Seizure Detection Using Wearable Device

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***Abstract*— Wearable devices that automatically detect and predict seizures could be life-changing technology for patients suffering from epileptic seizures. These devices can help in constant monitoring and detection of seizures. This research aims to produce a Machine Learning model to detect seizures which can be used in seizure detection wearable devices. With the help of multimodal sensors like Electrodermal Activity (EDA) and Accelerometer (ACC) accurate detection of seizure can be obtained. The system can analyse skin resistance and irregular heartbeats that could indicate an impending seizure. Overall, the research paper aims to demonstrate the potential of a machine learning model which can be used in wearable technology that can enhance seizure management and improve patient outcomes.**

Keywords—seizure, electrodermal activity, accelerometer, ML classifiers, Algorithm.

I. Introduction

Epileptic seizure affects approximately 50 million people worldwide. One of the greatest challenges in epileptic seizure is detecting a seizure and responding accordingly to avoid injuries and save lives. Therefore, seizure detection and prediction play a vital role in seizure treatment. But traditional methods such as using an EEG or video EEG to detect seizure are often expensive and not viable for everyday use. Hence developing a wearable device using machine learning model could be a paradigm-shifting technology in the field of epilepsy.

This research paper seeks to address the accurate detection of an onset seizure using various machine learning algorithms. The model must be trained using data which are obtained from various sensors. The system should be capable of collecting and storing physiological signals like EDA and ACC, which can help identify the occurrence of seizures. The model should be trained on a large dataset of labelled seizure and non-seizure data to learn the complex patterns and characteristics associated with seizures. The system should be designed to be highly sensitive and specific, to minimize false alarms and missed detections. The challenge in developing a machine learning model is to accurately differentiate between a seizure and other activities that may mimic a seizure, such as exercising, sleeping, or simply moving. The article concludes by presenting outlooks on wearable multi-functional sensing technology and its potential for use in precision medicine.

II. Literature Survey

1. SEIZURE AND ITS CLASSIFICATIONS:

This research paper focuses on the updated classification of seizures according to International League Against Epilepsy (ILAE). In the past decades, it has been difficult to classify epilepsy according to its types. Therefore, using current technologies and the lates t terminologies, we can further classify epilepsy, which was unclassifiable in the past. In this research paper, epileptic seizures are classified into four types: i. Generalized ii. Focal iii. Combined Generalized & Focal iv. Unknown.[12]

2. SENSORS:

In the research, a computer will record the time and length of the motions after receiving a Bluetooth signal from the device when it detects such movement. Six of the forty participants in their experiment experienced 8 tonic-clonic seizures. The tool picked up seven out of eight seizures. There were 204 instances when non-seizure movements were picked up, and each time the patient had the chance to cancel them. With the use of this technology, tonic-clonic seizure sufferers' caretakers might be informed when a seizure happens.[7][9][17]

3. MACHINE LEARNING CLASSIFIERS:

This paper reviews various machine learning algorithms for seizure detection and concludes that non-black-box classifiers, specifically decision forests, are the most effective. These classifiers handle seizure detection and classification. On the other hand, black-box classifiers may achieve high predictive accuracy, but they cannot generate interpretable logic rules.[1][3][14]

4. DETECTION OF SEIZURE:

A study on the usage of wearable devices in epilepsy monitoring units found that they helped monitor and track patients for long durations. The study utilized ML algorithms and biosensors that were embedded in the wearable devices. The sensor recorded ACC, PCG, and EDA. The first algorithm developed machine learning models that could detect the nine individual seizure types, whereas the second algorithm had models that could detect from the general spectrum.[8][10][14][17][20]

5. ELECTRODERMAL ACTIVITY (EDA):

This research aims at recording the electrodermal response during a seizure. For the experiment, the participant's EDA and EEG were constantly recorded. The experiment was successful in showing an increasing EDA response during ictal and postictal periods of seizure. It was observed that focal seizures had lower EDA response compared to others.[18][23]

6. WEARABLE DEVICES IN HEALTH CARE WHICH USES AI:

The article discusses the improvement of a variety of sensing technology for healthcare, focusing on wearable sensors. It explores various single and hybrid mechanisms used in wearable sensors, including self-powered systems, and discusses the challenges in integrating multiple sensors into wearable devices. The article emphasizes the need for self-powering sensors to achieve high sensitivity. The article concludes by presenting outlooks on wearable sensing technology and its potential for use in precision medicine.[10][20]

7. TREATMENT PLANS OF SEIZURE USING AI:

In this study, there were two main approaches that made use of computational studies. In the initial method, computerized diagnosis and prognosis prediction for specific patients were aided by AI and ML approaches. The second method replicated the patient's specific brain network dynamics in order to comprehend disease causes and choose the best course of treatment for each patient.6]

