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Systematic Analysis of Machine Learning Algorithms on EEG Data for Brain State Intelligence

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Electroencephalography (EEG) is a highly promising medium for brain-computer interfaces (BCI) with potentially extraordinary applications such as the direct control of prosthetics and exoskeletons. However, effective analysis and modeling of EEG data has been limited by its poor spatial resolution. EEG's low amplitude, brief and sporadic nature, compounded by extra-cranial noise, contribute to the difficulty of this problem. This systematic analysis provides strong evidence to guide future research in machine learning applied to real-time analysis of brain states using EEGs. The main goal of this research is to understand how the construction of data sets used in training models affects the accuracy of prominent machine learning algorithms, specifically: Random Forest, Boosting, Naïve Bayesian Classifier, k-Nearest Neighbors (KNN) and Support Vector Machine (SVM). Herein, we present a systematic method (N = 153) to test the accuracy of prominent machine learning algorithms when varying three main components of the training data set: the permutations of subjects, the number of unique data sets used to generate the training data set, and the number of samples in each training data set. Our results strongly indicate that Random Forest consistently yields superior results when analyzing EEG data compared to other prominent machine learning algorithms. Furthermore, a pilot investigation was conducted on a mean-normalized feature for EEG data analysis. The pilot analysis (N = 28) confirmed Random Forest's analytical superiority in EEG data, shows signs of improved accuracy, and identifies a distinctive correlation between beta and delta waves and their respective active or idle brain states.

Keywords: Electroencephalography, Systematic Analysis, Machine Learning, Random Forest, Boosting, Bayes, KNN, SVM, Data Mining.

I. INTRODUCTION

Renowned scientist and philosopher Galvani is remembered as the first person to identify electrical activity in living organism in the 18th century [1]. Later, in 1924, the celebrated electro-physiologist Hans Berger successfully recorded electrical activity from the human brain using a process now known as electroencephalography (EEG), which measures voltage oscillations due to the flow of ions in the neurons of the brain [1]. Today, EEG is one of the most popular non-invasive techniques by which to record brain activity in clinical and research settings. There is a wide range of cheaply accessible applications for the analysis and interpretation of these measurements. EEG data carries an immense potential in various areas including human computer interaction, psychology, and neurological sciences. It is desirable to create an application that takes EEG data and exposes it to various analytical techniques so the resultant brain states can be studied and predicted.

The increasing interest in EEG based brain-computer interfaces (BCI) is evident through the development of cheap EEG devices, for example, EPOC™ (Emotiv) and MindWave™ (NeuroSky, Inc.). EEG signals characterize the result of the neuron activities inside of a human brain. The brain emits electrical signals that can be measured by placing an electrode in contact with the scalp. The resulting EEG readings initially consist of a voltage measurement, on which a spectral analysis is then performed in order to observe the signal in the frequency domain. Table 1 lists the most commonly recognized frequencies ranges that are generated by different types of brain activity. Effective modeling and analysis of this EEG data has been limited due to the sporadic nature and noise from the extra-cranial sensor.

Electrical activity in the brain can therefore be analyzed in terms of the frequency ranges in which neural oscillations are observed and recorded. Measurements that are concentrated within each of these frequency bands are associated with certain mental states, and thus by analyzing the spectral content of the electrical impulses in the brain, a highly educated guess can be made as to what mental state a subject is in. This is the basic idea behind the categorical classification of brainwave data. A model is first constructed based on a pre-classified set of training data. This model can then be used to classify newly collected data.

EEG signals indicate that neural patterns of meanings in each brain occur in trajectories of discrete steps, whist the amplitude modulation in EEG wave is the mode of expressing meanings [2]. Zhou et al. have proposed some novel features for EEG signals to be used in brain-computer interface (BCI) system to classify left and right hand motor imagery [3]. The experimental results have shown that based on the proposed features, the classifiers using linear discriminant analysis,

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support vector machines and neural network achieve better classification performance than the BCI-competition 2003 winner on the same data set in terms of the criteria of either mutual information or misclassification rate.

