Exploring intended vs. non-intended EEG responses: A comparison of a logistic regression, linear discriminant analysis and support vector machine based signal classifiers to improve the efficiency of a P300 brain-computer interface

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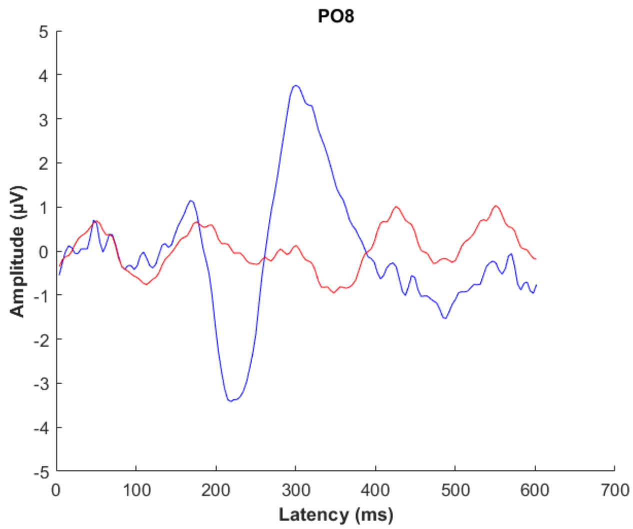
Abstract

Communication for people suffering from neurodegenerative diseases such as ALS and Parkinson's Disease is often limited. Fortunately, systems called brain-computer-interfaces allow a user to control a computer using brain activity. A specific type of BCI called a P300 speller is particularly useful for communication. The P300 speller works by eliciting the P300 wave using the oddball paradigm. However, typing speeds that are typically achieved with this device are extremely slow, with only a few words per minute being spelled. One solution to improve the speller is to implement signal classification algorithms that can prevent errors. Thus, in this study three different machine learning algorithms were used: logistic regression (LR), Linear discriminant analysis, and support vector machine. To test the effectiveness of each classifier, an algorithm was developed to iterate through a data set consisting of EEG data from users operating a P300 speller. The algorithm then trained and tested the classifiers. The LR classifier achieved a .88 accuracy, .69 precision, and .62 recall. The LDA classifier achieved a .90 accuracy, a .74 precision, and a .64 recall. Finally, the SVM classifier achieved an accuracy of .80, a precision of .28, and a recall of .4. Improving the P300 speller results in improving the overall typing speed that can be achieved. With increased typing speed, users of the P300s speller would be able to communicate more effectively with others, increasing their independence and decreasing the difficulty of their daily lives.

Introduction

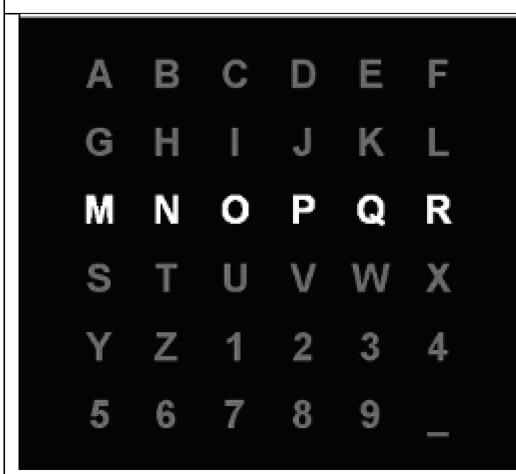
Currently, there are an estimated 16,000 people living with amyotrophic lateral sclerosis (ALS) in the United States and an estimated 10 million people living with Parkinson's disease worldwide (ALSA.org). These neurodegenerative diseases impact the person's social, physical, and mental health, as well the person's family and friends [12]. Along with many other neuro-debilitating diseases (e.g., cerebral palsy and multiple sclerosis), these people all have the risk of losing the ability to speak. Current systems that can re-enable communication such as manual typing and joystick-controlled tablets may be effective, but they are slow and require the ability to move limbs [13]. Furthermore, using these devices can be very tiresome and even impossible for people suffering from degenerative nervous system disorders. However, innovative systems such as brain-computer interfaces work around these disadvantages. Brain-computer interfaces (BCI) are devices that can be controlled using brain signals only, instead of relying on the peripheral nervous system [1]. One specific type of BCI that is especially useful for communication is the P300 speller [2]. This speller relies on the P300 wave, an event-related potential that is elicited by the brain in response to stimuli, due to the *oddball paradigm*. The oddball paradigm can be explained as having multiple, non-deviant stimuli being interrupted by a deviant stimulus - the oddball (Figure 1). It is the deviant stimulus that is recorded by the P300 speller.