8. ALERTING THE CAREGIVERS IN THE NEED OF TIME:

In this study, the goal was to develop a "fall detection" alarm system utilizing the motion sensor of a smartphone. With the person's GPS coordinates, it can sound an SOS alarm and start smartphone call and text alerts. The optimal spot for a smartphone in this is on the forehead or upper arm. 90% of the time, the location-based feature prevented respondents from falling asleep. The success percentage of the network communication was 100 percent. Age-based tests, which fall into the last group, have a success rate of 60–70% for those aged 7 to 32. This epilepsy support tool can recognize when someone is about to fall and send an SOS alert sound, call, SMS, and GPS location to a relative or healthcare provider to summon assistance immediately. [5]

III. PROPOSED SYSTEM

The suggested solution uses machine learning models that precisely recognize epileptic seizures. The system uses wearable sensors to gather information on physiological variables such as skin resistance, mobility, heart rate, and others. The system's major objective is to create a machine learning model that is extremely sensitive and focused and is capable of reliably detecting seizures in real time. To enable it to learn the intricate patterns and traits connected to seizures, the model should be trained on a sizable dataset of labelled seizure and non-seizure data. The study's main objective is to reduce the false alarm rate (FAR), which will raise the model's accuracy.

The creation of a wearable device-based seizure detection system is fraught with several technological difficulties. These consist of:

- It can be difficult to acquire high-quality data from sensors in a real-world setting because the sensors must be at ease and inconspicuous while accurately gathering crucial data.
- The data must then be analysed in order to draw out relevant elements that can be utilised to pinpoint when a seizure is occurring. It may be required to use sophisticated signal processing and machine learning techniques because of how intricate this process is.
- The classification of whether a seizure is happening requires the usage of the extracted features. This is often accomplished using machine learning methods, however due to the variety in seizure patterns, creating precise and trustworthy classifiers can be difficult.
- The technology must also be able to function in real-time, sending notifications as soon as a seizure starts. Data processing algorithms that are effective and optimized for speed and accuracy are needed for this.

IV. METHODOLOGY

In order to work with the dataset, necessary libraries were imported. The CSV file was read and stored in a variable to progress with the work. The raw dataset is then sliced into a smaller dataset of 25,000 rows. The features in the multimodal data are: accelerometery ACC (x-axis, y-axis, z-axis, and magnitude), heart rate variability (HR), blood volume pulse (BVP) and electrodermal activity (EDA). Firstly, the data was cleaned, and null or error values were replaced and fixed. The ACC values were highly correlated. By plotting the EDA and HR values, we recognised a variation and pattern in the data points. Accordingly, we set the threshold values and classified the data as 1 for the rows where thresholds were less than the actual data value and 0 for the rest. After that, the data were separated into training and testing sets. Then, to use the dataset, the machine learning algorithms were imported and put into use. The performance metrics and ROC curves of the machine learning algorithms were obtained.

Classification algorithms used:

The dataset was processed using the following machine learning algorithms: Logistic Regression, Random Forest Classifier, Gradient Boosting Classifier, SVM, KNN, GNB, and MLP.

- Logistic Regression: It predict the outcome of the dependent variable using the set of independent variables and provide a discrete value which is a probabilistic value lying between 0 and 1. The curve that we obtain from logistic regression gives the likelihood of something. In this case, the occurrence of seizures.
- Random Forest Classifier: The creation of the random forest by mixing the N decision trees occurs in the first of two phases, after which predictions are made for each of the trees. Decision trees are constructed using the K data points that are chosen from the training set.

- Gradient Boosting Classifier: Gradient boosting classifier makes use of the process of boosting to combine the predictors with poor accuracy into a model with strong accuracy. Each of the predictor here tries to improve on its predecessor by attempting to reduce the errors.
- SVM: SVM or Support Vector Machine helps in creating a hyperplane that can be used to segregate n dimensional space into classes. This helps us to classify the new and incoming datasets into the correct category. The extreme vectors which are used to create a hyperplane are known as support vectors.
- K-Nearest-Neighbor: KNN algorithm works by assuming the similarity between new data and available data. According to the similarity it assigns the new data to the most similar one. It stores the dataset at training phase and when new data arrives it classifies on the basis of similarity. It selects the K number of neighbours first and foremost and calculates the Euclidean distance between them. After counting the data points, it assigns them to the locations with the most neighbours.
- Gaussian Naïve Bayes: The Naive Bayes method, which uses the Bayes theorem as its foundation, is used to forecast an object's likelihood. The Bayes Theorem is used to calculate the likelihood of a hypothesis given prior information. The probabilities of the provided features are used to construct likelihood tables and transform the dataset into frequency tables. The posterior probability is then calculated using the Bayes Theorem.
- Multi-Layer Perceptron: It is a library provided by TensorFlow Python. Any input dimension can be changed into the desired dimension using it. It is a neural network with several layers.

