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Selection EEG Electrode Positions for Epilepsy Seizure Detection Using Total Power Spectrum and Machine Learning

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ABSTRACT

Detecting epileptic seizures poses significant challenges due to the complex and variable nature of EEG signals, particularly when aiming for implementation in wearable devices. The use of 64-channel EEG electrodes, while comprehensive, is impractical for wearable applications due to their size, cost, and the high computational load required for processing. The use of a single-channel EEG wearable device offers notable advantages, including reduced size and cost, making it more practical and comfortable for continuous monitoring in daily life. Additionally, the lower computational load enhances battery life and allows for real-time data processing, which is critical for timely seizure detection and intervention. This research investigates the detection of epileptic seizures using various machine learning algorithms and the power spectrum feature extraction method from EEG signals, aiming for application in wearable devices with a single-channel electrode. The study applied random forest (RF), K-nearest neighbor (KNN), decision tree (DF), support vector mechine (SVM), and logistic regression algorithms to assess their effectiveness. Results revealed that the power spectrum extraction method notably improved seizure detection accuracy, with RF and KNN achieving 93% and 92% accuracy respectively when using all EEG channels. When limited to a single channel, SVM demonstrated the highest accuracy of 82% with channel 3. These findings underscore the efficacy of the power spectrum method for EEG signal processing, providing significant improvements in accuracy and computational efficiency. The study concludes that the proposed approach is promising for enhancing epileptic seizure detection, suggesting further optimization for real-time application in wearable devices to develop accurate and efficient diagnostic tools.

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1. INTRODUCTION

Epilepsy is a prevalent neurological disorder, characterized by recurrent, unprovoked seizures that can vary in intensity and frequency. A person experiencing epilepsy seizures is characterized by sudden damage or alterations in specific areas of the brain. The World Health Organization (WHO) estimates that around 50 million people worldwide suffer from epilepsy seizure, affecting everyone of any age, gender, color, or nationality[1]. In individuals with epilepsy seizure, there is a disruption or increase in the electrical signals in the specific region of the brain that is responsible for communication and coordination of movement. This disorder induces involuntary behaviors or movements in the patient, such as transient episodes of vacant gaze, accompanied by sudden falls and convulsions, leading to a loss of bodily control and consciousness. The unpredictable nature of these seizures significantly impacts patients quality of life, often leading to physical injuries, psychological stress, social stigma, and economic burden. For individuals with epilepsy, the constant threat of a seizure disrupts daily activities, limits independence, and can impede educational and employment opportunities. Timely and accurate detection of seizures is crucial, as it allows for immediate intervention, potentially reducing the severity and duration of seizures and preventing complications. Relying on information from individuals close to the patient about the observed symptoms is the most straightforward method of diagnosing epilepsy seizure. Nevertheless, this approach is less precise and has the potential to result in an incorrect diagnosis. An electroencephalogram (EEG) is an alternative approach for identifying aberrant brain signals resulting from

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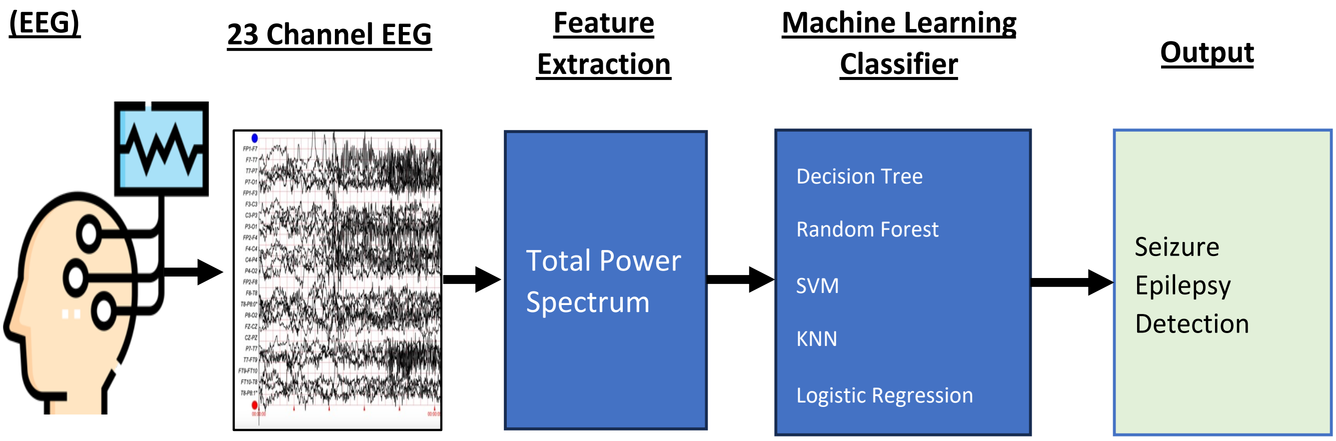