Figure 1: An image of a typical P300 event-related potential



The P300 speller works in a specific manner. First, a user thinks of their intended word, one letter at a time (e.g., J-U-M-P-S). While thinking of the first letter (J), the user is also looking at a matrix of letters on a computer screen while letters randomly flash amongst the alphabetical matrix (Figure 2). When the letter the user is looking at (and thinking of) flashes, (i.e., "J") a P300 wave is typically elicited. This P300 response is then read by the computer and the letter is recorded. However, this system has its issues. These include requiring a large amount of both effort and time by the user to operate effectively. According to a study conducted by Pineggar et al, 2010, fatigue increased in the users significantly when using a P300 speller to accomplish a copy spelling task from a mean of 2.74 to a mean of 3.72 on a 10-point system. One additional problem is that, while thinking of the letter J in the previous example, unintentional P300 flashes may also occur in the subject, due to the variety of extraneous stimuli that may mistakenly interfere with the intended letter [13].

Figure 2: A typical P300 matrix. The white letters are the flashing letters, which represent the deviant stimuli



These may include such stimuli as other letters flashing that are in the user's peripheral vision, or even unexpected loud noises or changes in temperature or lighting in the room. Thus, identifying and then filtering these unintended P300 responses is paramount for an efficient and effective P300 speller. This notion drives the current research. Overall, the variability in reasons why a typical P300 wave may be elicited in the first place has inspired many studies to look for ways to increase the P300 speller's ability in identifying intentional P300 flashes against unintentional P300 flashes. We will use three different types of machine learning algorithms to to attempt to improve classification of individual stimulus responses using different machine learning methods**.**

Review of Literature

A brain-computer interface (BCI) is a system that allows the user the ability to control a machine without the use of the peripheral nervous system. BCIs function by translating brain signals into output signals for a computer system [15]. One such computer system is a BCI speller, which allows the user to spell out words and sentences. This type of device is incredibly useful for people who are unable to communicate [2].

Currently, 16,000 people in the United States of America are living with Amyotrophic Lateral Sclerosis (ALS) (ALSA.org). 10 million people have Parkinson's worldwide and approximately 1 million people living in the United States have been diagnosed with aphasia [5][6]. All these diseases can lead to reduced control of muscles, resulting in the inability to communicate through natural, verbal means. Often, people who have these neurodegenerative diseases end up not being able to move any of their muscles other than their eyes. This is known as being in a locked-in state [17]. People in a locked-in state often suffer from depression due to being fully aware yet unable to communicate. Thus, there is a dire need for an effective, accurate, and efficient BCI speller.

P300 Speller

P300 spellers work by evoking the P300 event-related potential (ERP). ERPs are small voltages generated by the brain in response to stimuli [18]. To elicit the P300 ERP, a specific type of stimulus needs to occur. This specific stimulus can be realized using the oddball paradigm, in which multiple non-deviant stimuli are interrupted by a deviant stimulus. The P300 wave can be seen clearly on an electroencephalogram. To use a P300 speller, the user looks at a matrix of letters where each row or column flashes randomly. The flashing letters represent the deviant stimuli. When the letter that the user is looking at flashes, the P300 wave is elicited. Multiple P300 flashes are required to spell one letter because, with common spellers, multiple letters are flashed simultaneously.

Unfortunately, one large problem with the current P300 spellers is the slow operating speed that a user can achieve, often under ten characters per minute (about two words per minute), meaning the user cannot input letters quickly which results in slow words-per-minute [7]. This is because, for many systems, the user can only input one letter at a time; this restriction limits the user to only a couple of words per minute [7]. A commonly used metric to analyze how quickly a P300 speller can be used is called information transfer rate (ITR). The commonly known P300 speller proposed by Farwell and Donchin (2003) achieved an average of 5 words per minute and an ITR of .5 bits per second (bps) [3]. Currently, newer P300 spellers have achieved slightly higher ITRs between 1.7 and 2.4 bps [5][6]. Most of these newer P300 spellers made in the last five years employ the help of signal classifiers.

