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Development of a Multimodal Machine Learning Model for Seizure Detection Using Wearable Devices

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Abstract—This research explores the transformative potential of wearable devices designed to automatically detect & predict epileptic seizures, offering continuous monitoring & early detection capabilities. The study focuses on developing a machine learning model tailored for seizure detection in such devices, leveraging multimodal sensors such as Electrodermal Activity (EDA) & Accelerometer (ACC). By measuring skin resistance and identifying irregular heartbeats, which are signs of upcoming seizures, these sensors allow for precise seizure detection. The study intends to demonstrate the effectiveness of this machine learning model in wearable technology with the goal of improving patient outcomes and seizure management.

Index Terms—Seizure, Electrodermal Activity (EDA), Accelerometer (ACC), Classifiers, Electroencephalogram (EEG).

I. Introduction

Approximately 50 million people worldwide suffer from epileptic seizures. Identifying a seizure and reacting appropriately to prevent harm and save lives is one of the most difficult tasks in epileptic seizures. Therefore, a key component of seizure treatment is seizure detection and prediction. However, conventional techniques like employing an EEG or video EEG to identify seizures are frequently costly and impractical for daily use. Therefore, creating a wearable gadget with a machine learning model could revolutionize the way that epilepsy is treated. This research paper seeks to address the accurate detection of an onset seizure using a machine learning model. The model must be trained using sensor data obtained from wearable devices. The system should be capable of collecting and storing physiological signals like EDA & ACC, which can help identify the occurrence of seizures. A large dataset of labeled seizure and non-seizures should be used to train the model in order to uncover the complex patterns and characteristics associated with seizures. High sensitivity and specificity should be incorporated into the system to minimize false alarms and missed detections. It can be challenging to accurately differentiate a seizure from other behaviors that might resemble one, such as moving, sleeping, or exercising, when developing a machine learning model. In the conclusion of the article, opinions regarding wearable multifunctional sensing technology and its possible uses in precision medicine are discussed.

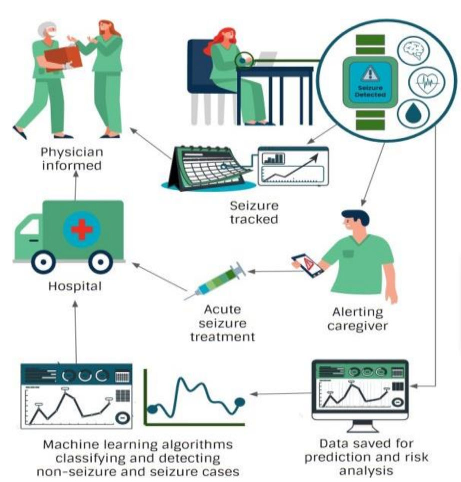

Fig. 1. Use Case Diagram

II. LITERATURE SURVEY

Alazzam et al. (2021) discuss a smart healthcare system that integrates IoT & machine learning for continuous patient monitoring. Their work contributes to the growing field of remote health monitoring, combining real-time data with AI-driven analytics [1]. Sharma & Kaushik (2023) explore sentiment analysis techniques applied to Twitter data, highlighting methods for uncovering user emotions & opinions, contributing to social media analytics & user behavior modeling [2]. Rosales et al. (2019) propose a smart stress detection system using physiological data & machine learning, advancing research on emotion sensing & stress management in wearable technology applications [3]. Rathore et al. (2024) present an innovative delivery management solution utilizing smart technologies, contributing to the logistics & e-commerce sectors by optimizing delivery efficiency through real-time tracking & data analysis [4]. Tang et al. (2021) establish a benchmark for seizure detection using wearable sensors & machine learning, marking an advancement in medical technology for epilepsy management through non-invasive monitoring systems [5]. Halimeh et al. (2022) investigate how wearable devices can monitor antiseizure medication effects on physiological parameters, providing insights into personalized treatment & enhancing patient care in epilepsy management [6]. Tabasum et al. (2022) explore microfluidic e-skin sensors for real-time health monitoring, contributing to the field of wearable sensors & bioelectronics for continuous health assessment, particularly for stress & hydration levels [7].

Munch Nielsen et al. (2022) propose a multi-modal wearable seizure detection system, combining various sensor technologies to improve accuracy in detecting seizures & enhancing epilepsy management through wearable medical devices [8]. Kaushik et al. (2024) present a deep learning-based approach to classify & predict Indian music, contributing to the intersection of AI, music theory, & cultural studies by leveraging hybrid deep learning techniques [9]. Zeng et al. (2022) review multi-functional wearable sensors used in healthcare, emphasizing their role in real-time health monitoring & the integration of diverse sensing technologies for improved diagnosis & personalized care [10]. Urbina Fredes et al. (2024) propose wavelet-based analysis for improving seizure detection accuracy through EEG signal processing, advancing the use of computational methods in epilepsy monitoring & management [11]. Majumder et al. (2019) design an energy-efficient IoT system to predict cardiac arrest, con- tributing to the development of smart health devices focused on early detection & prevention of critical medical events [12]. Sarmast et al. (2020) provide an overview of seizure & epilepsy classification, addressing current limitations & offering recommendations for improving diagnostic accuracy & treatment strategies in neurology [13]. Bornoiu & Grig- ore (2013) explore feature extraction techniques for stress detection, focusing on physiological signals, & contribute to the development of wearable systems for monitoring mental health [14].