TABLE 1. NEUROSKY BRAINWAVE FREQUENCIES

Brainwave Type	Frequency Range
Delta	0.5 Hz to 2.75 Hz
Theta	3.5 Hz to 6.75Hz
Low Alpha	7.5 Hz to 9.25 Hz
High Alpha	10 Hz to 11.75 Hz
Low Beta	13 Hz to 16.75 Hz
High Beta	18 Hz to 29.75 Hz
Low Gamma	31 Hz to 39.75 Hz
Mid-range Gamma	41 Hz to 49.75 Hz

The vast implications of using EEG data to analyze brain states include designing brain-computer interfaces (BCI) whereby users can give instructions to a machine via brain activities, as well as the use of brain state models in healthcare-related fields. The combination of electroencephalographic data with modeling methods in fields such as data mining and bioinformatics could be used to diagnose disease in advance, thereby increasing the probability of a successful cure.

The study of brain waves using specific stimulus and quantification of dominant waves has been successfully done utilizing the linear regression model [4]. The research group found that the upper alpha wave is up-regulated during brainwave study under music stimulus, and as the subject listens to a song which was previously known, alpha waves then became dominant. This study showed the positive correlation between alpha wave generation and memory function. In another research study where logistic regression, K-nearest method, and neural network back propagation method were applied to 50 epilepsy patients and 50 normal humans, it was found that different classification systems gave variety of predictions. Also, the process of filtering the brain wave data had influence in the net model structure [5]. This study underscores the complexity that lies with the classification of brain waves, and the prediction of the model is directly proportional with the increase in the constant variables associated with the modeling equation [5,6].

For brain state modeling, two types of research models have been used: statistical models and micro models. For example, statistics models are built by applying statistical analysis to collected data from meditation practitioners, while micro models try to catch physiological features of the brain state under examination. Current literature shows that both methods are used in the study of complementary and alternative medicine practices, which include meditation. One approach is to study finite differences between what takes place within the minds of those who practice meditation, and those who do not. Such an endeavor is an avenue towards modeling a wide range of brain states [7]. Loizzo et al. performed a 20-week contemplative self-healing program study, which showed that a contemplative self-healing program can be effective in significantly reducing distress and disability among the testers [8]. Habermann et al. on the other hand, performed a long-term (5-20 years) project to investigate the use of complementary and alternative medicine and its effects on the testers' health [9]. Comparisons across different groups of people are also found. For example, in a 6-week mindfulness-based stress reduction program, subjects assigned to the program demonstrated significant improvements in psychological status and quality of life compared with usual care [10]. Another comparison is found where a group of Qigong practitioners were compared to a control group and positive indicators were found in the study [11].

The analytic methods that are the focus of this research include a number of statistical classification methods. Quite generally, each of these Machine Learning algorithms works by gleaning distinguishing features from a set of pre-classified training data that is fed into the algorithm, upon which a statistical model is constructed. Based on the built model, any new data can then be analyzed, compared to the model, and assigned to a particular class. Thus we can see that this process involves two discrete phases, which are: (1) data modeling and (2) data classification. It is then our proposal that through EEG data collection and the Machine Learning techniques mentioned above, it should be possible to implement a wide range of specific applications which can provide useful functions to the user. One conceived implementation is an embedded system which would be capable of performing a real-time analysis of EEG data, as it is collected. A device such as this, when given unclassified EEG data, would then be able to classify the brain state of the user into one of a number of different classes, depending on the particular models available to the system, and how these models were trained. As the data is classified, the system would provide an indication to the user of which brain state the incoming data most closely resembles.

II. METHODS

EEG Data Collection

Samples were collected from 3 healthy subjects using the Neurosky Mindwave Mobile headset, a single-sensor EEG device. Samples were either taken during the morning or during the afternoon. Two samples were taken at each time, an "Active" sample and an "Idle" sample. Each "Active" sample consisted of five minutes (± 10 s) during which subjects were continuously doing two-digit multiplication. Each "Idle" sample consisted of five minutes of relaxing with closed eyes. For the idle sample, subjects were first given five minutes to mentally relax before data collection began. All collections were done in the same room, in a controlled climate and using the same EEG Neurosky sensor.

Computational Framework

While R has an abundance of machine learning packages and statistical support, its performance made it impractical for real-time data analysis as illustrated in Table 2. Given the speed of the computations in while maintaining accuracy, all computations were done in C++.

The algorithms were implemented using OpenCV Machine Learning package in C++, with each algorithm developed with two discrete phases: training and classification. The independent implementation of the training and classification phases allowed for the flexibility in analyzing the results from various permutations in models and test data. Two layers of bash scripting were used to systematically automate the analysis. The first layer of bash scripting connected the incremental steps in Figure 1 by handling the input and output of intermediate data files, such as models generated from machine learning algorithms, and executed the algorithm that was written in C++. It also handled the modeling and testing permutations framework as discussed later. The second layer of bash scripting was then used to link the first layers together. This framework is illustrated in Figure 1.