Signal Classifiers

In order to improve the ITR of P300 spellers, signal classifiers have been implemented that can discern between intentional P300 flashes and unintentional ones. This is impactful on the ITR because the signal classifier can help decrease the number of errors that occur when spelling words. Signal classifiers are a type of computer algorithm that separates intentional and purposeful P300 waves from unintentional ones. One type of signal classifier used is linear discriminant analysis.

Linear Discriminant Analysis

Studies have tried to increase the ITR of P300 spellers using different types of signal classifiers. In one study by Panicker and Sun (2010), a two-classifier training approach was used to improve the ITR. These classifiers were Fisher’s linear discriminant analysis and Bayesian linear discriminant analysis. These two classifiers are similar in that their purpose is to find a linear combination of features that separates two or more classes of objects (i.e., intentional and unintentional P300 flashes). However, they differ from each other because Fisher's LDA finds a linear combination of the variables that maximize the ratio of the between-group sum to that of the within-group sum in achieving a good separation while Bayesian LDA works by assigning the observed unit (P300 signal) to a category with the greatest posterior probability. In other words, Fisher’s LDA looks to find the variables that affect classification, and then calculate the mean of each of those variables. Fisher’s LDA then classifies based on the mean divided by the variance. Bayesian LDA works by applying probabilities for one class or another based on the observed features [20]. These two classifiers then built upon each other, comparing the certainty of each classifier and outputting a final result. This final classifier was able to achieve an average ITR of 37 bpm [9]. Multiple other signal classifiers have also been devised and implemented since, including stepwise linear discriminant analysis (SWLDA) and logistic regression analysis (LR). We will be using LR in this study to classify intentional and unintentional P300 waves.

Stepwise Linear Discriminant Analysis

SWLDA is often used when there are many features or predictors that can be used to classify data because SWLDA automatically picks the indicators that can best classify the data.

Logistic Regression

One of the signal classifiers used in our study was the logistic regression (LR) classifier. LR is used when the data is categorical by nature. Categories can consist of true or false, yes or no, and one or zero. In our study, the categories were intentional or unintentional. The LR classifier creates a decision boundary where if certain data is over the specified boundary, it is classified as one category, and if it is below the boundary, it is classified as another category [11]. With relation to P300 spellers, if the signal appears to be intentional, it gets classified under one category, and if it seems to be unintentional, it gets classified under the other category. Logistic regression classifiers are a very simple method for signal classification and will be used as a comparison for the other signal classifier used in this study: A support vector machine classifier.

Support Vector Machines

Support vector machines are a type of machine learning algorithm. The SVM separates data elements from each other using their associate feature values. The SVM then approximates a hyperplane that separates the different feature planes. The SVM then selects specific samples from both planes that are closest to the hyperplane. These samples are called support vectors. The separation between the hyperplane and the support vectors is called the margin. The SVM works to maximize the margin to create the most generalized decision boundary (Fig 3). The SVM will be the second classifier used in the study.

Precision and Recall

In order to compare different signal classifiers, the precision and the recall will be found. Precision is the number of true positives (the correct signal classification) divided by the number of true positives and false positives (incorrect, intentional classification). The recall is the number of true positives divided by the number of true positives and the number of false negatives(incorrect, unintentional classification). In essence, precision compares the total correct intentional classifications with all the intentional classifications, correct or incorrect. Recall compares the total correct intentional classifications with all the possible correct intentional classifications.

Dataset

The data used in this study were from 81 different subjects, collected over the course of multiple previous studies and trials. The data were de-identified and anonymous.

Research Focus

My study will look to compare the LR, LDA, and SVM signal classifier as well as compare different parameters with training and testing the classifiers. The different parameters will consist of different sized train and test groups, as well as data shuffling. Different kernels will be compared for the SVM as well. To compare the classifiers and their different parameters, a python program will be written that implements the signal classifiers, trains the classifiers, and tests the classifiers. The program will also calculate the average accuracy, precision, and recall that each classifier achieves. Additionally, the various parameters for each classifier will also be compared.