Fig. 1. Proposed method: epilepsy seizure detection using total power spectrum and machine learning

epilepsy seizure. An electroencephalogram (EEG) involves the detection and recording of electrical impulses in the brain by placing approximately 64 electrodes on the scalp [2]. The primary concerns with the use of 64 electrodes for measuring are the discomfort experienced by the patient and the limited ability to move throughout the operation. Furthermore, this method requires a significant amount of time, as it requires a meticulous examination of each individual's EEG results to confirm the presence of epilepsy seizure. The development of wearable devices that use fewer electrodes, such as single-channel systems, making continuous monitoring more practical for everyday use. These advancements allow for real-time data collection and processing, which is essential for timely seizure detection and intervention.

One approach for addressing the challenges in diagnosing epilepsy seizure using EEG measures is to employ machine learning algorithms to aid in the detection of epilepsy seizure from EEG readings. Various machine learning methods, such as decision trees (DT), random forests (RF), support vector machines (SVM), K-nearest neighbors (KNN), and others, have been employed for epilepsy seizure prediction [2], [3], [4], [5] . Utilizing machine learning in the assessment and examination of brain waves obtained from EEG readings offers numerous benefits, such as enhanced precision in the identification and categorization of brain wave patterns. An exemplary instance involves the utilization of SVM and convolutional neural network (CNN) for forecasting epilepsy seizures, attaining an accuracy rate 85% and 90% [6]. This research uses Fast Fourier Transform (FFT) and Principal Component Analysis (PCA) for feature extraction. Other studies use deep learning methods with convolutional neural networks (CNN) to detect epilepsy seizures, achieving an accuracy of 99% [7]. The studies [6] and [7] have complex computations, making them challenging to implement on wearable devices. Therefore, a wearable device requires efficient algorithms with lower computational complexity and power consumption to ensure real-time processing and extended battery life.

To address computational issues in microcontroller processing, this research will use power spectrum feature extraction. This method offers the advantage of highlighting specific frequency patterns associated with epileptic activity, improving detection accuracy[7]. It reduces noise and enhances signal quality, facilitating more reliable predictions. Additionally, its computational efficiency allows for real-time analysis, crucial for timely intervention in epilepsy management. On the other hand, mechine learning algorithms that have demonstrated high accuracy and low computational cost in previous studies, such as Decision Tree (DT), Random Forest (RF), Support Vector Machine (SVM), k-Nearest Neighbors (k-NN), and Logistic Regression, will be used [2], [3], [4], [5]. The accuracy achieved by these algorithms in previous studies ranges from 85% to 94%.

Thus, this research aims to utilize many machine learning algorithms with power spectrum feature extraction on different electrode channels to make predictions about epilepsy seizures. The outcomes of these predictions will then be utilized to ascertain the most appropriate channel for predicting epilepsy, and the high-accuracy channel will subsequently be incorporated into wearable EEG equipment. Choosing a single-channel EEG wearable device offers significant benefits, including a smaller size and lower cost, making it more practical and comfortable for daily continuous monitoring. Additionally, this research will identify machine learning algorithms that achieve high accuracy with lower computational demands. Moreover, the reduced computational load enhances battery life and enables real-time data processing, which is crucial for prompt seizure detection and intervention. The results of this study are expected to

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help minimize computational costs in wearable devices, enhancing both efficiency and user comfort.