Finally, a Python script was used to parse through the results of the secondary analysis to generate the final results.

All computations were completed on University of Houston – Downtown's Grid Server (grid.uhd.edu). The server was monitored so that no substantial processes (>20% CPU, > 20% RAM) were concurrently running.

Primary Data Analysis Process

Data was first preprocessed on Neurosky's device using its proprietary analysis – first, raw signals were passed through a band-pass filter to remove frequencies < 0.5 Hz and > 50 Hz. Secondly, the signals were decomposed using Fast Fourier Transform to obtain component frequencies from the eight main brain wave bands as illustrated in Table 1.

A variety of models were created using each of the algorithms: Random Forest, Naïve Bayesian, Boosting, Support Vector machine, and k-Nearest Neighbors. The method in which the data samples for each model were chosen is more specifically described in the Data Sample Selection Framework for Modeling section below. Each selection of data samples was used to create five models, each from one of the algorithms. After the models were created, they were tested with a generic set of test samples. The test samples contained 1 "Active" sample and 1 "Idle" sample from the same subject. In total, there 19 generic test samples.

When each model is classified with a generic test sample, a confusion matrix is generated which shows the percentage of each test sample the model predicted correctly. The aggregate results of all confusion matrices is further analyzed in the permutation analysis, described later.

TABLE 2. R AND C++ COMPUTING PERFORMANCE

	R (Single Core)	R (Multi-Core)	C++ (Single-Core)
Boosting	3,008 sec. 94.8%	-	0.071 sec. 98.0%
Random Forest	11.603 sec. 96.1%	5.818 sec. 96.4%	4.117 sec. 97.7%
KNN	6.657 sec. 84.8%	-	2.304 sec. 94.2%

(N = 10,000 lines)

Data Sample Selection Framework for Modeling

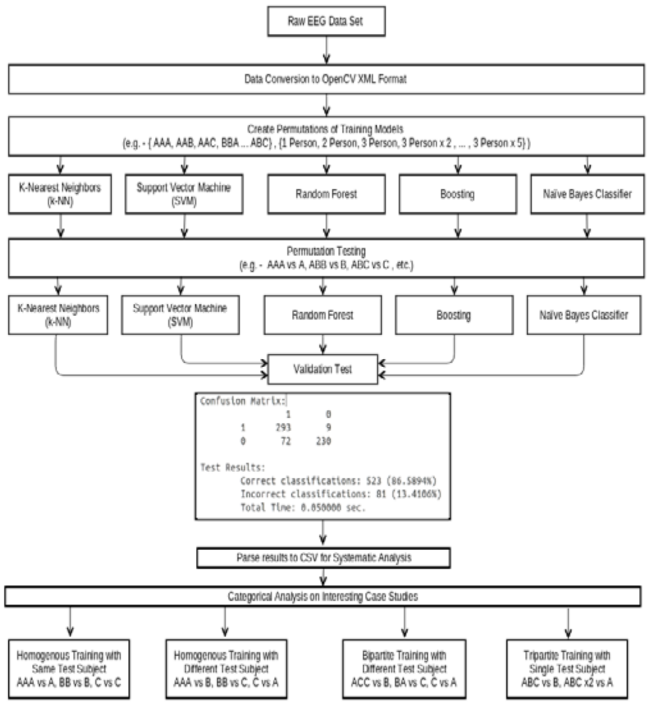
Models were created based on the *number* of data sets used. The number of data sets used were: one, two, and three. Every combination of models was satisfied. In other words, for the single-sample models, there were models comprised of A, B and C. In two-sample models, there were models: AA, AB, AC, BB, BC, CC. In three-sample models, there were models: AAA, AAB, AAC, BBB, BBA, BBC, CCC, CCA, CCB, and ABC. Following the first three types, models with 6, 9, 12 and 15 samples were made. However, they were all made in multiples of ABC, where six sampled models were ABC x2 (AABBCC), nine sampled models were ABC x3 (AAABBBCCC), and so on. In all cases, the size of the resulting model was kept constant at two sizes by using $\frac{1}{n}$ of the proportion of each data sample for a model with n distinct samples. For the 1 sampled and 2 sampled models and $\frac{1}{2n}$ proportion was also used. For example, for the 1 sampled model, 100% of the sample was used. In the 2 sampled model, 50% of each sample was used; 3 sampled, 33%, etc. In total, there were 18 one-sampled models sets (9 using 100%, 9 using 50%. Of each 9, 3 samples were made for each subject. i.e. 3 samples * 2 sizes * 3 subjects = 18 samples), 24 two-sampled model sets, 30 three-sampled models, and 6 six, nine, twelve and fifteen sampled-models. This process was designed to reveal how a more diverse set of data affects classification accuracy. The testing of two file sizes, $\frac{1}{n}$ and $\frac{1}{2n}$, will demonstrate how changing the size data set in the model affects the classification accuracy. Each combination of datasets was used to generate five models, one for each algorithm. By this we will be able to discover how the selection of algorithm will affect classification results.