V. RESULT

Utilising the multimodal data gathered from wearable devices, various machine learning algorithms' performance was assessed for identifying seizures. In this research Logistic Regression, Support Vector Machine, K-Nearest Neighbors, Naive Bayes, and Multilayer Perceptron, was evaluated and compared using the perfomance metrics. The results are based on raw unlabeled data consisting of Accelerometer (ACC), Heart Rate (HR), Electrodermal Activity (EDA), Blood Volume Pulse (BVP) and Temperature of one patient recorded for 6 hours consisting of approximately 32 Lakh rows of data points which was then cut into smaller data of 25,000 data points.

The main challenge was working with many features. As the dataset consisted of multimodal signals, it was difficult to evaluate the data using given parameters as the dataset was unlabeled. Although this research only concentrated mainly on two features EDA and ACC, both the features were extracted and evaluated separately. The performance of different classification algorithms is shown below.

Table 1.1: Performance on multimodal dataset

Machine Learning Algorithms	**Accuracy**	**Precision**	**Recall**	**F_Score**
Logistic Regression	97.2%	94.8%	95.9%	95.3%
Support Vector Machine	97.2%	94.7%	95.6%	95.2%
K-Nearest Neighbors	96.3%	94.6%	92.3%	93.4%
Naive Bayes	96.6%	92%	97.9%	94.6%
Multilayer Perceptron	97.4%	94.8%	96.5%	95.6%

Fig 1.1: ROC curve of MLP

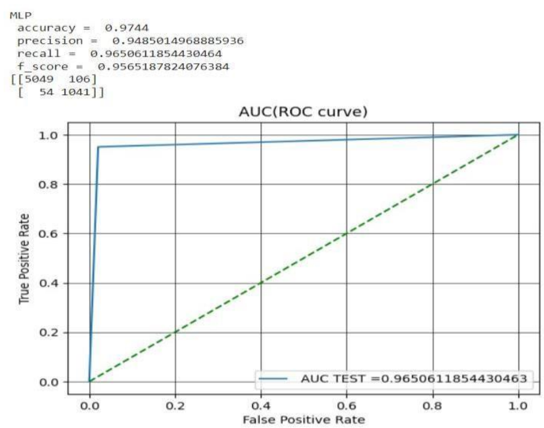
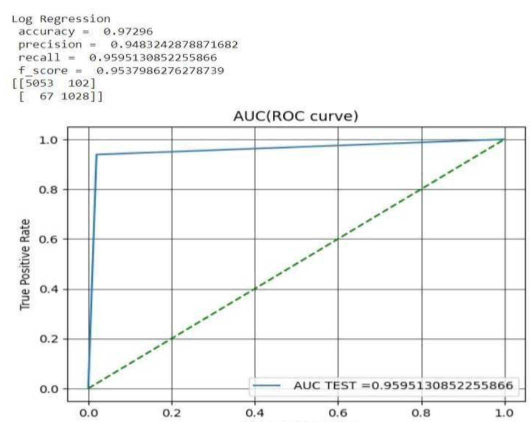


Fig 1.2: ROC curve of Logistic Regression



VI. CONCLUSION

In the study of the multimodal datasets, among all the classifiers tested it is evident that the MLP classifier transcended in performance, as evidenced by its accuracy of 97.4%, precision of 94.8%, recall of 96.8%, and F-score of 95.6%. The performance metrics(accuracy, precision, recall and f_score) of the Logistic Regression method were all high, at 97.2%, 94.8%, 95.9%, and 95.3% respectively. The Support Vector Machine Algorithm's F-score was 95.2% because it had the best accuracy (97.2%), Recall of 95.6%, but a lesser precision (94.7%). The K-Nearest Neighbours and Naive Bayes methods performed the worst overall, with accuracy ratings of 96.3% and 96.6%, respectively. These findings imply that the MLP classifier performs better than other classifiers evaluated in this work and is capable of handling multimodal datasets. The MLP classifier's good classification performance may be due to its capacity for handling non-linear interactions between the features and the target variable, which is crucial in multimodal datasets.

These findings imply that seizure detection using wearable device data can be successfully accomplished by machine learning algorithms. The Multilayer Perceptron and Logistic Regression algorithms demonstrated the greatest results and would be appropriate for wearable seizure detection systems. More investigation is required to assess how well these algorithms perform on larger and more varied datasets, as well as to examine the viability and usability of real-time seizure detection systems using wearable technology in clinical settings.

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