Classification of EEG Signals and Application of HPC using PARAM on the Algorithms for Performance Optimization.

Abstract

Non-invasive electroencephalogram (EEG)-based brain-computer interfaces (BCI) are distinguished by the method used to assess brain activity and the manner in which distinct brain signals are converted into commands that operate an effector. Many people's lives have been changed by Brain-Computer Interfaces, particularly those whose movement and ability to communicate are impaired. In this study, we evaluate different classification algorithms using different dimensionality reduction techniques on the dataset containing visual evoked, steady state visual evoked and motor image EEG signals. Machine Learning models such as Logistic Regression, SVM, k-NN, Random forest, Decision trees, boosting models and neural networks have been used for binary and multiclass classification. Other than evaluating the accuracies of the classifying models, the computational time of each algorithm is observed and high performance computing was applied using PARAM Siddhi AI to optimize the performance of the algorithms.

Keywords: Brain Computer Interface(BCI), Motor Imagery, Classification, Fast Fourier Transformation (FFT), Independent Component Analysis (ICA), High Performance Computing (HPC)

Introduction

A Brain Computer Interface(BCI) which is also known as brain machine interface is an artificial intelligence system which establishes a bridge between humans and electronic devices. The initial step of BCI technology is to record brain signals for further analysis. The brain activity can be recorded by planting sensors inside the body(invasive) and using external sensors(non-invasive). Invasive sensors provide high temporal and spatial resolution whereas non-invasive recordings provide low temporal resolution which are relatively cost efficient. The recordings for the non-invasive technique are conducted by placing electrodes at different locations over the scalp of the person, following the international 10-20 system (Klem et al., 1999)[1] and are termed as Electroencephalography (EEG). BCI relies on different types of EEG signals, Event Related Potentials (ERP) that are P300s, steady-state visually evoked potentials (SSVEP), or event-related desynchronization.

Need

EEG-based BCI systems are used for detecting changes in brain patterns produced by either a voluntary or an involuntary instruction by the person. BCI technology can play a vital role for helping people with neuromuscular disabilities by translating the person's thoughts via signals into instructions using the electronic device. The information obtained from the signals is useful for diagnosing and analyzing various brain diseases and brain conditions. If brain illnesses go undiagnosed, they can lead to death. Early identification of brain illnesses is critical for lowering the modality rate. Some other use cases involve BCIs used as a neurofeedback training tool to improve cognitive performance. Some new studies demonstrate the involvement of BCI tools to improve one's performance in work by detecting their attention level in comparison to the importance of the given task (Alexandre Gonfalonieri et al., 2020)[2]. In 2019 (Mahnaz Arvaneh et al., 2019)[3], a modified P300 based speller paradigm is discussed which was later used as an engaging neurofeedback training game to enhance P300. In another study (Yunsick Sung et al., 2012)[4], a methodology is proposed for the development of BCI serious games. It describes an architecture, authoring tools, and development process of the proposed methodology, and applies it to a game development approach for patients with mild cognitive impairment as an example. Another article (José Ceclio et al., 2016)[5] presents a BCI framework for processing brain signals generated by imagining processes, which may be utilized in conjunction with serious games to teach or increase the autonomy of physically disabled persons.

Motivation

The end goal of BCI is to help people with neuromuscular disabilities such as spinal cord injury, cerebral palsy,etc. The rapid growth of research in the field of Brain Computer Interface can eventually lead to improved approaches and more reliability to aid people with severe disabilities and development of technology as well. Brain-computer interface technology is the focus of a rapidly expanding research and development enterprise that is peaking the interest of scientists, engineers, clinicians, and the general public. Its future achievements will be determined by advancements in three critical areas. Signal-acquisition hardware for brain-computer interfaces must be portable, portable, safe, and capable of operating in all environments. In this study, we focus on EEG Steady-State Visual Evoked Potential Signals (SSVEP). These are natural responses by the brain to repetitive stimuli, and their frequency of presentation may vary. SSVEP is widely used in BCI due to high reliability and high transfer rate.

Challenges

The processing and interpretation of EEG signals is a challenging task due to its complexity. These tasks include segmenting various structures from anatomical MRIs, numerical solution of the electromagnetic forward issue, signal denoising, a solution to the ill-posed electromagnetic inverse problem, and adequate statistical control. Other major challenges also include the number of artifacts and inaccurate readings. SSVEP faces problems in addressing the zero-class and identifying when users do not intend on selecting anything. For the Visual Imagery, there is a difficulty in interpreting the performance of visual imaging (and any type of mental imagery in general): some people may have high performance, but this is owing to the use of alternative methods that do not require imagery in the target modality. To assess mental imagery and the capacity to discern between distinct forms of imagery, an experimental paradigm must be properly devised.