Model & Test Permutation Data Analysis

With the numerous samples of data, specific permutations of data samples were selected for modeling, in which each permutation generated 5 models, one for every algorithm.

The permutations of data sets are outlined in Figure 2, which illustrates the three fundamental categories of modeling permutations: subject-specific models, which tests a subject with a model that is comprised entirely of the same subject's data; non-inclusive model, which tests a subject that is comprised entirely not of the subject's data; and an all-inclusive model, which tests a subject with data that includes the subject as well as other subjects. This method will demonstrate how the inclusion or exclusion of the test subject's data affects classification results.

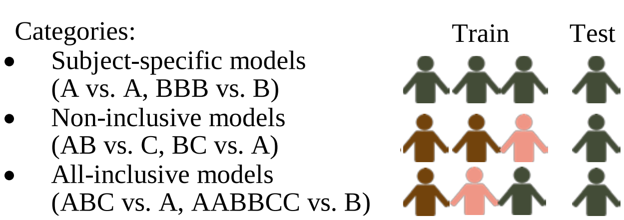
Figure 1. Data Analysis Framework



III. RESULTS

The analysis of the results obtained on test data sets from same subject as well as different subjects showed that the Random Forest algorithm provides the highest percentage of correct classifications (Figures 2 and 3). The highest accuracy level reached by Random Forest was 84%, which occurs in the cases where a model was trained using three data sets from the same subject and then tested against data sets from the same subject. The results from our tests of the Boosting method were the second most accurate, after Random Forest.

Figure 2. Testing Permutation Variations

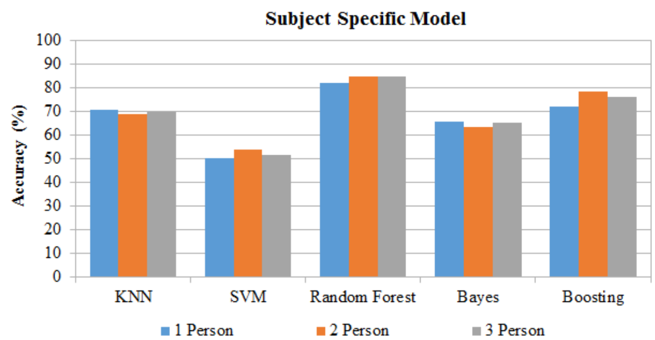


Homogeneous training models incorporating data from two unique data sets seem to provide the highest accuracy rates (78%) for Boosting, followed closely (76%) by the homogeneous models that were trained with three data sets.

Selection of Algorithm	Large effect
Percent of Data used	No effect
Increasing Number of Unique Individuals	Little effect
Increasing Number of Samples Used for Training	Little effect

In certain cases, the Naive Bayes classifier also produced relatively accurate results (Figures 3 and 4). When using an all-inclusive training model composed of 4 data sets from each subject, the accuracy of Bayes reached an average of 75%. When compared to the 68% accuracy of the all-inclusive models trained with only 1 data set from each subject, it is tempting to conclude that the addition of more unique training data to an all-inclusive Bayes model will result in an increased accuracy, however the accuracy level actually goes down when increasing from 1 to 2 data sets from each subject, and again when increasing from 4 to 5.

Figure 3. Classification results comparison from subject specific model.