Farooq et al. (2022) review machine learning techniques for seizure detection, summarizing various algorithms & their applications, providing valuable insights for researchers & developers in the field of medical AI [15]. Chen et al. (2009) study the effects of seizures during pregnancy on women with epilepsy, offering important clinical insights into mater- nal health & pregnancy management for epileptic patients [16]. Beniczky et al. (2021) discuss clinical guidelines for automated seizure detection using wearable devices, advancing epilepsy care through continuous monitoring & improving seizure management in clinical practice [17]. Wang et al. (2024) introduce a dual-stream neural network for epileptic seizure detection, advancing the use of multimodal data to enhance detection accuracy & real-time monitoring for epilepsy patients [18]. Sikarwar et al. (2023) focus on IoT-driven solutions to optimize parking management in smart environments, contributing to the development of smart city technologies & urban mobility solutions [19]. Rathore et al. (2023) apply Recurrent Neural Networks (RNN) for customer segmentation in banking, enhancing personalized marketing & customer service strategies through advanced machine learning techniques [20]. Sharma et al. (2023) propose a methodology for partitioning customers using K-Means clustering & the RFM model, contributing to customer-centric revenue strategies & marketing optimization in business intelligence [21]. Kaushik et al. (2023) tackle hate speech detection using ensemble learning & Long Short-Term Memory (LSTM) networks, enhancing real-time content moderation in smart environments & digital platforms [22].

III. PROPOSED SYSTEM

The proposed solution leverages a machine learning model to accurately detect seizures in epileptic patients. This system employs wearable sensors to collect physiological data, including skin resistance, mobility, heart rate, and other variables [23]. The main goal is to create a very accurate and sensitive model that can identify seizures in real time. To do this, a sizable labeled dataset comprising both seizure and non-seizure cases must be used to train the model in order to find intricate patterns and characteristics linked to seizures. A key focus of the study is minimizing the false alarm rate (FAR) to enhance the model's accuracy [24].

Developing a wearable seizure detection system presents several technical challenges:

Data Collection: Acquiring high-quality sensor data in real-world scenarios can be difficult, as sensors must be comfortable, unobtrusive, and capable of accurately capturing critical information.

Data Analysis: Extracting meaningful features to identify seizure events requires advanced signal processing and machine learning techniques due to the complexity of seizure patterns.

Classification: Determining whether a seizure is occurring based on extracted features is challenging due to the variability in seizure manifestations, requiring precise and reliable machine learning classifiers.

Real-Time Functionality: The system must operate in real-time, sending immediate alerts upon seizure detection. This demands highly efficient and optimized data processing algorithms for both speed and accuracy [25].

This approach provides a foundation for creating an effective seizure detection system tailored for real-world use.

IV. METHODOLOGY

Pandas, NumPy, Matplotlib, and Seaborn were among the necessary libraries imported in order to analyze the dataset. The dataset was taken out of a CSV file and put into a variable. Twenty-five thousand rows were taken out of the raw dataset. Features including heart rate variability (HR), blood volume pressure (BVP), electrodermal activity (EDA), and accelerometery (ACC: x, y, z, magnitude) were included in the multimodal dataset. In order to replace or fix null and incorrect values, data cleaning was done. While trends in EDA and HR were displayed graphically, a strong correlation was noted in the ACC values. Rows with values below the thresholds were designated as 0, and the remaining rows were designated as 1. Training and testing sets were then created from the dataset. The data was analyzed using imported machine learning algorithms, which produced performance metrics and ROC curves. **Classification Algorithms Used:**