In this study, we classify Visual Imagery EEG Signals for the development of brain computer Interface by comparing different feature engineering techniques such as Fast Fourier Transformation, Hanning Window, Independent Component Analysis and classifying models such as logistic regression, SVM classifier, k-NN, Random forest and decision trees, along with that boosting algorithms and deep learning models. Later on, the algorithms are ported to PARAM by applying HPC for performance optimization.

Background

In this Section, we clarify about the terms used for the EEG analysis to gain an insight. This includes the difference in Evoked Potential, Visual evoked Potential, steady state visual evoked potential signals and Visual Imagery for Motor Imagery. A brief review of high performance computing has also been discussed in this section.

Evoked Potential

Evoked potentials (EP) are electrical impulses recorded from the scalp following activation from an external stimulus. Evoked potentials are classified into three types based on their response to different stimuli: visual, auditory, and somatosensory evoked potentials. Event-related potential (ERP) refers to both EP and brain responses triggered by cognitive processes formed in response to external stimuli. The most commonly used is P300.

Visual Evoked Potential

Visual evoked potentials (VEPs) are brain activity modulations that occur in the visual cortex in response to visual stimuli. They are simple to detect because moving the stimulus closer to the center visual area greatly increases the amplitude of VEPs. These are further classified in different categories such as Transient VEPs , Steady-state VEPs, Whole field VEPs, Half field VEPs, Part field VEPs, etc.

While the user must keep his gaze fixed on a specific point on the screen. These exogenous signals are ineffective when dealing with patients with severe amyotrophic lateral sclerosis (ALS) or users with uncontrolled eye or neck movements which cause artifacts in the data collected.

Steady-State Visual Evoked Potential

Small amplitude stable VEPs, dubbed "steady-state" visually evoked potentials (SSVEPs) of the human visionary system, were created. As a result, steady-state visual evoked potentials (SSVEPs) are defined as potentials induced by changes in the visual field at frequencies greater than 6 Hz.

When a user is exposed to periodic stimuli, SSVEP is robustly produced in the occipital lobes of the brain (Jasper HH et al., 1999)[6]. SSVEP is often obtained from multiple electrode sites such as Oz, O1, O2, Pz, P3, P4, and some nearby areas to the occipital region. While 4–60 Hz is the most often utilized SSVEP frequency range, the resonance phenomena is most typically detected around 10, 20, 40, and 80 Hz.

Visual Imagery

Visual imagery is a paradigm that does not require any further external equipment and is based on visual perception experience. When a user uses visual imagery, he or she imagines a picture or movement as if sketching one. Brain impulses from the frontal area to the occipital area, which contains the visual cortex, are involved in visual imagery. Visual imagery, in particular, may be studied in multiple frequency ranges such as delta, theta, and alpha band, with the prefrontal and occipital lobes being most active. Visual imagery-based brain processes produce the delta band in the prefrontal lobe and the alpha band in the occipital lobe.

High Performance Computing

The use of supercomputers and parallel computing techniques to address complicated computational problems is known as high-performance computing (HPC). Parallel computing is when many compute pieces work together to solve a problem. In this study we have used PARAM Siddhi AI for our computations. PARAM Siddhi-AI is a high-performance computing-artificial intelligence (HPC-AI) supercomputer that is by far the fastest created in India, with a Rpeak of 5.267 Pflops and a Rmax of 4.6 Pflops (Sustained). Through speedier simulations, medical imaging, and genome sequencing, AI aids research in innovative materials, computational chemistry and astrophysics, health care system, flood forecasting, and Covid-19 use.

Related Work

There have been numerous studies conducted in the area of EEG Classification on different types of datasets using a number of classifiers and preprocessing techniques.

The datasets used for the following literature review are the BCI Competition illustrating a wide variety of feature engineering techniques and pipelines implemented.

In the paper by Natasha Padfield et al.[7], it discusses how different approaches have been used to reduce the effects of noise in EEG signals with the aim of increasing the accuracy and robustness of BCI systems. Linear denoising approaches, though effective, smooth out sharp transitions in EEG signals, which may result in salient signal characteristics being deteriorated, and it is proposed that nonlinear filtering techniques such as multiscale principle component analysis (MSPCA) are a better alternative, since they effectively remove noise but preserve sharp transitions Classification approaches used in the literature include linear discriminant analysis (LDA), support-vector machines (SVMs), *k*-nearest neighbor analysis, logistic regression, quadratic classifiers and recurrent neural networks (RNNs)[8].