The accuracy of KNN ranged from 57% at the lowest, to 70% at the highest (Figure 3, 4, 5). The lowest results were produced in the non-all-inclusive tests against a non-included subject, and also in the all-inclusive(x4) tests. K-NN achieved the most accurate results in the single-person, single-dataset tests. SVM consistently output results hovering around 50%, a rate that could be achieved by random guessing. Our suspicion is that SVM is not well suited to the classification of our Brainwave data, possibly due to our selection of parameters. We tested the SVM algorithm with four different kernel types: Linear, Polynomial, Sigmoid, and Radial Basis Function. The variation of the kernel had no effect on the accuracy level of SVM's classifications, which remained firmly at 50% in all cases. In the case of all-inclusive training, the inclusion of additional training data did have a small effect on the accuracy of the algorithms, but not in a consistent manner.

Figure 4. Test result comparison from non-inclusive models.

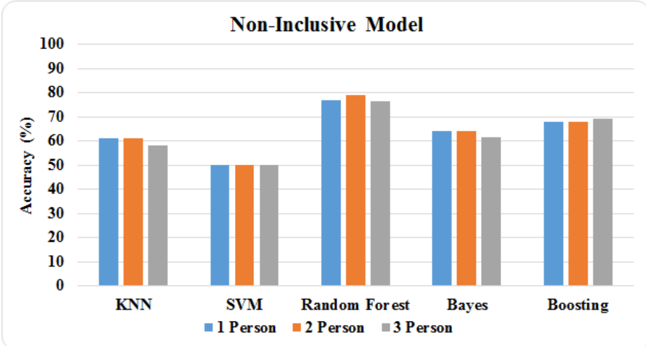
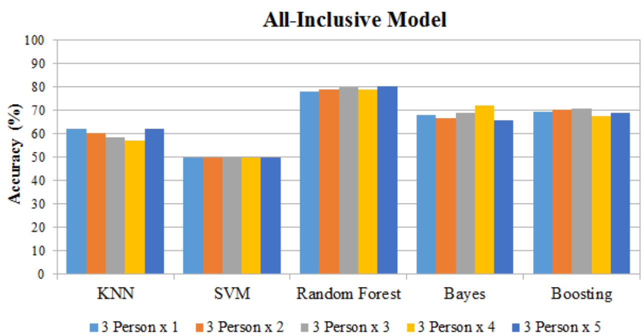


Figure 5. Test result comparison from all-inclusive models.



IV. PILOT ANALYSIS ON NORMALIZED MEAN DATA

The pilot analysis using the normalized-mean feature indicated significant improvements in classification accuracy compared to using solely the raw data. The pilot analysis (N = 28) confirmed that Random Forest yields the highest accuracy.

In order to take another approach to understanding the structure and pattern of the data sets from a different perspective, the machine learning techniques can be applied to the central tendency and deviation features inherent in the data sets. Here, we conducted a pilot analysis (N = 28) to compare the performance of the algorithms on normalized mean data sets with our previous analysis of the raw data. The data for each major brain wave was normalized to scale the data between 0 and 1. Furthermore, the mean and standard deviation were both used for the analysis. The normalized value of e_i for variable E in the i^{th} row was calculated as:

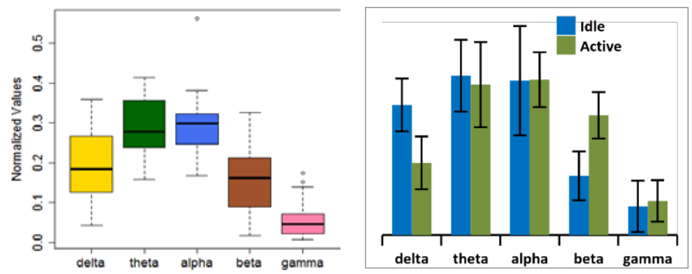
$$\text{Normalized } (e_i) = \frac{e_i - E_{min}}{E_{max} - E_{min}}$$

Where, E_{min} = the minimum value for variable E
and E_{max} = the maximum value for variable E.

The box-plot in Figure 6a depicts the numerical spread of the normalized brain wave data for active and idle brain states. The combined data set consisting of all the five major brain waves shows analogous data variability, as well as the presence of a few outliers amongst alpha and gamma wavelengths. The outliers are eliminated for further analysis.

The comparison of mean and standard deviation among different brain waves in idle and active states clearly shows that delta waves and beta waves have significant differences (Figure 6b). Delta waves are seen to be clustered at higher values in idle states while beta waves are clustered at lower values, and vice versa in the active brain state. Correlation analysis corroborates that there exists a negative correlation between delta and beta waves during active and idle brain states (Table 3). This negative correlation can be visualized using the scatter plot in Figure 6a, where it can be seen that idle brain waves tend to cover higher x-axis coordinates while active waves are found more in higher y-axis coordinates.