Objectives

1. Design and create Python script that incorporates an LR, LDA and SVM signal classifier
2. Calculate the average *accuracy* that an LR, LDA and SVM signal classifier can achieve with different parameters and compare
3. Calculate the average *precision* that an LR, LDA and SVM signal classifier can achieve with different parameters and compare

4. Calculate the average *recall* that an LR, LDA and SVM signal classifier can achieve with different parameters and compare

Hypothesis

Ho1: The SVM classifier will not achieve higher accuracy than the LR and LDA classifier.

H1: The SVM classifier will achieve higher accuracy than the LR and LDA classifier.

Ho2: The SVM will not achieve higher precision than the LR and LDA classifiers.

H2: The SVM will achieve higher precision than the LR and LDA classifiers.

Ho3: The SVM will not achieve a higher recall than the LR and LDA classifiers.

H3: The SVM will achieve a higher recall than the LR and LDA classifiers.

Methods

My Role in the Study

I am enrolled in a three-year science research program at my high school. After one year of reviewing literature that discussed P300 spellers and their many positives and drawbacks, I became curious about how different types of artificial intelligence could increase the effectiveness of the P300 speller. After reading more journal articles on this topic, many of which were written by my mentor, Dr. William Speier at the University of California, Los Angeles, I reached out to him, and he agreed to work with me. We decided to focus on how to implement a convolutional neural network as a signal classifier.

In the second year of my program, I began by teaching myself how to write Python and use different types of data manipulation techniques. I taught myself by first taking a few online courses and attempting small projects to learn how to use different data analysis methods including linear and logistic regression. This took approximately one and a half years. Additionally, my mentor provided me with previously written code that I could use as an example of ways to work with EEG data further. I also began familiarizing myself with different types of machine learning algorithms such as logistic regression and support vector machines. To do this, I looked at previously written code containing these techniques.

Ultimately, utilizing Python and the skills I taught myself, I wrote a program that ran different signal classifiers on previously collected data. Creating this program was a major challenge for me as it was the first time, I had tried to create such a complicated computer program. At points where I could no longer figure issues out on my own, my mentor would provide me with hints and tips to help me move forward with my study. Once the program was written, I applied the program to the data set provided to me by my mentor. Doing this provided me with the results of my study.

Data Background

Sets of EEG data were collected prior to the study. These data were collected by administering P300 spelling trials for the participants. The 81 participants were all healthy adults who had little to no experience with BCIs. The data consists of the EEG results. The participants were asked to spell target words using the P300 speller. The system used a 6x6 character grid, row and column flashes, and an interstimulus interval of 125 ms.

All EEG data were collected using BCI2000 and analysis was performed offline using Python (version 3.9). Two analysis methods were implemented in the study, logistic regression and support vector machines. Both of these analyses were accessed through Scikit-learn [21] in collaboration with the Python library NumPy [22].

Classification

To use the different types of signal classifiers, a program was written that determines which parts of the data will be useful. It determines this by finding all the time points that correspond to when an intended letter was flashed on the matrix.

The Sklearn Python library was used to implement LR. LDA and SVM classifiers. The EEG signals were assigned to one of two classes: those that corresponded to intended character outputs and those that corresponded to unintended character outputs. To train the three classifiers, the data was separated into two groups, one for training and one for testing.

Evaluation

The evaluation of the success of the P300 speller can be separated into three different measures: the percent *accuracy*, the *precision*, and the *recall*.

In order to determine the accuracy, the number of correct classifications was divided by the total number of classifications.

To determine the average recall of the classifiers, the number of correct, intentional classifications was divided by the number of incorrect, unintentional classifications plus the number of incorrect intentional classifications.

To determine the average precision of the classifiers, the number of correct, intentional classifications was divided by the number of correct, intentional classifications plus the number of incorrect, intentional classifications.

Results and Discussion

The goal of this study was to evaluate three classifiers to improve the efficiency of a P300 spellers. While evaluating the classifiers the average accuracy, precision, and recall were calculated.

To calculate the accuracy of each classifier, the number of correct classifications was divided by the number of total classifications. After training and testing the SVM (kernel = RBF) with equally sized train and test sets, the initial accuracy was .19, the average precision was .16 and the average recall was .96. This means that the SVM was making an error with classification. Clearly, this is not the expected result. Past studies have demonstrated that SVMs can achieve an accuracy closer to .83 [24].