2. MATERIALS AND METHOD

A. Proposed Method

In order to place the EEG sensor on wearable technology, this research aims to determine the ideal location for the electrode to detect epileptic seizures. The suggested procedure for processing EEG data acquired from 23 electrode sites is shown in Figure 1. It involves first computing the total power spectrum, then applying Fast Fourier Transform (FFT) to change the frequency domain, and lastly, categorizing the data using the most effective machine learning model. The use of the total power spectrum would be very appropriate, considering that there are differences in the frequencies of normal EEG and EEG for epileptic seizures. For normal EEG, the maximum EEG frequency is 30 Hz[8]. At the same time, for epileptic seizures, it can reach above 40 Hz[8]. So, the total power spectrum can be an appropriate feature extraction for pattern recognition to detect epileptic seizures with EEG signals. In this research, is trained several machine learning methods, but just five of the most accurate methods, such as decision trees, random forests, KNN, SVM, and Logistic regression, were presented in this study.

B. Dataset EEG Epileptic

This study uses a dataset from the CHB-MIT Scalp EEG Database[9], which consists of EEG recordings from 22 pediatric subjects with intractable seizures. Subjects have an age range of 5 to 19 years with gender females and males. Each subject has been recorded with a 23-channel EEG to capture the normal and epilepsy seizure states. One instance dataset consists of 1 second of 256 sample EEG signals with label class, seizure of normal EEG class. The total number of datasets is 37664 samples, which consist of 29590 normal classes and 8074 epilepsy seizure classes.

C. Power Spectrum

In this study, features for epileptic seizure detection resolve to be extracted from the whole power spectrum. The most frequent method for characterizing electroencephalograms is the power spectrum[10]. Biomedical signal patterns with varying frequencies can be effectively identified using the power spectrum[11]. Where the FFT will be used to translate the EEG signal from a time domain signal to a frequency domain ($X(f)$), and the result will be raised to the power of two, following Eq. (1). Next, using Eq. (2), the power spectrum (P_i) at each frequency is added up to determine the total power spectrum.

$$Power\ Spectrum\ (P_i) = |X(f)|^2\ (v^2/Hz) \tag{1}$$

$$TotalPower = \sum_{i=1}^{M} P_i (v^2/Hz) \tag{2}$$

where is $i = 1,2,3, \dots M$.

D. Machine Learning

In the following stage, every feature or EEG channel will be trained to swiftly distinguish between normal and epileptic seizures. GridsearchCV is used to find the optimal machine learning model[12], [13]. A statistical technique called cross-validation is used to gauge how well machine learning models are working. It entails splitting the dataset into smaller groups, using some smaller groups to train the model, and using the remaining subsets to validate it. For any machine learning model, GridsearchCV is a function that allows for automatic parameter adjustment. Combining all of the model's parameters carries out the training procedure repeatedly. In cross-validations, every possible set of parameters for a single model is trained several times based on the number of subset datasets. As a result, the machine learning model employed to determine the most appropriate electrode position from the EEG becomes increasingly reliable. Finally, the optimal model for each EEG channel characteristic will be found in this study, and the most accurate EEG channel for seizure detection will also be identified.

GridsearchCV utilizes only accuracy as a metric to verify the machine learning model. However, these metrics are deemed inadequate because the datasets for the epilepsy seizure and normal classes are unbalanced. As a result, the confusion matrix, precision, recall, and F1-score are employed to assess how well a particular model predicts each class. The model is further validated using the confusion matrix, precision, recall, and F1-score parameters to see the prediction performance for each class after the optimal model is derived from the highest accuracy value.

Since the goal of this research was to develop epilepsy seizure detection for wearable devices, only simpler machine learning models were employed. Thus, a variety of supervised learning techniques were selected for experimentation, including SVM, Logistic regression, KNN, Decision tree, Naive Bayes, and a few ensemble learning techniques like Random Forest and AdaBoast[13]. The decision tree, SVM, KNN, Logistic Regression, and Random Forest machine learning models were shown to have the highest accuracy.

The decision tree method utilizes Gini impurity or Gini entropy to assess the impurity at each node, which is then applied in the CART (Classification and Regression Tree) framework to establish thresholds within the decision tree. The learning process entails identifying the optimal

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threshold (t_k) for each feature (k) by minimizing the CART cost function (J), as depicted in Eq. (3)[14].

$$J(k, t_k) = \frac{m_{left}}{m} G_{left} + \frac{m_{right}}{m} G_{right} \tag{3}$$

where $G_{left/right}$ is measure impurity of the left and the right subset and $m_{left/right}$ is number of instances in the left and the right subset.