Figure 6. Visualization of normalized data sets using box plot for brain waves(a), comparison of mean and standard deviation among brain waves in idle and active brain state(b).

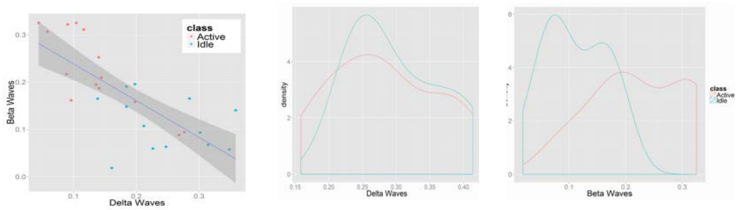


Delta waves (0.1-3Hz) are a dominant range for the idle state and beta waves (13-30Hz) are dominant in an active state. The results also showed an interesting and significant difference between these two waves. To further investigate this, we decided to focus on these two representative waves for active and idle state respectively. Also, the understanding of the pattern of the dominant waves, delta and beta waves, for idle and active states will be an important step in deciphering the complexity of brain waves in different states. The density graphs in Figure 7b further support the idea that there exists a distinctive pattern of delta and beta waves during active and idle states. To understand these dissimilar features of delta and beta waves, we decided to utilize the previously used statistical machine learning techniques to explore any deep inherent differences.

TABLE 3. CORRELATION ANALYSIS OF BRAIN WAVES

	delta	theta	alpha	beta	gamma
delta	1				
theta	0.53	1			
alpha	-0.53	-0.50	1		
beta	-0.75	-0.63	0.08	1	
gamma	-0.36	-0.51	-0.07	0.35	1

Figure 7. Scatter plot for major brain waves in active and idle brain states (a). Density graph of Delta waves (0.1-3 Hz) and Beta waves (13-30 Hz) during active and idle brain states (b).

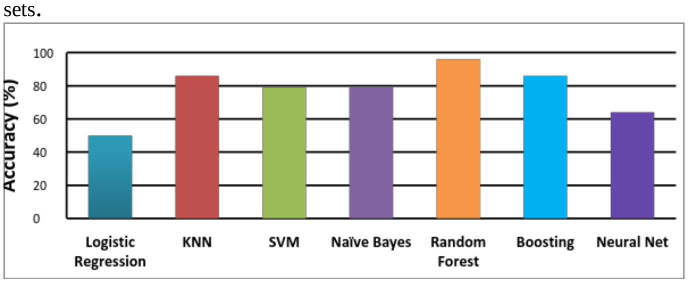


Classification based machine learning algorithms were again implemented to survey the best algorithm with which to predict the brain states, while utilizing only delta and beta waves as the features of importance. The main challenge in this process was the problem of data separation for each brain wave at different brain states. Generally, the brain wave data from different states tend to cluster together, which creates difficulties when the classification algorithms attempt to draw a best fitting separation line. Since we are interested in comparing the performance of each algorithm in terms of the correct prediction rate, all fourteen samples were used to train the algorithm and standard cross-validation techniques were used to test the error rate of the model. Table 4 shows that out of seven machine learning algorithm used, Random Forest showed 4% error rate, while Boosting and k-Nearest-Neighbor (k-NN) with n=4, showed less than 20% error. Similarly, SVM, Naïve Bayes, neural net, and logistic regression showed higher error rates respectively (Figure 8).

TABLE 4. SUMMARY OF CLASSIFICATION BASED PREDICTION SCORES.

	Model							
	Train	logit reg.	knn	svm	naïve bayes	random forest	boost	neural net
Idle	14	11	13	11	11	14	13	13
Active	14	3	11	11	11	13	11	5
Error Rate	0.00	0.50	0.14	0.21	0.21	0.04	0.14	0.36

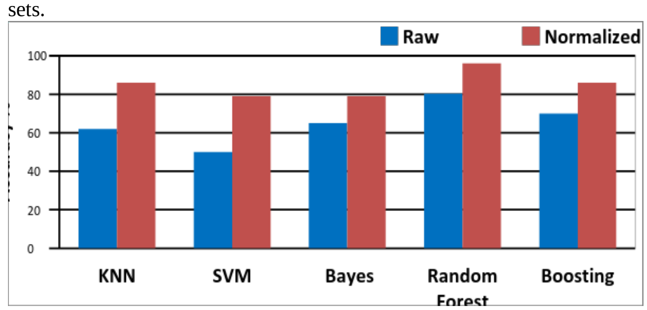
Figure 8. Comparison of common machine learning algorithms on test data sets.