In another paper proposed by Byoung-Hee Kwon et al.[9], a new method for decoding visual imagery from EEG signals using visual perception guided network training method. They calculated the changes of the power in the alpha frequency range of visual perception and visual imagery data to understand the characteristics of each data and to use visual perception data for training the network. Using the tendency of the calculated power, visual perception data was modified for the visual imagery classification network. The average classification performance of visual images using visual perception data while utilizing the suggested technique was 0.7008.

Asif Mansoor et al.[10] discusses obtaining higher classification accuracies by using deep neural networks, deep neural networks which are the same as the single-layer neural network but with hidden layers added in between the input and output nodes. Other than deep neural networks, other classifiers have also been mentioned such as adaptive classifiers, tensor classifiers, transfer learning approach.

Paper	Feature Extraction Method	Feature Selection Method	Feature Selection Method	Classification Accuracy
Rodríguez-Bermúdez & García-Laencina, 2012 [11]	AAR modeling, PSD	LARS/LOO-Press Criterion	LDA with regularization	62.2% (AAR), 69.4% (PSD)
Kevric & Subasi, 2017[12]	Empirical mode decomposition, DWT, WPD	Kaiser criterion	*k*-NN	92.8% (WPD)
Zhou et al., 2018[13]	Envelope analysis with DWT & Hilbert transform	None	RNN LSTM classifier	91.43%
Kumar et al., 2017 [14]	CSP & CSSP 5	None, FBCSP, DFBCSP, SFBCSP, SBLFB, DFBCSP-MI	SVM	Classification accuracy was not quoted.
Yu et al., 2014[15]	CSP	PCA	SVM	76.34%
Baig et al., 2017[16]	CSP	PSO, simulated annealing, ABC optimization, ACO, DE	LDA, SVM, *k*-NN, naive Bayes, regression trees	90.4% (PSO), 87.44% (simulated annealing), 94.48% (ABC optimization), 84.54% (ACO), 95% DE

Table 1: A comparison of the different combinations BCI structures

Proposed Work

This paper in the application of binary and multiclass classification models on the dataset collected by Fernandez-Fraga, S M et al[17]. Different preprocessing techniques for feature engineering have been researched and comparisons have been drawn. The data is classified into three different classes which are Visual search experiment, Five box test and Motor Imagery test. The motor imagery dataset was further classified into different visual images such as Stabilization image, Left hand open, Right hand open, Both hands open, Left hand closed, Right hand closed or Both hands closed using optimum models making it a multiclass classification problem. Different feature engineering techniques are being used for comparisons, these include Fast Fourier Transformation, Hanning Window, Independent Component Analysis. Machine learning models like logistic regression, SVM classifier and random forest were applied to train the data for the binary classification and K-NN, Random forest and decision trees for multiclass classification. Along with that boosting algorithms and deep learning models have also been applied.

Dataset

EEG dataset was explored to visualize and analyze data for further knowledge. The data was obtained by 29 volunteers. The EEG signals were obtained by a portable, high resolution multi-brand equipment Emotiv Epoc + EEG model. The equipment consists of 16 electrodes, 14 data channels, and 2 reference channels, all of which are located in the usual places of the 10–20 system as shown in *Figure 1*. On further exploration, it was found that the first row contains information about the data: subject number, date of creation of the data, transfer rate, identification of the subject, identification of the columns, and units. Columns 3–16 contain the information for each of the electrodes based on the international system 10–20: AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4. Transfer rate is 128 bits per channel; the response frequency is 0.2-45 Hz with a resolution of 14-16 bits per channel and a dynamic range of ± 4.17mV. Flickering frequencies of 0.895 Hz.