Random Forest is an ensemble technique that aggregates multiple decision trees, where each tree is trained on a different subset of the data selected through the bagging method. This approach creates numerous decision trees, and the final prediction is made based on the majority vote across all individual trees. The k-Nearest Neighbors (k-NN) algorithm is a simple, non-parametric method used for classification and regression. The formula for calculating the distance between two points, which is fundamental to the k-NN algorithm, is typically the Euclidean distance. The Euclidean distance (d) between two points $x = (x_1, x_2, \dots x_n)$ and $y = (y_1, y_2, \dots y_n)$ in n-dimensional space is given by equation (4).

$$d(x, y) = \sqrt{\sum_{i}^{n} (x_i - y_i)^2} \tag{4}$$

Support Vector Machine (SVM) is a supervised learning algorithm used to classify data into two distinct classes or to keep data within a boundary for regression tasks. In this study, SVM is employed for classification purposes. Equation (5) demonstrates the prediction method used by SVM [14].

$$\hat{y} = \begin{cases} 0 \; if \; \boldsymbol{w}^T \boldsymbol{x} + b < 0, \\ 1 \; if \; \boldsymbol{w}^T \boldsymbol{x} + b \geq 0, \end{cases} \tag{5}$$

where w is a a vector of weights corresponding to the features $x_1, x_2, \dots\ x_n$ and b is the bias term, a constant that adjusts the decision boundary. The term $w^T x$ represents the dot product of the weight vector w and the feature vector x.

Logistic Regression, a technique used for binary classification, is a regression method that models the probability of a binary outcome based on one or more predictor variables. It employs the sigmoid function to calculate the probability of instances, which in turn determines the class output. Equation (6) is utilized for making predictions [14].

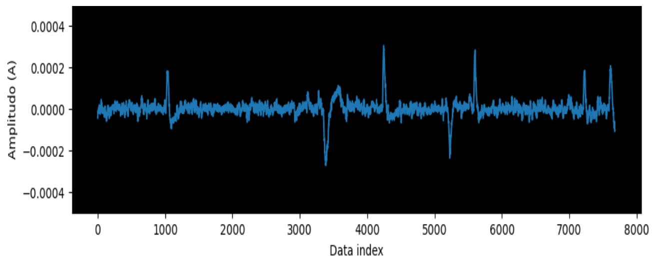
$$\hat{y} = \begin{cases} 0 \; if \; \hat{p} < 0.5, \\ 1 \; if \; \hat{p} \geq 0.5, \end{cases} \tag{6}$$

where $\hat{p}$ is the probability derived from $h_\theta(x)$ that an instance x belongs to the positive class.

3. RESULTS

Figure 2 (a) and (b) show the EEG signals of a non-epileptic seizure patient and an epileptic seizure patient, respectively. The diagram clearly depicts a notable disparity between the average patient and those afflicted with epilepsy. The power distribution of the EEG signal is uniformly distributed among the frequency bands, depending on the level of wakefulness or activity. However, in the case of individuals with epileptic seizures, the power distribution tends to be elevated in particular frequency ranges when compared to typical brain activity. Seizures are defined by abrupt surges in intensity, specifically in the low-frequency ranges (1-4 Hz).

The research involves analysing an EEG signal dataset, which includes EEG signals from both normal people and patients who may have epileptic seizures, as shown in Fig. 1. The signals are further analysed for feature extraction using the Fast Fourier Transform (FFT), which yields a power spectrum. Fig. 3 displays the obtained power spectrum. Fig. 3 clearly demonstrates that the power spectrum in these frequency bands remains consistent and evenly distributed, indicating a well-functioning and healthy brain across various states of consciousness and activity. During seizures, the power spectrum exhibits significant peaks in specific frequency ranges, which suggest increased brain synchronization and abnormal electrical discharges. The outcomes derived from this power spectrum will thereafter undergo additional processing utilizing various machine learning algorithms to predict which patients possess normal brain wave patterns and which individuals have indications of epilepsy seizures.



