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Article

Epileptic seizure detection using machine learning on electroencephalogram data

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SUMMARY

It is estimated that more than 1% of people in the US have epilepsy, a life-threatening neurological disease characterized by recurrent, unprovoked seizures, due to abnormal electrical activity in the brain. The diagnostic process for epilepsy is very extensive and results in many misdiagnoses. We hypothesized that the implementation of machine learning, specifically utilizing Support Vector Machine (SVM), on preprocessed electroencephalogram (EEG) data would lead to improved accuracy in detecting epileptic seizures. Our study explored the application of machine learning in epileptic seizure detection using EEG data and aimed to improve the accuracy while limiting false positives. The study utilized a preprocessed EEG dataset and evaluated five machine learning models—Logistic Regression, K Nearest Neighbors (kNN), Random Forest, Neural Network, and SVM. We optimized model performance using hyperparameter tuning, the process of optimizing the parameters of a machine learning model to improve its performance, with a particular emphasis on recall. Results reveal that the SVM model outperforms others, achieving an accuracy of 96.77%, precision of 94.27%, and recall of 88.87%. We concluded by underscoring the need for further research to enhance model metrics, encompassing diverse datasets, alternative preprocessing techniques, and addressing privacy issues. This work contributes to advancing epilepsy diagnosis through machine learning applications, with implications for future developments in healthcare.

INTRODUCTION

Epilepsy, a neurological disorder marked by frequent seizures caused by irregular electrical activity in the brain, can be life-threatening since seizures are so unpredictable and can occur in dangerous situations. The timing of a seizure could result in a car accident, dangerous fall, or drowning. Specifically, people with epilepsy are 15-19 times more likely to drown than the average person (1). There are many types of seizures that can result in dangerous situations such as absence seizures, which can cause staring into space and rapid blinking; tonic seizures, which can cause muscles in the body to become stiff; atonic seizures, which can cause muscles in the body to relax; and clonic seizures, which can cause periods of jerking and shaking (2). Seizure detection is a very difficult and extensive process in which many people are misdiagnosed with epilepsy. In the United States alone, 3.4 million people have epilepsy, but it is estimated that one in five of these people are misdiagnosed, meaning that they do not have epilepsy but are diagnosed epileptic (3). Additionally, even with a diagnosis provided by a panel of experts, the false positive rate remains around five percent (4). Furthermore, epilepsy and seizures can result in comorbidities such as anxiety and depression (5). The dangers of epilepsy make it important to diagnose quickly and accurately so that patients can get the seizure prevention medication that they need.

The diagnosis of epilepsy is challenging because epileptic seizures are transient and may be mistaken for other conditions. In contrast to other seizures, epileptic seizures occur without obvious external cause, making them especially difficult to identify. Electroencephalogram (EEG) signals can be used to measure the abnormal electrical activity of the brain of an individual with epilepsy. Epileptic brain activity can include patterns, such as repetitive spikes or sharp waves. These patterns can also be present in between seizures. Though EEG and magnetic resonance imaging (MRI) are the two most important diagnostic techniques in epileptology, they can be easily misinterpreted (3). There is potential for these misinterpretations to be mitigated with the use of artificial intelligence (AI) (6, 7).

The most common method of detecting seizures is to analyze EEG signals from the brain. EEG is a neuroimaging technique used to record the spontaneous electrical activity of the brain. Even though EEG data is very commonly used, these signals are very long and complicated. Therefore, the process of understanding and finding patterns in EEG data can be very time-consuming and difficult. The longer that a diagnosis takes, the more emotional and physical burden patients and their families have (3). Machine learning, otherwise known as artificial intelligence, can be used to make this diagnosis process more efficient and aid doctors in diagnosing epilepsy more accurately.

Machine learning techniques are increasingly being used in epilepsy research, with applications in automated seizure detection, analysis of imaging and clinical data, epilepsy localization, and prediction of medical and surgical outcomes (6). Machine learning is being harnessed to automate seizure detection. For instance, Biswal et al. successfully trained a Naïve Bayes classifier using 3,277 EEG reports that were categorized as either having seizures or not, and containing epileptiform discharges or not (6). This classifier achieved exceptional performance, with an area under the curve performance index, which quantifies the ability of a binary classification model to discriminate between positive and negative classes, of 99.05% for identifying reports with seizures and 96.15% for recognizing reports with epileptiform discharges when tested on a set of 39,695 reports (6).

