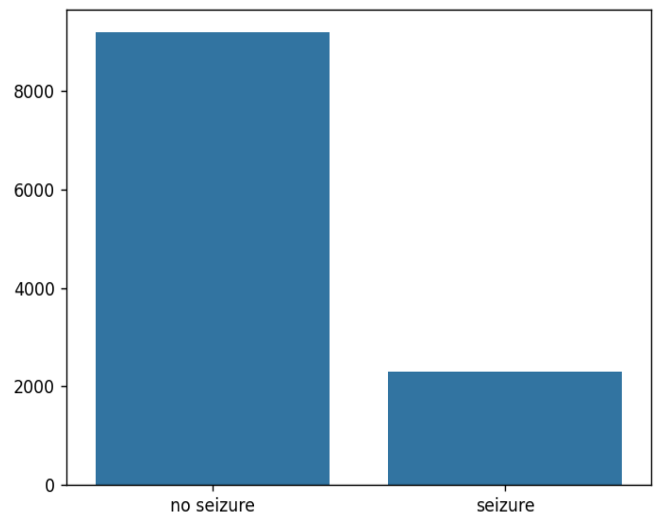


Fig -2: Report classification

3.2 DATA PREPROCESSING

A. Load Data:

Import the Dataset:

Load the EEG seizure recognition dataset and examine the columns for any missing or irrelevant data.

Data Cleaning:

Remove any redundant columns, such as unnamed or index columns, to ensure the dataset is well-structured and relevant.

B. Handle Missing Values

Imputation:

Check for missing values in the dataset. Although the dataset may already be clean, use imputation techniques (e.g., filling with mean or median values) if necessary.

Data Consistency:

Ensure all feature columns are complete, and apply imputation only if required to maintain consistency.

C. Feature Engineering and Transformation

The combined data needs to be aligned so each sample has both a clinical vector and an image.

Standardization:

Apply feature scaling using standardization (Z-score normalization) to ensure all numerical features have a mean of 0 and a standard deviation of 1.

Label Conversion:

Convert the target variable to a binary classification format if necessary (e.g., converting seizure labels to 1 and non-seizure labels to 0).

D. Split the Data

Training and Test Sets:

Split the preprocessed data into training and test sets using an 80-20 ratio to ensure a robust evaluation of the model's performance.

E. Scaling and Normalization

Scaler Implementation:

Use StandardScaler from sklearn to scale the training and test sets, ensuring that the model's input features are normalized.

Fit and Transform:

Fit the scaler to the training set and transform both the training and test sets accordingly.

F. Data Preparation for Model Training

Data Structuring:

Format the processed data into a structure that can be fed into the Support Vector Machine (SVM) classifier for training and evaluation.

Feature Alignment:

Ensure feature columns and target labels are aligned and correctly processed.

4. MODEL EVALUATION AND COMPARISION

A. Common metrics for binary classification (Seizure detection) include:

- **Accuracy**: Percentage of correct predictions over the total predictions.
- **Precision**: The proportion of true positives among predicted positives (sensitivity to false positives).
- **Recall (Sensitivity)**: The proportion of true positives among actual positives (sensitivity to false negatives).
- **F1 Score**: Harmonic mean of precision and recall, balancing them.
- **Confusion Matrix**: A table showing true positive, true negative, false positive, and false negative counts.

5. CONCLUSIONS

This project focused on developing a machine learning-based seizure recognition system using Support Vector Machine (SVM) to classify EEG signals into seizure and non-seizure events. The dataset was thoroughly pre-processed to ensure data quality, including feature scaling, and was then split into training and test sets for validation.

The SVM classifier demonstrated strong performance, achieving an accuracy of approximately 97.57%. The model's precision, recall, and F1-scores confirmed its balanced capability in detecting seizures while minimizing false positives and negatives. The confusion matrix visualization highlighted its accurate classification performance.

The project showcased the effectiveness of traditional machine learning techniques like SVMs for seizure detection, emphasizing their potential in real-world healthcare applications such as epilepsy diagnosis. This contributes to the development of automated tools that assist neurologists by providing timely and accurate seizure monitoring. Future work could explore integrating deep learning models, utilizing larger datasets, and enabling real-time data processing to enhance detection accuracy and reliability.

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