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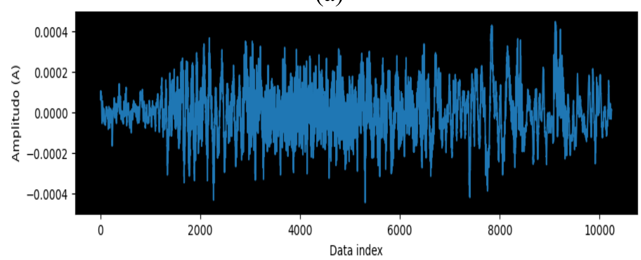

(b)

Fig. 2. EEG signal: (a) Normal EEG Signal, (b) Seizure EEG Signal

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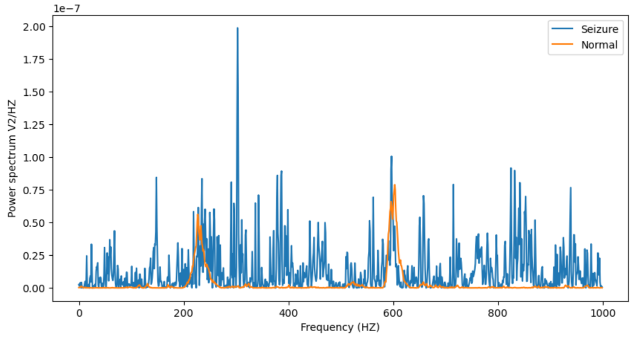


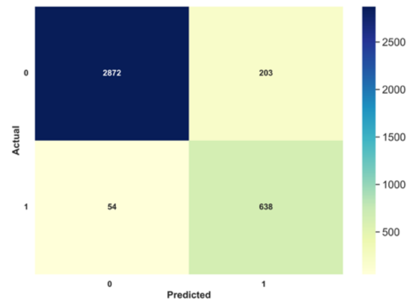
Fig. 3. Power Spectrum

The evaluation results of the best machine learning models for all EEG channels are shown in Table 1. Using only one EEG channel, the machine learning model is unable to distinguish between normal and epileptic seizure classes, according to the analysis of all the best models. With 80% accuracy, SVM is the best machine learning model for a single EEG channel. According to the data presented in Table 1, when using only a single EEG channel, channel 3 is the most optimal choice as it yields an accuracy of approximately 82%.

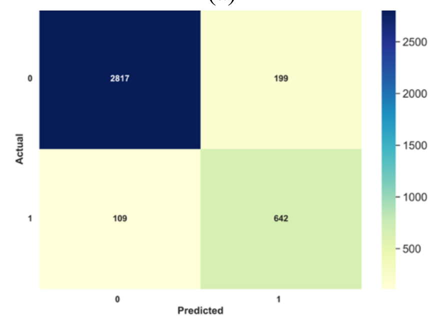
Table 1. Accuracy classification for each channel of EEG

Channel EEG	RF	KNN	DT	SVM	Logistic
Channel 1: FP1-F7	70%	77%	70%	79%	79%
Channel 2: F7-T7	72%	79%	72%	81%	21%
Channel 3: T7-P7	74%	79%	74%	82%	21%
Channel 4: P7-O1	74%	80%	74%	81%	21%
Channel 5: FP1-F3	76%	76%	76%	79%	79%
Channel 6: F3-C3	71%	77%	71%	80%	21%
Channel 7: C3-P3	72%	78%	72%	81%	21%
Channel 8: P3-O1	70%	77%	70%	80%	21%
Channel 9: FP2-F4	71%	78%	71%	81%	60%
Channel 10: F4-C4	77%	75%	77%	81%	29%
Channel 11: C4-P4	70%	76%	70%	79%	79%
Channel 12: P4-O2	70%	77%	70%	80%	79%
Channel 13: FP2-F8	73%	74%	73%	79%	79%
Channel 14: F8-T8	74%	79%	74%	79%	79%
Channel 15: T8-P8	72%	78%	72%	81%	21%
Channel 16: P8-O2	71%	78%	71%	80%	60%
Channel 17: FZ-CZ	71%	77%	71%	80%	21%
Channel 18: CZ-PZ	74%	75%	74%	80%	31%
Channel 19: P7-T7	75%	79%	75%	80%	20%
Channel 20: T7-FT9	71%	78%	71%	79%	79%
Channel 21: FT9-FT10	71%	78%	71%	80%	21%
Channel 22: FT10-T8	71%	77%	71%	79%	79%
Channel 23: T8-P8	75%	73%	75%	81%	31%
All Channel	93%	92%	88%	85%	63%

Nevertheless, the random forest and KNN models are the two machine learning models with the best performance, with accuracy values of 93% and 92%, when we mix all EEG channels for machine learning features. It is find that epileptic seizures cannot be accurately detected by utilizing a single EEG channel. The accuracy results obtained demonstrate the shortcomings of the machine above learning techniques. The dataset uses the normal class and seizure epilepsy imbalance, which can impact the machine learning model's performance. In contrast to logistic regression and SVM, the KNN and Random Forest approaches perform well for imbalance classes in the dataset[15].