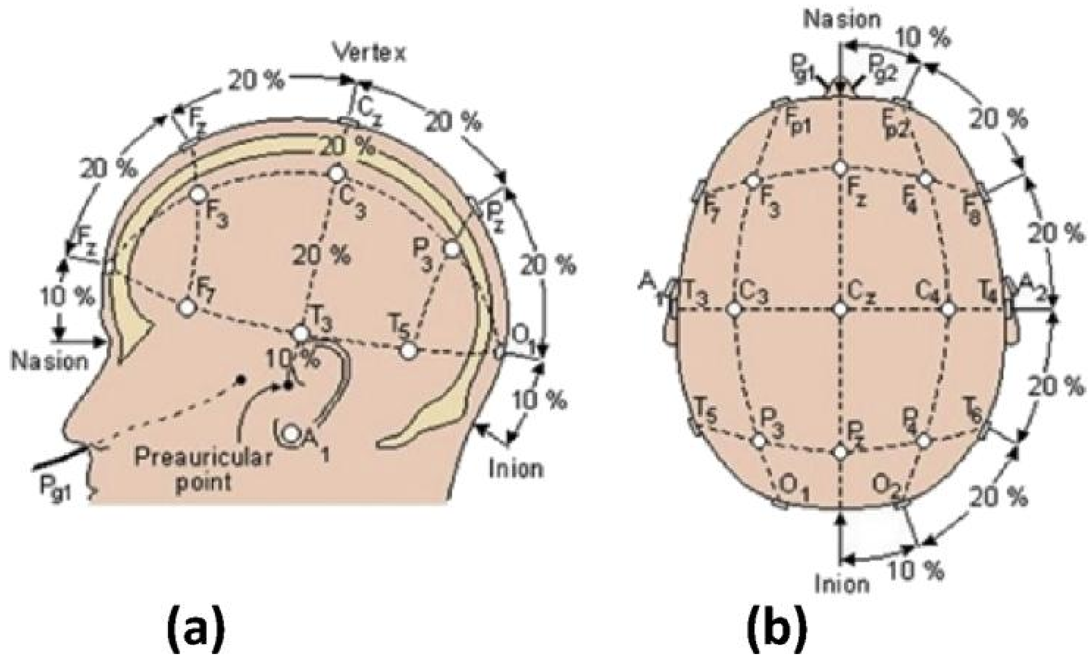

Figure 1: Location of electrodes in the International System of Electroencephalography Societies 10–20. (a) Side view. (b) Top view. (Olivas, 2010)[18].

The dataset is a collection of visual evoked, steady state visual evoked and motor image.The visual search test involves a person seeking for a tiny stimulus within photos of a natural setting, such as a forest or a river. The stimulus emerges in a random location within the image between 8 and 16 seconds after the image begins; the subject must not perform any action when the stimulus appears, merely locating his position on the screen with his gaze. A dark screen with a length of 3000 ms substitutes the picture 1000 ms later, and the test is repeated five times. Because the time required to display the stimulus on the screen changes, so does the duration of the test[19].

The steady state visual evoked test, often known as the five box test, is used to collect information about stimuli in brain signals during a basic attention exercise by displaying a group of five boxes on a screen. The goal here is to distinguish between stimuli that are relevant to attention and those that are not. During the experiment, individuals focused their attention on a cross, above which five boxes (boxes) were continually shown. Each test block is 76 seconds long, and one of the boxes was a different color (green). During the testing periods, the placement of this table was randomized. In a random order, a series of circles were displayed momentarily in each of the five boxes.Each time a disc appeared in one of the frames recorded from subjects who attended the random sequences of entire discs appearing briefly inside one of the five empty squares that were exhibited, the user was requested to focus (Townsend and Courchesne 1994). The 1.6 cm (0.63 in) square contours are shown on a black background at horizontal visual angles of 0° ± 2.7° and 5.5° ± of fixation. One of the five general lines was green and the other four were blue throughout each block of 76 seconds of the trials[20].

The motor imagery test involves giving the test participant pictures that mimic any portion of the body in a certain order to best serve the aim of this test. In the middle of the 1366x768 pixel screen, artificial color pictures of 800x600 pixels are shown. The stimuli utilized are computerized representations of human hands; each stimulus includes a color code to help the test participant identify them. The closed hands are blue, while the open hands are red.The goal of the test is for the test subject to construct a mental image of the portion of the body that symbolizes the image while seeing the image, resulting in a brain impulse that can be recorded and registered by the acquisition system. To help the test subject identify the pictures, there is a cross in the middle of the test with the subject's perspective centered and images of the extremities on the sides (corresponding with the hands), all on a fully white backdrop[21].

Each event (motor imagery shown) lasts 5 seconds on the screen; this provides a framework for reaction and capture of the brain signal. The complete test lasts 30 seconds. The events included the following images to be shown to the volunteer for 5 seconds each. These images are: 1) Stabilization image 2) Left hand open 3) Right hand open 4) Both hands open 5) Left hand closed 6) Right hand closed 7) Both hands closed. The graph in *Figure 2* shows the time of resting state EEG signals of the 14 channels with respect to the voltage. This helps us to see any data discrepancies clearly.