Table 1: Confusion matrix created for the SVM classifier using RBF

Confusion Matrix for SVM	Predicted No	Predicted Yes
Actual No	0	1000
Actual Yes	0	200

However, looking at the confusion matrix for the SVM [kernel = RBF], it becomes clear that the SVM classifier is classifying everything as intentional, the minority class (Table 1). As a result, the classifier correctly identified every intentional P300 flash, rather than intelligently deciding between intentional and unintentional, which leads to the recall being as high as it is.

The classifier is also identifying every unintentional P300 flash as intentional, which is why the accuracy and precision are so low. In order to directly address this error, we changed the type of kernel being used to classify to a polynomial-based kernel. This led to improved classification with an accuracy of .80, a precision of .27, and a recall of .40. While the precision and recall are still low, they are high enough to signify that the classifier is making intelligent decisions, rather than solely predicting one class or another 100% of the time. Indeed, using an SVM with a polynomial kernel is an improvement.

Next, we compared the SVM to the LR and the LDA classifiers. The LR classifier achieved an accuracy of 88%, a precision of 69%, and a recall of 62%, while the LDA classifier achieved an accuracy of 90%, a precision of 74% and a recall of 61%. Comparatively, the SVM did not perform as well (Figure 3a, 3b &3c). This may be due to the small data set used to train the SVM.