Nahzat and Yağanoğlu conducted a study applying

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the same data that will be used in this study with different methods (7). The authors used the Bonn University epileptic seizure dataset to train and test a variety of machine learning algorithms (7). They used Principal Components Analysis (PCA) feature reduction technique to improve the accuracy of machine learning algorithms for predicting epilepsy (7). PCA is a statistical technique that can be used to reduce the dimensionality of a dataset while preserving the most important information (7). This can be beneficial for machine learning algorithms, as they can often be more accurate when they are trained on less noisy data. The study found that the Random Forest algorithm with PCA feature reduction produced the best results, with an accuracy of 97% (7).

Machine learning can be used for epileptic seizure detection. For seizure detection, EEG data is commonly analyzed using one of the following classifiers: kNN, Random Forest, SVM, or Neural Network. We focused primarily on machine learning applications to automate seizure detection (6, 7). We are tackling a supervised classification problem that deals with numerical and categorical data. Our primary objective was to develop a classification model that can accurately assign labels to the data points based on this data. By leveraging this model, we aimed to provide actionable insights and predictions for real-world applications, ultimately enhancing decision-making processes in the field of epileptic seizure detection. Based on our research, we hypothesized that the implementation of machine learning, specifically utilizing SVM in comparison to our four other machine learning models, on preprocessed EEG data would lead to improved accuracy in detecting epileptic seizures. We hypothesized that SVM would be the most successful model in classifying EEG signals because of its strength in classifying non-linear data allowing it to be very applicable to EEG data classification. The integration of machine learning into epileptic seizure detection represents a pivotal advancement in the accuracy and efficiency of diagnosis. Our hypothesis that implementing machine learning, particularly SVM models, on preprocessed EEG data would improve detection accuracy, which underscores the potential of these technologies. While challenges such as dataset diversity and privacy concerns remain, the significant benefits for patient outcomes and diagnostic speed are undeniable. Continued investment in research and validation studies will be crucial in realizing the full potential of machine learning applications in clinical practice, ultimately advancing the management and treatment of epilepsy.

RESULTS

Machine learning techniques have the possibility to revolutionize the future of epileptic seizure detection by making the diagnosis process more efficient and accessible. In our experiment, each machine learning model was tested on the same epileptic seizure and non-seizure EEG data. Our dataset had 11500 samples of short EEG data with 2300 seizure cases and 9200 non-seizure cases split 75:25 training to testing data (8). We tested five machine learning models: Logistic Regression, kNN, Random Forest, SVM, or Neural Network. Logistic Regression is a statistical model used for binary classification that estimates the probability of a binary outcome based on one or more predictor variables using a logistic function (7). kNN is an algorithm that classifies a data point based on the majority class of its k nearest neighbors in the feature space (7). Random Forest is an algorithm that constructs multiple decision trees during training and outputs the mode of the classes or mean prediction of the individual trees for classification or regression tasks (7). SVM is a supervised machine learning model that finds the optimal hyperplane to separate classes in the feature space, maximizing the margin between different classes (7). Finally, a Neural Network is a computational model inspired by biological neural networks, consisting of interconnected nodes organized in layers, which learns to map input features to outputs through iterative training (7). Through our experiment, we were able to determine the best and worst machine learning models for this case of epileptic seizure detection.

First, each model was evaluated by comparing accuracy, precision, and recall (**Table 1**). The Random Forest model and the SVM model performed similarly. Since we are dealing with medical data, it was important that we detect all seizure data (true positives), so the recall performance matrix is especially important. Therefore, we deduced that the SVM model performed the best as it had the highest recall of 88.87%. The SVM model had an even higher accuracy of 96.77% and precision of 94.27% compared to the Random Forest model. Since we are dealing with medical data false negatives are of higher concern than false positives because this could put the patient's life in danger. Therefore, the recall percentage is more important than the precision metric. Though the precision percentage of SVM is not the highest in comparison to kNN with 99.71% or Random Forest with 95.40%, since the recall percentage is of higher concern than precision and there is a negligible difference in precision percentage, overall SVM model is the best for this use of seizure detection. On the other hand, the machine learning model that performed the worst was the Logistic Regression model. This model had the lowest accuracy of 64.83%, the lowest precision of 25.54%, and the lowest recall of 42.55% (**Table 1**).