(a)



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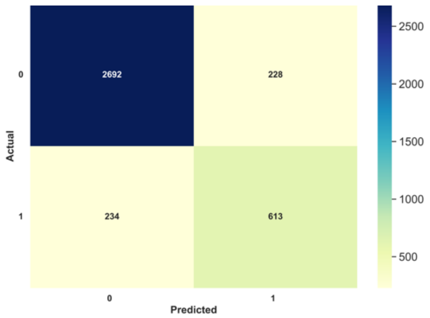

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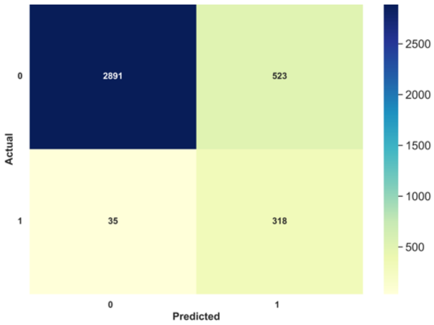

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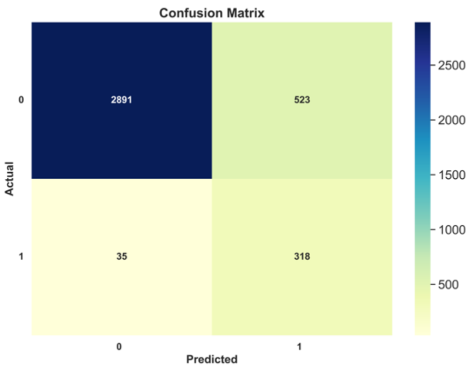

(e)

Fig. 4. Confusion Metrix Two Best Machine Learning Model with All Channel EEG: (a) Random Forest, (b) KNN, (c) Decision Tree, (d)SVM, and (e) Logistic Regression.

Table 2. Performance matrix two best machine learning model with all channel EEG

Precision					
Classes	Random Forest	KNN	Decision Tree	SVM	Logistic Regression
Normal	96%	96%	92%	99%	99%
Seizure	76%	76%	72%	38%	38%
Recall					
Classes	Random Forest	KNN	Decision Tree	SVM	Logistic Regression
Normal	93%	93%	92%	85%	85%
Seizure	83%	85%	82%	90%	90%

F1 Score					
Classes	Random Forest	KNN	Decision Tree	SVM	Logistic Regression
Normal	95%	95%	92%	91%	91%
Seizure	81%	81%	73%	53%	53%

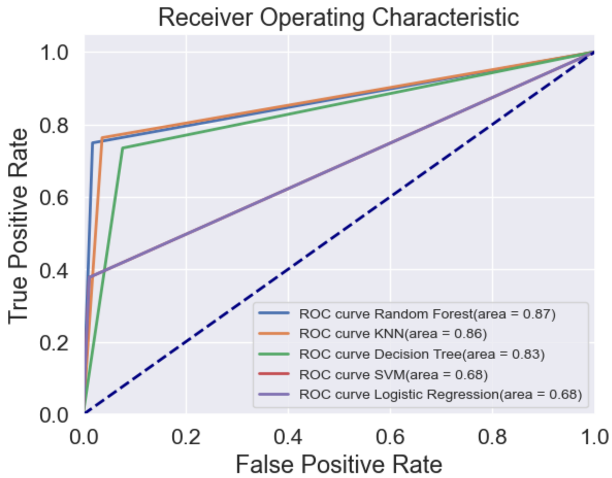

Fig. 5. ROC For All Machine Learning

The performance of various machine learning classifiers is displayed on the ROC (Receiver Operating Characteristic) curve, as shown in Fig. 5. The ability of each curve to discriminate between the positive and negative classes is represented by the area under the curve (AUC). Of the models displayed, the Random Forest classifier performs the best, as evidenced by its highest AUC of 0.87. When it comes to accurately categorizing positive and negative cases, the random forest model has the highest probability. The highest AUC values of the Random Forest and KNN classifiers suggest that perform the best overall.