Fig 3a: Results of the logistic regression

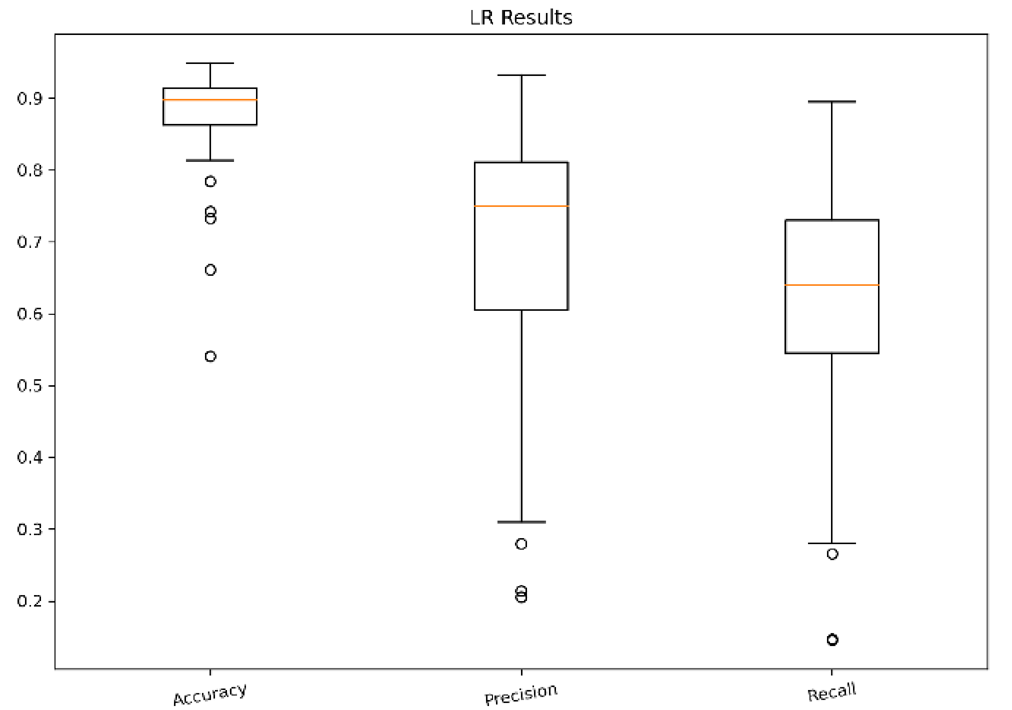


Fig 3b: Results of linear discriminant analysis

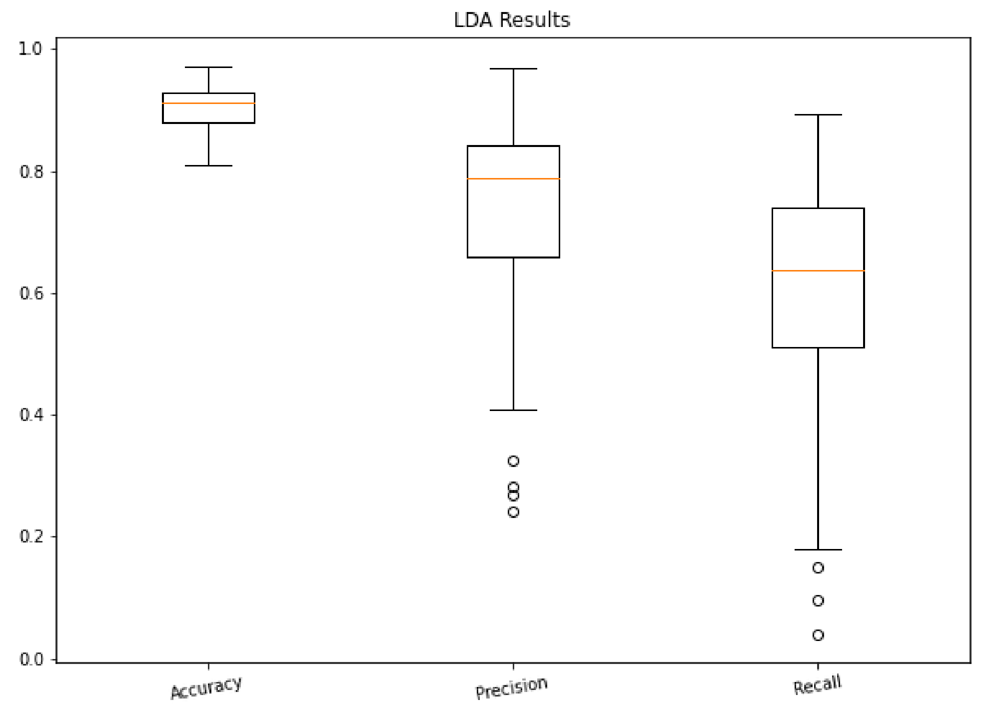
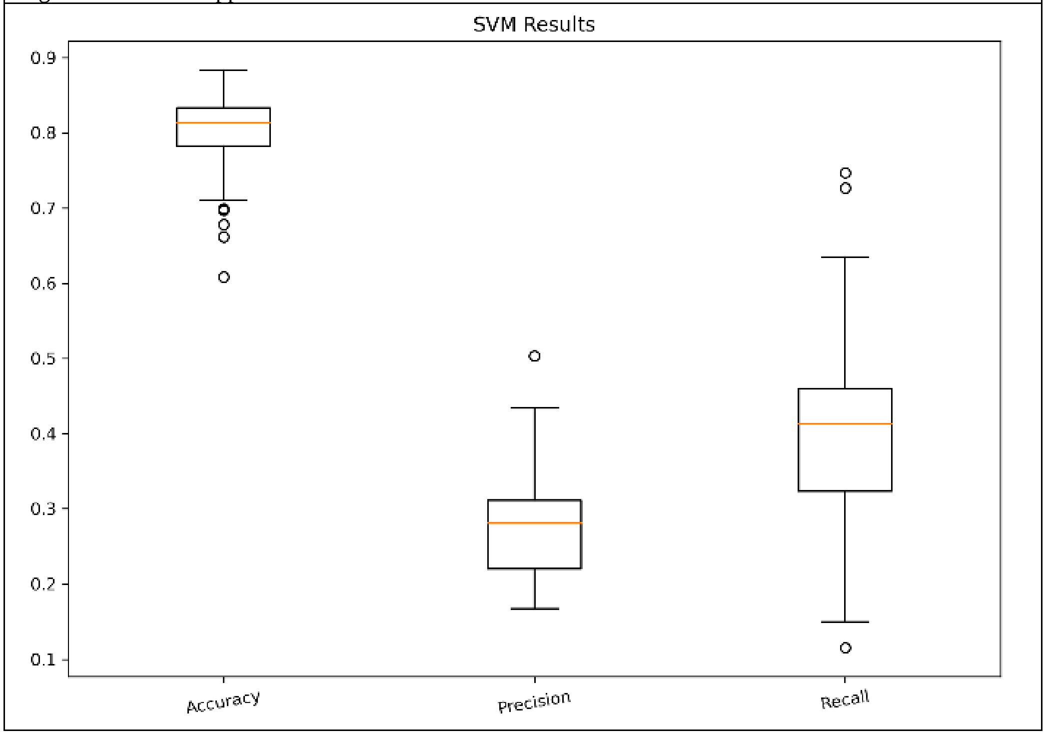