Next, we evaluated the false positives and false negatives identified by each model with confusion matrices (**Figure 1**). A confusion matrix is a table that displays the counts of true positives, true negatives, false positives, and false negatives to summarize the performance of a classification model. The Logistic Regression model had the weakest performance (**Figure 1**). It resulted in 691 false positives and 320 false negatives (**Figure 1**). The false negatives are especially concerning because in real-life applications the machine learning model would not detect that there was seizure activity present in the EEG sample for 320 samples, which

Model Name	Accuracy (%)	Precision (%)	Recall (%)
Logistic Regression	64.83	25.54	42.55
K Nearest Neighbors	92.52	99.71	61.58
Random Forest	95.72	95.40	81.87
Neural Network	87.09	63.17	80.07
Support Vector Machine	96.77	94.27	88.69

Table 1: Trained machine learning model performance metrics. This table contains accuracy, precision, and recall metrics percentage results for each of the machine learning models trained in this experiment: those machine learning models being Logistic Regression, K Nearest Neighbors, Random Forest, Neural Network, and Support Vector Machine.

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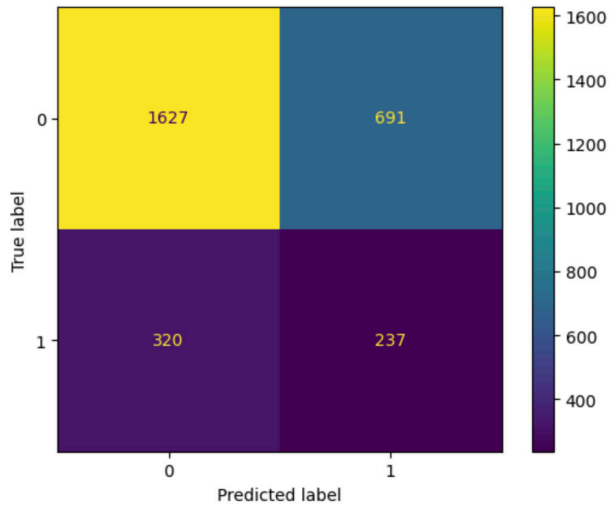

Figure 1: Confusion matrix of logistic regression model. Confusion Matrix depicting false positives (top right quadrant), false negatives (bottom left quadrant), true positives (bottom right quadrant), and true negatives (top left quadrant) of Logistic Regression Model trained on EEG signal data. Confusion matrix imported from scikit-learn Python library applied to trained and tested Logistic Regression Model. Note that 1 represents seizure data and 0 represents non-seizure data. The gradient from yellow to purple indicates the number of samples that fall into each of the four categories, purple being the lowest and yellow being the highest number of samples.

could endanger 320 lives.

We also used a confusion matrix to depict the performance of our kNN machine learning model (**Figure 2**). This model performed significantly better in comparison to the Logistic Regression model. The kNN model resulted in only one false positive. However, it identified 214 false negatives (**Figure 2**). We can speculate that this is because we had overall more data samples of non-seizure activity than seizure activity, so when comparing to the two closest neighbors, the neighbor is more likely to be labeled as non-seizure data than seizure data.

Although the Random Forest model performed well in precision and accuracy as depicted through the 456 true positives and 2296 true negatives and only 22 false positives, the model still struggled in recall highlighted by the 101 false negative cases (**Figure 3**).

The confusion matrix of the Neural Network machine learning model helped us assess and visualize the overall performance of the model (**Figure 4**). The Neural Network performed substandard in comparison to the Random Forest and even kNN models. This model resulted in 260 false positives and 111 false negatives (**Figure 4**).

Based on our conclusions, the SVM learning model performed the best out of the five models we trained and tested (**Table 1, Figure 5**). The SVM model had 78 false negatives, which is the lowest number of false negatives out of all the five models. Moreover, this model performed the best in recall and performed well in accuracy and precision as well.

DISCUSSION

In summary, our study delved into employing machine learning for detecting epileptic seizures using EEG data, aiming to enhance the extensive and often misdiagnosed diagnostic process for epilepsy. We assessed five machine learning models—Logistic Regression, kNN, Random Forest, Neural Network, and SVM—utilizing a preprocessed EEG dataset. We optimized model performance through hyperparameter tuning, focusing particularly on improving recall.