The data analysis results demonstrate that the EEG data was more accurately classified with the tree-based algorithm Random Forest, while for other algorithms such as probability-based naïve Bayes and entropy-based neural net, the results did not achieve a competitive error rate. The Boosting and k-NN models performed almost equivalently in predicting brain states (Figure 8). These observations might be different for large sample sizes, however this analysis does agree with the raw data analysis in conveying the finding that the tree-based Random Forest learning algorithm is efficient in predicting brain states by analyzing EEG brain waves data for both raw and normalized mean data sets.

Figure 9 shows a comparison of all tested machine learning algorithms on normalized mean vs raw datasets. Random Forest algorithm showed the lowest misclassification rate overall. This similarity in the performance of different algorithms with both raw and normalized mean data sets suggests that the pattern of brain waves are conserved from lower raw values to higher level of mean analysis. The overall higher values for normalized data sets might be due to testing on models using cross-validation techniques on trained data sets, while for raw data sets separate train and test data sets were used. The inconsistency shown with SVM algorithm requires further investigation as the accuracy of SVM depends to a great degree on the type of kernel used by the algorithm, and the values of the parameters passed to the algorithm during the training phase. A combination of a certain kernel and a set of parameters may have resulted in inconsistent misclassification rates.

Figure 9. Comparison of algorithm performance on raw and normalized data sets.



IV. CONCLUSION

In this research, we have discovered that the Random Forest algorithm shows better performance with both raw and normalized mean data sets when compared to common machine learning algorithms used in EEG data analysis. Surprisingly, the size of the training data set has minimal effect on the accuracy while the number of unique data sets used to generate the training data considerably improves the accuracy and decreased the variance in overall results. The pilot analysis using the normalized-mean feature indicated significant improvements in classification accuracy compared to using solely the raw data. The pilot analysis (N = 28) confirmed that Random Forest yields the highest accuracy. We compared these results with the efficiency of common machine learning algorithms on normalized mean data sets.

This finding could be implemented for large scale data analysis using all major brain waves with a larger sample size. Moreover, we have explored how the variation of testing and training data affects the accuracy of each algorithm that was tested, finding a small but measurable increase in accuracy when increasing the number of samples included in the training process.

We have also identified an evident pattern of delta and waves in idle and active brain states. The unique features of delta and beta waves among major five brain waves is an interesting finding which could be implemented in recognizing brain states with a greater degree of accuracy. As mentioned previously, the level of importance placed on individual features within the datasets has a large impact on an algorithm's ability to accurately classify brain states. Furthermore, we have built a prototype of a data analysis framework that could be scaled to conduct a real time brain wave analysis on large data sets utilizing parallel computing architecture.

V. FUTURE DIRECTIONS

The prospective work on an enhanced brain wave modeling system should incorporate all the major brain waves and appropriately address variables such as specific regions of the brain, inconsistency within samples, limitations of the recording device, and the integration of knowledge from neurobiology to increase understanding of certain brain functions. There are center points in our brain which generate different types of waves. For example, in Parkinson's disease, the substantia-nigra region in the mid brain starts to dysfunction, which ultimately leads to impaired motor movement and lack of coordination. The method of separately analyzing the important known regions of the brain will provide better insight into the generation of brain waves. Additionally, it is imperative that future brain wave modeling studies contemplate the rigorous time series analysis of brain waves to decipher trend, irregularities, cycles, seasonality and other variations among waves during different states.

Therefore, improvised and advanced machine learning modeling system which include all major brain waves rather than just a dominant representative will be implemented on data collected from Emotive device, which has additional sensors to improve the quality of the signal, thereby improving the potential accuracy of the classification. The project aims to address the complexity of classification of brain waves data by modeling the major brain waves independently with clinically significant brain regions combined with an in-depth time-series analysis. This will achieve an efficient and predictable brain wave modeling system which has potential application in both the hospitality and clinical industries for self-controlled deep brain relaxation and early diagnosis of various brain abnormalities respectively.

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