1. **Logistic Regression**
   Logistic regression predicts categorical dependent variables based on independent variables, outputting probabilities between 0 and 1. The regression curve provides likelihoods, such as predicting the occurrence of seizures.
2. **Random Forest Classifier**
   Random Forest builds a forest by combining multiple decision trees. The trees are constructed using randomly selected subsets of training data, and predictions are made by aggregating outputs from all trees.
3. **Gradient Boosting Classifier**
   Gradient Boosting combines weak predictors to create a stronger model. Each predictor corrects the errors of its predecessor, enhancing the overall accuracy.
4. **Support Vector Machine (SVM)**
   SVM identifies a hyperplane to separate n-dimensional space into classes, enabling accurate classification of new datasets. Support vectors are the data points used to define this hyperplane.
5. **K-Nearest Neighbors (KNN)**
   KNN assigns new data points to the most similar category based on the proximity of K nearest neighbors. The Euclidean distance is calculated to determine similarity, and classification is based on the majority of neighboring data points.
6. **Gaussian Naïve Bayes (GNB)**
   GNB applies Bayes' Theorem to predict an object's likelihood. It calculates probabilities of features, constructs likelihood tables, and computes posterior probabilities to classify data points.
7. **Multi-Layer Perceptron (MLP)**
   MLP, a neural network with multiple layers, transforms input dimensions into desired outputs. Implemented using TensorFlow, it effectively handles complex datasets.

This approach ensures accurate classification by leveraging diverse machine learning techniques tailored to the dataset's characteristics.

V. RESULT

This study used multimodal data gathered from wearable devices to assess how well various machine learning algorithms detected seizures. Logistic Regression, Support Vector Machine, K-Nearest Neighbors, Naive Bayes, and Multilayer Perceptron were among the algorithms evaluated. Metrics like accuracy, precision, recall, and F-score were used to compare performance. The dataset consisted of raw, unlabeled data with approximately 3.2 million data points recorded over six hours from a single patient. This data was divided into smaller segments of 25,000 data points and further split into training and testing modules.

A significant challenge in this research was the data labeling process, which involved identifying erroneous values and analyzing sensor signal fluctuations. One notable issue was the presence of highly correlated features, particularly the "acc magnitude" feature. To mitigate errors, this feature was excluded from the dataset. After its removal, the remaining features were used to evaluate the models. Furthermore, tree-based classification methods were tested but resulted in overfitting due to the high levels of noise in the data. These insights emphasize the importance of data preprocessing and feature selection in achieving robust performance for seizure detection using machine learning techniques.

VI. CONCLUSION

The MLP classifier demonstrated superior performance, achieving an accuracy of 97.4%, precision of 94.8%, recall of 96.8%, and an F-score of 95.6%. Logistic Regression also performed well, with accuracy, precision, recall, and F-score values of 97.2%, 94.8%, 95.9%, and 95.3%, respectively. The Support Vector Machine (SVM) algorithm achieved high accuracy (97.2%) and recall (95.6%) but slightly lower precision (94.7%), resulting in an F-score of 95.2%. In contrast, K-Nearest Neighbors and Naive Bayes performed comparatively worse, with accuracy scores of 96.3% and 96.6%, respectively, making them the least effective methods in this analysis.

TABLE I
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%

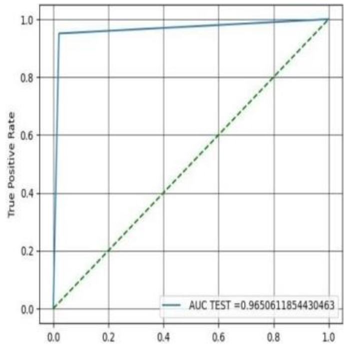

Fig. 2. ROC Curve of MLP

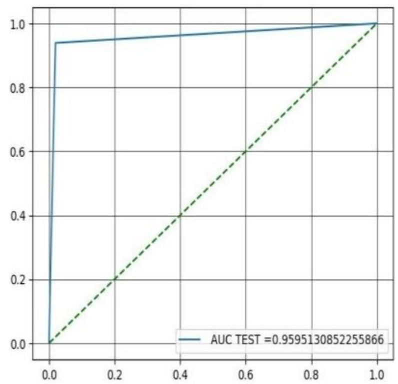

Fig. 3. ROC Curve of Logistic Regression

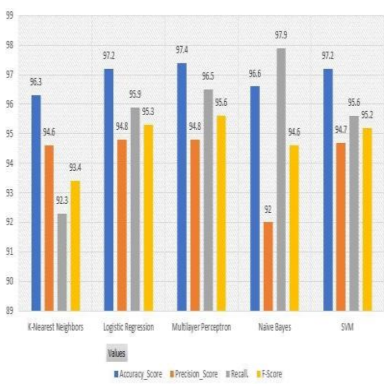

Fig. 4. Performance Metrics

These results suggest that the MLP classifier can handle multimodal datasets and outperforms other classifiers assessed in this work. The MLP classifier performs well in classification because it can manage non-linear interactions between the target variable and the features, which are crucial in multimodal datasets. These results suggest that machine learning algorithms can effectively detect seizures using data from wearable devices. Wearable seizure detection systems would benefit from the Multilayer Perceptron and Logistic Regression algorithms, which showed the best results. More research is needed to evaluate these algorithms' performance on bigger and more diverse datasets and to look at the practicality and usability of wearable technology-based real-time seizure detection systems in clinical settings.

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