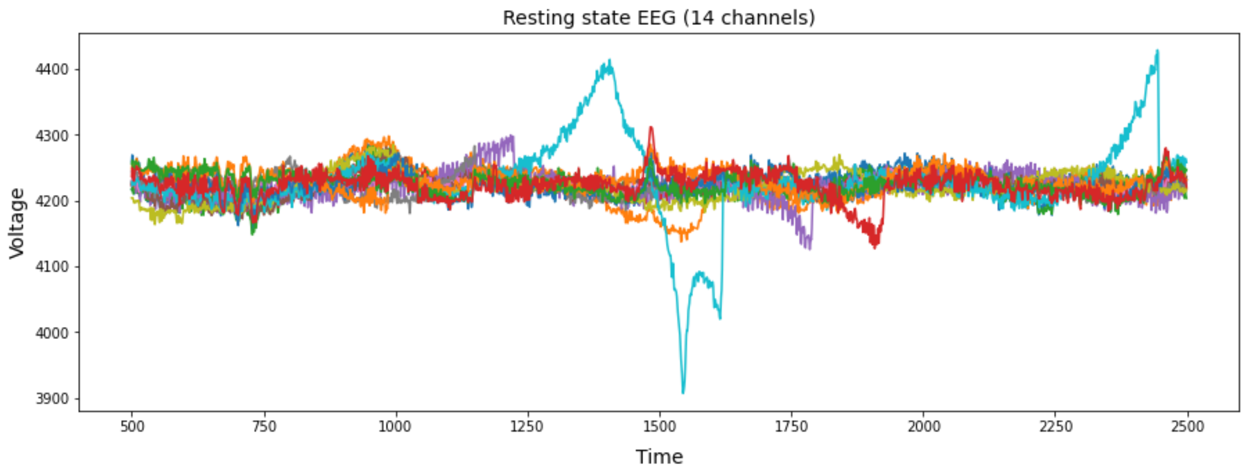

Figure 2: Resting State MI EEG Signals (14 Channel)

Data Preparation

The data was prepared for three different tasks. For the first task which was for binary classification, 3 tests for a single subject were merged and target variable was created assigning 1 for the motor imagery test and 0 for the other two tests. The data was shuffled for data imbalance and then trained.

In the second task, The dataset was again classified using multiclass classification by assigning different target variables to each test, i.e, 0 for five box test, 1 for hand shake test and 2 for visual search test.

The last task of the given problem statement was to classify the hand shake test dataset, also known as the motor image task dataset of all 29 volunteers into a Stabilization image, Left hand open, Right hand open, Both hands open, Left hand closed, Right hand closed or Both hands closed. The target variable was created by assigning different values to the different images ranging from 0 to 6, i.e, 0 for Stabilization image, 1 for Left hand open, 2 for Right hand open, 3 for Both hands open, 4 for Left hand closed, 5 for Right hand closed and 6 for Both hands closed for a single volunteer. The imbalance of the dataset was dealt by removing the stabilization image task.

Feature Engineering

The retrieved features must capture significant signal properties that can be exploited to distinguish task-specific brain states. Some BCIs employ a feature selection procedure in which only the most discriminant characteristics from a given feature set are supplied to the classifier in order to save computation time and increase accuracy. In this study, two different techniques have been used and compared with each other.

In the first method a combination of hanning window and Fast Fourier Transformation was used for feature engineering. First the data were chopped up into overlapping 1-second ‘frames’ and a Hanning window was applied then FFT was applied to transform data for each frame from time domain to frequency domain. EEG data may be analyzed utilizing frequency domain feature analysis methods such as the Fast Fourier Transform. This approach analyzes EEG data using mathematical procedures or instruments. The Hanning window is one of several windowing functions used to smooth data. It is sometimes referred to as an apodization (which means "removing the foot," i.e. smoothing discontinuities at the start and end of the sampled signal) or tapering function. The graph shown below in *Figure 3*, demonstrates the amplitude and frequency with respect to time of a snippet of EEG signals after subtracting the average and applying hanning window and fast fourier transformation. This method was used for the feature engineering of the signals by transforming them into frequency domain