These five machine learning models were chosen because previous studies showed their success in detecting epileptic seizures from EEG data and because these models were widely known to be useful in similar classification problems. For example, Nahzat and Yağanoğlu used the same dataset combined with different preprocessing techniques and found 96% accuracy with their kNN model, 97% accuracy with their Random Forest model, 90% accuracy with their SVM model, and 91% with their Artificial Neural Network model. In comparison to this study, our study had similar but different results. For example, our experiment achieved a 95.72% accuracy with the Random Forest classifier, which was in line with the 97% accuracy achieved by the study conducted by Nahzat and Yağanoğlu. However, their study achieved a 90% accuracy with SVM while ours achieved 96.77% accuracy. This difference was attributed to the use of PCA feature reduction in their preprocessing procedure and the selection of different hyperparameters. For example, we chose 2 for our k neighbors while they chose 1. Furthermore, we decided not to use PCA feature reduction because this technique assumes that the data was linear, and EEG data was non-linear; therefore, the use of this technique could result in the loss of important information in the data.

Each of the models used in this study had strengths in classification problems similar to the classification problem of seizure detection. For example, Logistic Regression was a

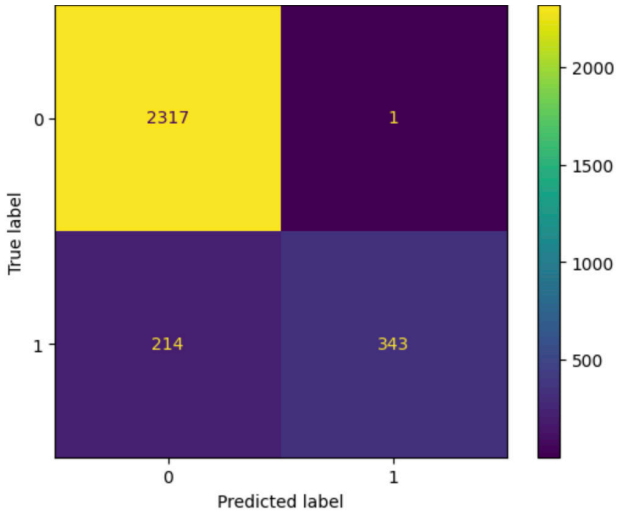

Figure 2: Confusion matrix of k nearest neighbor model. Confusion Matrix depicting false positives (top right quadrant), false negatives (bottom left quadrant), true positives (bottom right quadrant), and true negatives (top left quadrant) of K Nearest Neighbor Model trained on EEG signal data. Confusion matrix imported from scikit-learn Python library applied to trained and tested K Nearest Neighbor Model. Note that 1 represents seizure data and 0 represents non-seizure data. The gradient from yellow to purple indicates the number of samples that fall into each of the four categories, purple being the lowest and yellow being the highest number of samples.

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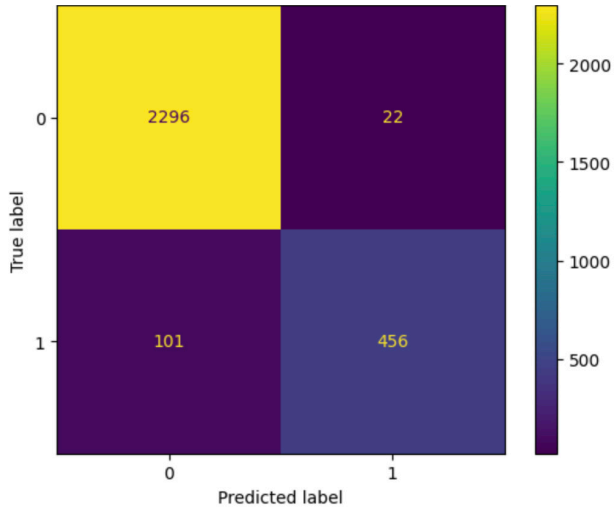