4. DISCUSSION

As seen in Table 1, the highest accuracy values for epilepsy prediction using RF and KNN are 93% and 92%, respectively. Compared to a previous study, which enhanced the accuracy of epileptic seizure predictions by optimizing the selection of EEG channels, that study achieved an average prediction accuracy of 92.42% with the selected channels, whereas using all channels in their research only achieved an accuracy of 71.13% [4]. Therefore, this method is highly effective because it does not require selecting the best channels. Additional investigations employ the RF algorithm to identify epileptic seizures by utilizing the Tunable-Q Wavelet Transform (TQWT) to extract time-frequency characteristics from EEG signals [3]. The study achieved a 93% level of

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accuracy. The overall comparison from other method and this work can be seen at Table 3.

Both prior studies used feature extraction techniques that if the techniques implemented on a microcontroller for wearable devices, could place significant computing burdens. Therefore, using the power spectrum for feature extraction results in lower computational demands and enables easy implementation on wearable devices.

Table 3. Comparison this works and other works

Reference	Feature extraction	Classifier	Accuracy (%)
Ra et al. [4]	Permutation entropy	KNN	92.42
Pattnaik et al. [3]	TQWT	RF	93
This work	Power spectrum	KNN RF	92 93

Additionally, the implications of applying machine learning using power spectrum for epilepsy prediction are significant. The research demonstrates that power spectrum feature extraction can achieve high accuracy in predicting epileptic seizures, as evidenced by the results obtained using single-channel or multi-channel EEG data. This approach not only enhances the practicality and comfort of wearable EEG devices by reducing their size and computational requirements but also maintains a high level of prediction accuracy. Consequently, this method can facilitate real-time monitoring and timely intervention for epilepsy patients, potentially improving their quality of life and reducing the risks associated with unexpected seizures. The successful integration of this technology into wearable devices could revolutionize epilepsy management, making advanced monitoring accessible and affordable for a broader population.

As explained in Section Three, this method can use a single channel for application in wearable devices. By using a single channel, specifically the third channel, this research achieved an accuracy of 82% with a machine learning algorithm. However, using a single channel has several drawbacks when applied to EEG wearable devices. Using a single channel in EEG devices poses several challenges, including limited spatial information, which reduces the ability to capture comprehensive brain activity. Additionally, single-channel EEGs are more susceptible to noise and artifacts, which can distort the signal and lower the accuracy of brain state detection. Despite these limitations, single-channel EEGs offer advantages in terms of cost, size, and user comfort, making them suitable for certain applications like continuous daily monitoring.

5. CONCLUSION

This study aimed to find the best channel and machine learning algorithm to detect epilepsy seizures that can be used in a wearable device. This study improves the detection of epileptic seizures using the RF, KNN, DT, SVM, and logistic methods with power spectrum extraction features from EEG signals. The results demonstrated that using the power spectrum for feature extraction significantly enhances the accuracy of epilepsy seizure detection, achieving 93% and 92% accuracy rates for RF and KNN with all channels. If the wearable devices are using only one channel, the best algorithm to use is SVM, which achieves an accuracy of about 82% on channel 3.

These findings suggest that power spectrum feature extraction is a highly effective method for EEG signal processing, offering a substantial improvement over traditional methods in terms of accuracy and computational efficiency. While the method shows high accuracy, the computational demands of the power spectrum might be challenging for real-time applications on wearable devices. Future research should explore optimizing the power spectrum for real-time applications and integrating it with low-power microcontroller technologies to develop efficient wearable seizure detection devices. Overall, this study provides a promising approach for improving epileptic seizure detection, paving the way for more accurate and accessible diagnostic tools.

For future work, we aim to explore the integration of multi-channel EEG data to further enhance the accuracy and reliability of seizure prediction models. Additionally, investigating advanced noise reduction techniques and adaptive algorithms that can dynamically select the most relevant features in real-time will be crucial. This research also plan to conduct extensive clinical trials to validate the practical effectiveness of the developed wearable devices in diverse real-world settings. Expanding the scope of our research to include other neurological conditions that can benefit from similar predictive modelling and wearable technology applications will be another important direction. Ultimately, our goal is to create a comprehensive and user-friendly system that leverages the latest advancements in machine learning and biomedical engineering to significantly improve patient outcomes and healthcare efficiency.

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