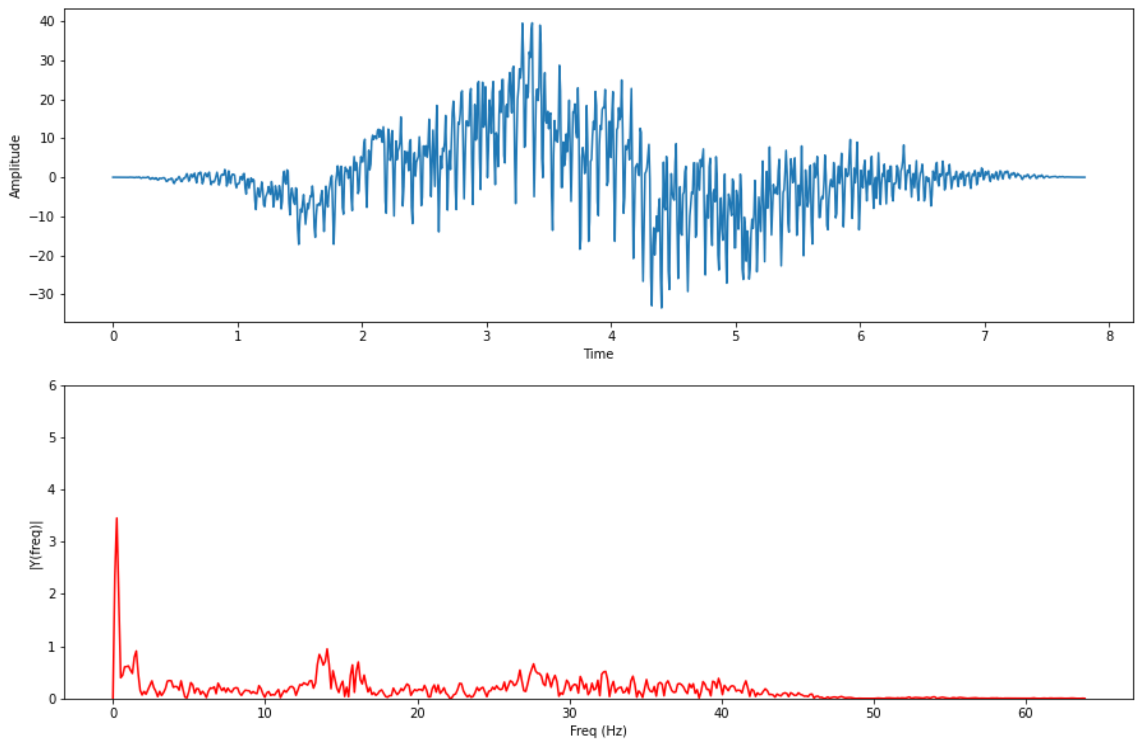

Figure 3: Amplitude vs Frequency after Subtracting Mean and applying Hanning Window and FFT

For the second method Independent Component Analysis is being used for feature selection. An alternative approach is being used where the data is preprocessed from the start using Independent Component Analysis(ICA). Because of its capacity to filter away artifacts from the data, ICA is frequently used during the signal preprocessing step in EEG analysis. When recording multi-channel signals, the advantages of employing ICA become most obvious. On analyzing the ICA transformation, it was found that channel F3, P7 and FC6 contained artifacts which may be eye blinks or other movements. The below graph, *Figure 4*, displays the before and after state of the 3 channels, i.e, F3, P7 and FC6 after applying ICA transformation which was used for artefacts removal to obtain higher accuracy.