Fig 3c: Results of support vector machine



Future research should look to use different parameters for the SVM, such as linear or radial basis function (RBF) based classification as the parameters used in this study may not have been the most effective. The RBF kernel was used to test the data during this study; unfortunately, it was unable to train effectively, leading to the classifier only classifying P300 waves as unintentional. Increasing the size of the dataset and using th RBF kernel may result in improved accuracy, precision, and recall. Potentially increasing the size of the data set would allow the RBF SVM to train and test properly.

Using more powerful classifiers can also improve the results of the study. One such classifier could be a convolutional neural network (CNN). A CNN is a type of artificial neural network that has been extensively for image recognition. Pertinent to this current study, Vernon, et al., (2018) investigated if using a convolutional neural network (CNN) to classify P300 flashes is feasible. Researchers chose to use CNNs because these neural networks have been shown to be proficient in image recognition and pattern detection; this is essential as intentional and unintentional P300 waves may appear noticeably different on EEG scans [5]. CNNs are particularly good for image recognition due to being easier to train and reduce the dimensionality of the images [16]. In Vernon, et al., researchers found that using a convolutional neural network to classify P300 flashes as either intentional or unintentional is feasible. However, in the proposed model, empirical evidence was not provided to demonstrate the usage of the CNN signal analyses. They showed that using a CNN is in fact a feasible method to classify P300 flashes but did not actually train and test the CNN and compare it against other signal classifiers. Thus, future research should look to use a CNN to classify intentional and unintentional P300 waves.

Currently, spelling letter by letter is slow and time consuming. The goal of P300 spellers is to make the lives of people who need to use them easier. Letter by letter spelling creates new issues for the users. Therefore, using different techniques is necessary. For example, natural language processing algorithms could also be implemented to increase the number of words per minute. One study already implemented an NLP algorithm and achieved 40%-60% increase in the bit rate [16] meaning that using NLP algorithm improved the typing speed. This study however had six participants and used a simple natural language processor. Future studies should look to use more people and more advanced NLPs.

Another limitation with current P300 spellers is that they are unable to detect intention, sarcasm, and other subtleties of language. This can lead to misunderstood sentences even if the P300 speller spelled everything correctly. BCI's have been shown in previous studies to possess the capability of detecting and recognizing different emotion from the wearer [25]. Theoretically, these two types of BCIs, the P300 speller and a BCI geared towards emotion recognition, could be used in conjunction to create a type of P300 speller capable of recognizing sarcasm and other subtleties of language.

Conclusion

P300 spellers are incredible pieces of technology that can be used to change people's lives. Unfortunately, these devices have issues. They are slow to use, require large amounts of effort, and are not always accurate This study demonstrated how different types of machine learning P300 signal classifiers compare to each other. To contrast the three signal classifiers, logistic regression linear discriminant analysis and support vector machines, the signal classifiers were first trained and then tested on the same previously collected dataset composed of 81 different participants. During the study, the LDA classifier achieved the highest accuracy and precision while the LR achieved the highest recall. These findings demonstrate different signal classifiers that can be used to improve the typing speed of P300 spellers.

Originally during the study, an RBF kernel for the SVM classifier was used. However, the SVM was unable to train effectively using this kernel, which resulted in the classifier not being able to recognize intended and unintended P300 flashes. Additionally, during the study we planned to record new data using an EEG machine. Due to Covid-19, we were unable to obtain a functioning EEG machine. Future research should look to use a larger dataset, which should improve the ability for the SVM with an RBF kernel to train.

This study demonstrated that LR, LDA, and SVMs can be used to improve typing speed for BCI spellers. This means that people who rely on BCI spellers, they can communicate more naturally. Communicating more naturally allows these people more independence where the can live their daily lives with less discomfort.

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