Figure 3: Confusion matrix of random forest model. Confusion Matrix depicting false positives (top right quadrant), false negatives (bottom left quadrant), true positives (bottom right quadrant), and true negatives (top left quadrant) of Random Forest Model trained on EEG signal data. Confusion matrix imported from scikit-learn Python library applied to trained and tested Random Forest Model. Note that 1 represents seizure data and 0 represents non-seizure data. The gradient from yellow to purple indicates the number of samples that fall into each of the four categories, purple being the lowest and yellow being the highest number of samples.

very efficient machine learning model, and this speed could be invaluable in medical situations. Additionally, Logistic Regression could use many factors and vectors to classify data, making it very adaptable. kNN was also very adaptable in that the k neighbors parameter could be tuned, as done in this study, to get more specialized results. The Random Forest model's hyperparameters could also be tuned to achieve more accurate results. An advantage of the Random Forest model was that it built on the decision tree classifying model, so increasing the number of trees (in turn increasing the number of features observed) significantly increased the accuracy of the model. However, increasing the number of trees also increased the training time of the model and slowed the model down. Thus, Random Forest was the model that took the longest time to train. Neural Network was another model that could be less efficient as more hidden layers were added; however, it had a strength in classifying complex nonlinear relationships like fluctuating EEG data. Finally, SVM was also known to perform well in classifying non-linear data, allowing it to be very applicable to EEG data classification. Thus, each of these models was carefully chosen based on their advantages and past successes in classifying EEG data.

The results demonstrated that the SVM model surpassed other models, achieving an accuracy of 96.77%, a precision of 94.27%, and a recall of 88.69%. However, due to potential dataset-specific overfitting and concerns regarding generalizability and privacy, further research was warranted to properly address these concerns. Future investigations should involve diverse datasets, alternative preprocessing techniques, and address privacy issues. Nonetheless, our study contributed to the advancement of epilepsy diagnosis through machine learning applications, holding promise for future healthcare developments.

On the other hand, our results demonstrated that the Logistic Regression model performed worse than the other four models, with the lowest accuracy of 64.83%, the lowest precision of 25.54%, and the lowest recall of 42.55%. This model did not perform well probably because little optimization and hyperparameter tuning could be applied to it. Additionally, Logistic Regression, being a linear model, may have struggled with the non-linear and fluctuating nature of EEG data, which could contain complex patterns that were not easily separable in a linear fashion. Furthermore, this model might have performed better with scaled data rather than the unscaled EEG data with which it was trained and tested.

Though we were able to find success with the SVM machine learning model, there were still a lot of limitations to this method and this study. One limitation was that we were only able to train our machine learning models on one single dataset. Our single dataset was rather large, consisting of 11,500 samples, considering medical data was often smaller and difficult to acquire; however, it still raised questions of generalizability (8). Since we were only able to test one dataset, we could not be sure that the model did not overfit to the data. We also did not know if we would get similar accuracy, precision, and recall with another set of data. Additionally, when considering real-life applications, there were a lot of concerns that people and patients had about privacy and AI. Patients might not trust an AI the way they would trust a doctor (even though a doctor would still supervise the AI), and patients might not want their data to be used to make the AI more accurate. Another concern with AI in the medical field was that most of the models we had tested, and essentially all machine learning models, had a "black box" quality to them, meaning that scientists were unsure about what really happens within the model and how the AI makes decisions.

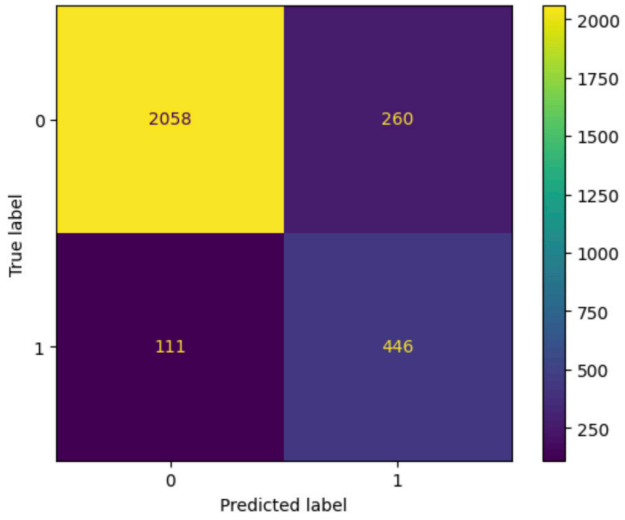

Figure 4: Confusion matrix of neural network model. Confusion Matrix depicting false positives (top right quadrant), false negatives (bottom left quadrant), true positives (bottom right quadrant), and true negatives (top left quadrant) of Neural Network Model trained on EEG signal data. Confusion matrix imported from scikit-learn Python library applied to trained and tested Neural Network Model. Note that 1 represents seizure data and 0 represents non-seizure data. The gradient from yellow to purple indicates the number of samples that fall into each of the four categories, purple being the lowest and yellow being the highest number of samples.