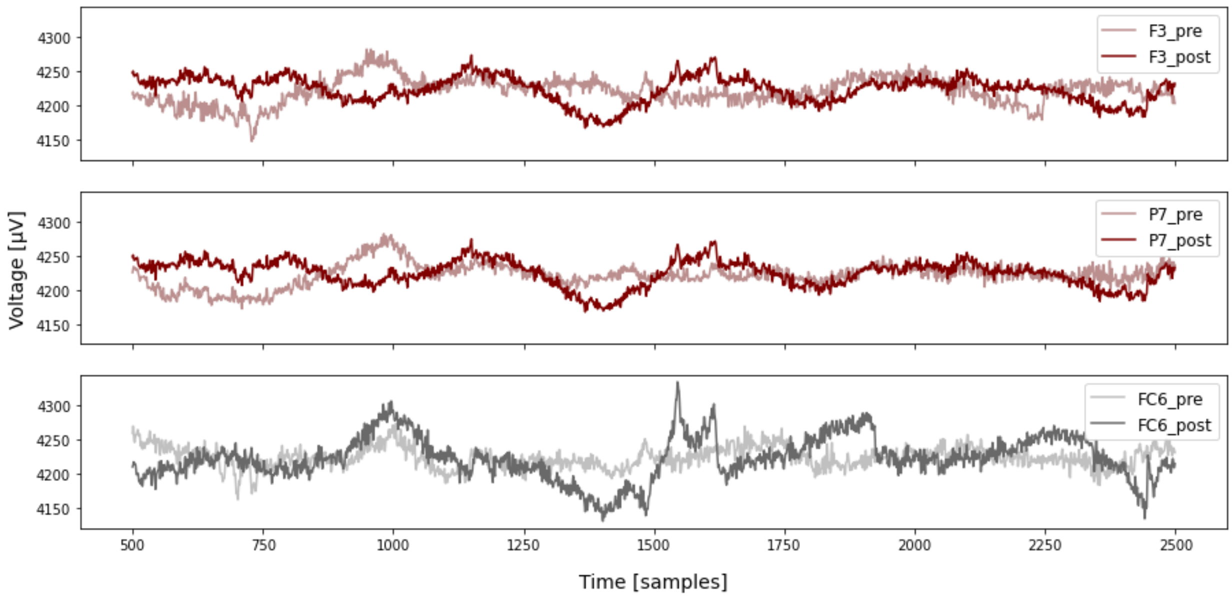

Figure 4: Voltage vs Time before and after ICA

Classification Algorithms

In this paper, we have used different classification algorithms to compare their accuracies. These algorithms are:

Logistic Regression- Logistic regression is a classification technique that uses supervised learning to estimate the likelihood of a target variable. There are only two feasible classes since the nature of the goal or dependent variable is dichotomous. It is commonly employed when the classification problem is binary; true or false, yes or no, and so on. It may, for example, be used to forecast if an email is spam (1) or not (0). The sigmoid function is used in logistics regression to calculate the likelihood of a label.

Support Vector Machine- SVM is a prominent Supervised Learning technique that is used for both classification and regression issues. However, it is mostly used in Machine Learning for classification problems. The SVM algorithm's purpose is to find the optimum line or decision boundary for categorizing n-dimensional space so that we may simply place fresh data points in the proper category in the future. A hyperplane is the optimal choice boundary. SVM selects the extreme points/vectors that aid in the creation of the hyperplane.

Random Forest- Random Forest is a well-known machine learning algorithm from the supervised learning approach. It may be used to solve classification and regression problems in machine learning. It is built on the notion of ensemble learning, which is a method that involves integrating several classifiers to solve a complicated issue and enhance the model's performance. Random Forest is a classifier that uses a number of decision trees on different subsets of a given dataset and averages them to enhance the predicted accuracy of that dataset.

K- Nearest Neighbor- The k-nearest neighbors (k-NN) technique is a non-parametric supervised learning approach. The result is class membership. A plurality vote of its neighbors classifies an item, with the object allocated to the class most prevalent among its k nearest neighbors (k is a positive integer, typically small). If k = 1, the item is simply assigned to the class of the object's single nearest neighbor.

Decision Trees- Decision Trees (DTs) are a type of non-parametric supervised learning approach that may be used for classification and regression. The objective is to build a model that predicts the value of a target variable using basic decision rules derived from data attributes. A tree is an example of a piecewise constant approximation.

XGBoost- XGBoost is a distributed gradient boosting toolkit that has been developed to be very efficient, adaptable, and portable. It builds machine learning algorithms using the Gradient Boosting framework. XGBoost offers parallel tree boosting (also known as GBDT, GBM) to address a wide range of data science issues quickly and accurately.

Results and Discussion

In this section, the discussion of the results is being carried out. The metrics used for the classification vary to the task performed:

1. The model evaluation used for binary classification was roc-auc performance measurement.
2. The model evaluation used for the multiclass classification for the other two tasks was done by examining the classification report and classification matrix for the accuracy.

The AUC - ROC curve is a performance metric for classification issues at various threshold levels. AUC is the degree or measure of separability, whereas ROC is a probability curve. It indicates how well the model can discriminate between classes. The greater the AUC, the better the model predicts 0 classes as 0 and 1 classes as 1. Classification accuracy is the number of correct predictions divided by the total number of input samples.

The second part of this paper focuses on the computational time taken by the different classifier algorithms used. The time has been compared by porting the algorithms on PARAM by applying High Performance Computing for performance optimization. The comparisons have been discussed in the later sections.

Results

The machine models selected for the binary classification of Visual search experiment, Five box test and Motor Imagery test EEG signals are Logistic regression, Support Vector Machine classifier and Random Forest classifier. XGBoost is a gradient boosted decision tree solution developed for dominative competitive machine learning speed and performance. The hyperparameters of the model were tuned using Grid search CV Algorithm and Random search algorithm. A deep learning model with two hidden layers with ReLU activation functions and an output dense layer with sigmoid activation function with 50 epochs and 32 batch sizes was created. The Adam function was utilized as the optimizer's loss function, coupled with binary cross entropy. The binary cross entropy compares each projected probability to the actual class result, which might be 0 or 1. The score is then calculated, which penalizes the probabilities depending on their distance from the predicted value. That is, how close or far the value is to the real value. The negative average of the log of corrected predicted probabilities is known as binary cross entropy. The computation time is recorded in seconds for all the classifications.

Model	Training	Testing	Time Duration (in seconds)	HPC Time Duration (in seconds)
Logistic Regression	0.6	0.61	1	1
SVM	0.77	0.73	24	13
Random Forest	0.94	0.7	2	3
XGBoost	0.91	0.7	3	3
Deep Learning	0.92	0.89	85	63

Table 2: Binary Classification

The dataset was again classified using multiclass classification by assigning different target variables to each test. The machine models selected for the multiclass classification of Visual search experiment, Five box test and Motor Imagery test EEG signals are K- Nearest Neighbor, Decision Tree classifier and Random Forest classifier. Gradient Boosting is an excellent strategy to tackle multiclass problems that suffer from class imbalance concerns since the dataset comprises three target variables, making it a multiclass classification problem with imbalance data. The aim behind "gradient boosting" is to take a weak hypothesis or weak learning algorithm and make a sequence of changes to it that will enhance the hypothesis/strength. This Hypothesis Boosting method is based on the concept of Probability Approximately Correct Learning (PAC). Gradient boosting classifier is therefore used in conjunction with grid search CV to choose the optimal parameters. The deep learning model's architecture for multiclass classification included two hidden layers with activation functions ReLU and tanh, as well as an output layer with softmax activation and 17 epochs. Because it comes under multiclass classification, the optimizer employed the Adam function with sparse categorical cross entropy as its loss function. Sparse Categorical Cross-entropy is applicable to a subset of use situations, and the implementation can vary to speed up the computation. In the context of classifiers, the loss function sparse categorical cross entropy interprets the final layer as a collection of probabilities for each conceivable class, and the output value as the class number.

Model	Accuracy	Time Duration (in seconds)	HPC Time Duration (in seconds)
k-NN Classifier	0.73	1	0
Decision Trees	0.6	0	0
Random Forest	0.72	2	1
Gradient Boost	0.66	16	13
Deep Learning	0.69	42	4

Table 3: Multiclass Classification

The last task of classifying the motor imagery dataset was done by using multiclass classification algorithms such as K-NN Classifier, Decision Trees, Random Forest Classifier, SVM. Boosting algorithms such as gradient boosting and the deep learning model mentioned above for the multiclass problem was also used for classification. Two different pre-processing techniques have been researched and compared with all the classifying algorithms to obtain better accuracies. Other than reviewing the accuracies, the computation time has also been calculated for performance optimization of the algorithms.

The classifying models were first implemented by using fast fourier transformation and hanning windows for feature engineering and gave out results shown in *Table 4*.

Model	Accuracy	Time Duration (in seconds)	HPC Time Duration (in seconds)
k-NN Classifier	0.44	9	8
SVM	0.25	240	145
Decision Trees	0.34	4	2
Random Forest	0.4	7	6
Gradient Boosting	0.34	120	109
Deep Learning	0.35	49	14

Table 4: Motor Imagery Classification with FFT

Similarly, the same models were implemented using Independent component analysis to extract the best channels and remove the artefacts. The results obtained are demonstrated in *Table 5*.

Model	Accuracy	Time Duration (in seconds)	HPC Time Duration (in seconds)
k-NN Classifier	0.66	22	20
SVM	0.29	940	635
Decision Trees	0.45	8	4
Random Forest	0.53	18	14
Gradient Boosting	0.42	217	192
Deep Learning	0.45	91	24

Table 5: Motor Imagery Classification with ICA

Conclusion and Future Work

In this study, we explore EEG signals based on VEPs, SSVEP and Visual imagery by implementing various dimensionality reduction techniques and classification algorithms. The data was grouped for the application of binary and multiclass classification. In addition, we applied high performance computing using PARAM Siddhi AI to optimize the performance of the algorithms.

The above results showcase that for binary classification, the deep learning model gave out the highest accuracy of 0.92 when implemented with high performance computing and least overfitting whereas for the multiclass classification of Visual search experiment, Five box test and Motor Imagery test EEG signals, K-NN classifier gave the highest accuracy of 0.73 and least computational time. Furthermore, the classification of motor imagery EEG signals using FFT in comparison with using ICA as feature engineering, the usage of Independent Component Analysis gave out higher accuracy making K-NN classifier the best model out of the others giving 0.66 classification accuracy. The comparison of computational time can also be seen wherein PARAM gave better results for each algorithm used for classification.

The accuracy can be improved by exploring various other dimensionality reduction techniques such as principal component analysis, linear discriminant analysis, etc and other classifying models. These results may not be perfect but can be insightful to understand the basics of EEG signals to further work on improving the brain-computer interfaces which can be fruitful for the future.

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