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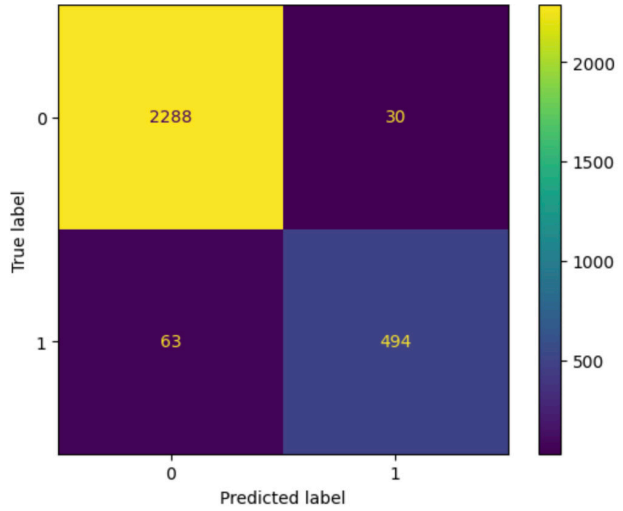

Figure 5: Confusion Matrix of Support Vector Machine Model. Confusion Matrix depicting false positives (top right quadrant), false negatives (bottom left quadrant), true positives (bottom right quadrant), and true negatives (top left quadrant) of Support Vector Machine Model trained on EEG signal data. Confusion matrix imported from scikit-learn Python library applied to trained and tested Support Vector Machine Model. Note that 1 represents seizure data and 0 represents non-seizure data. The gradient from yellow to purple indicates the number of samples that fall into each of the four categories, purple being the lowest and yellow being the highest number of samples.

Because of this, it was difficult and sometimes impossible for the outcome to be traced out.

Though we went through a thorough process to ensure that no errors occurred throughout the experiment, there were still areas where data leakage might have occurred. We took specific precautions to avoid any methods that might inadvertently expose the models to the test dataset during training, which would compromise the integrity of our study. For example, we ensured that all data preprocessing was performed after separating the data into training and testing data. The main processes that might have caused data leakage were the data preprocessing and the hyperparameter tuning. To mitigate this, we carefully ensured that the test data was not used during any part of the training process, thus maintaining the separation between training and test datasets. Additionally, we chose not to scale the data to preserve the natural characteristics of the EEG signals, as we were concerned that scaling might alter the original signal patterns. However, we acknowledged that some machine learning models performed better with scaled data. If we had scaled the 'x' train and 'x' test data (not necessary for the 'y' data as it only contained binary values of 0s and 1s), we might have observed different results. The consequences of this unscaled data might mean that one dimension dominated the other dimensions causing the machine learning model to unfairly weigh the larger dimension more. Therefore, unscaled data may have resulted in data that did not fully reflect the models' capabilities in classifying EEG data.

We observed that seizure datasets had more spikes and variations in the signals. In the future, we recommended generating features that would capture these spikes either through outlier detection techniques or through calculations of standard deviations of various window sizes. We also aimed to extend this study with more datasets. Additionally, in this paper, we used the most common machine learning models that were applied to this area of seizure detection, and in the future, a larger variety of machine learning models should be explored. Furthermore, multiple datasets could be used and preprocessed to fit the format of this dataset so that our machine learning models would have a larger scope of data and become more generalizable. Finally, we suggested that this methodology be tested again with the addition of scaling the "x" train data and the "x" test data, as results will likely be different. Our work still contributed to epileptic seizure detection with machine learning because we were able to achieve high performance with multiple machine learning models, especially SVM.

MATERIALS AND METHODS

A preprocessed and reshaped version of a dataset widely used in detecting epileptic seizures was utilized in this study (7). This dataset was collected by the University of Bonn, and it is available for public use on Kaggle (8). The data is numerical EEG data signals that contains EEG data in a .csv file (6, 8). The original dataset (before it was preprocessed) consisted of 500 individuals' EEG signals for 23.5 seconds, each with 4097 data points. The data was divided into 23 chunks, each containing 178 data points for 1 second of EEG signal by the author of the dataset (7). Overall, this dataset has 11500 samples in total. This preprocessing allowed us to have more data points that are each shorter, which is a tradeoff that makes the machine learning models more generalizable. This version of the dataset was created to simplify access to the commonly used EEG dataset (8). Each data sample is labeled with five possible values: 1 = Recording of seizure activity, 2 = EEG from the area where the tumor was located, 3 = EEG activity from the healthy brain area, 4 = Eyes closed, 5 = Eyes open (8).

First, the data was preprocessed to make it more applicable to our purpose of seizure detection. To start with, we checked if there were any null values in the dataset using the isnull function from the pandas data frame. After determining that there are no null values within our data, we removed the column of string IDs for individual samples as they were unused and only hindered the process of training the ML models. We dropped this column using the pandas drop function. Then, we separated the "y" data (categorical data) from the "x" data (numerical data EEG signal data). After this separation, the "x" data contained the numerical EEG signal data while the "y" data contained the categories of 1, 2, 3, 4, and 5 corresponding to each sample. The "y" data was further modified so that the categories of 2, 3, 4, and 5 all correlate to zero (are replaced with "0") because these are all non-seizure classifications and did not serve our purpose of differentiating between seizure and non-seizure data (not the specifics of the non-seizure data). As a result of this preprocessing our final "y" dataset contained all seizure data classified as "1" and all non-seizure data classified as "0". The data was not scaled.

Then, using scikit-learn's train_test_split function, we divided the "x" and "y" data into a training dataset and a testing dataset (9). The data was made up of 75% training data and 25% testing data. This dataset division yielded 8,625 samples in the training data and 2,875 samples in the testing data. Moreover, the completely preprocessed data was used to

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train and test the machine learning models. The train section of the "x" and "y" data was used to train the models. After the models were trained, they were used to classify the test section of the "x" data as seizure data (1) or non-seizure data (0). The accuracy of the classifications was then checked by the corresponding "y" test data. Our data was trained on the following machine learning models: Logistic Regression, K Nearest Neighbors, Random Forest, Neural Network, and Support Vector Machine. These specific machine learning models were chosen based on what previous studies, such as the one conducted by Shamriz Nahzat and Mete Yağanoğlu, had the most success with.

For each of the models, we went through the same following steps to test and train the models. First, the model was imported from the scikit-learn library (9). Then we trained the model by fitting the "x" train and "y" train data. Then, we tested the model by predicting classifications for the "x" test portion of the dataset. Finally, we evaluated the performance of these models using accuracy, recall, and precision, and compared the predicted classification to the "y" test data (actual classification). The following formulas were used to calculate accuracy, recall, and precision where TP stands for true positive, TN stands for true negative, FP stands for false positive, and FN stands for false negative.

$$Accuracy = \frac{TP + TN}{TP + FN + FP + TN}$$

$$Recall = \frac{TP}{TP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

After creating our models and testing the original/basic models, the hyperparameters were tuned to control and adjust the behavior of our models to obtain an improvised model with optimal performance. The results were obtained with the optimized parameters resulting from our hyperparameter search. In order to tune these hyperparameters, we used the Gridsearchcv function from the scikit-learn libraries (9). This function not only helped us find the best parameters for our models, but also cross validated them. Gridsearchcv is a cross-validation technique that uses K fold to increase the likelihood that there will be a good amount of seizure data samples and non-seizure data samples in the testing dataset. We also used Gridsearchcv to search the hyperparameter space for two of our models: Random Forest model and kNN model. For the Random Forest model, we explored the depth of the model which means the number of decision trees that the model will generate. Two to ten trees were experimented with to determine that ten was the optimal hyperparameter for the number of trees. For the kNN, model we explore the number of neighbors (K-neighbors) that the algorithm should take into consideration. We tested between two and ten neighbors and got the best results with two neighbors. The results of our final models with ideal hyperparameters and Gridsearchcv are displayed (**Table 1**).

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