An Automated approach for task evaluation using EEG signals

Project report submitted to
Indian Institute of Technology Kharagpur
in fulfillment for the award of the degree of
Bachelor of Technology in
Mechanical Engineering
By

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Autumn, Spring Semester, 2018-2019
May 3, 2019

DECLARATION

We certify that -

1. The work contained in this report is original and has been done by us under the guidance of our supervisor.

2. The work has not been submitted to any other institute for any degree or diploma.

3. We have followed the guidelines provided by the institute in preparing the report.

4. We have confirmed to the norms and guidelines given in the ethical code of conduct of the institute.

5. Whenever we have used materials from other sources, we have given due credit to them by giving their details in the references.

Date: 01/05/2019

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CERTIFICATE

This is to certify that the dissertation report titled, **An automated approach for task evaluation using EEG signals** submitted by **Vishal Anand** (15ME33004) and **Zaki Ahmed** (15ME33029) to the Indian Institute of Technology Kharagpur is a record of bonafide project work carried out by them under my supervision and guidance. The report fulfills all requirements as per the regulations of this institute. Neither this report nor any part of it has been submitted for any degree or academic award elsewhere.

Date:

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Acknowledgment

We express our deep sense of gratitude to our guide Prof. Debasis Samanta for his valuable guidance and inspiration throughout the course of this work. We are thankful to him for his kind help, assistance and support and his motivation towards this project. It has been a great experience working under him in the cordial environment.

We are equally obliged in honor of Mrs. Sreeja S R whose incessant encouragement and moral support inspired us to complete our work.

Abstract:

The cognitive workload is a demand placed upon a human for mental resources while performing a task. Mental Workload Measurement (MWM) refers to the task of estimating mental workload levels. MWM has application in various fields like aviation, driving, critical military or space mission, safety at work and wellbeing of human resources.

The study goal was to evaluate whether Electroencephalography (EEG) estimates of mental workload captured as subjects tried to build SolidWorks model of varying levels of complexity and difficulty and whether the EEG data can be used to predict the level of mental workload the subjects are subjected to. Subjects (N=8) tried to build a series of complex models on SolidWorks while wearing an EEG headset that generated estimates of sustained mental workload each second.

We Correlate between the EEG signal frequencies and the model complexity by various models applying after feature extraction part and training of the classifier to predict the actual mental workload the subjects are subjected to. Additionally feature selection using various method was done to figure out the best features for classification and finally, decision results of the classification results from the different modalities are performed like Bayesian, KNN, SVM, XGBoost, MLP.

Contents

Keywords: User Evaluation, Human-Computer Interaction (HCI), Brain-Computer Interface (BCI), EEG Signal Processing, Mental Workload/ Cognitive Workload Estimation.

Introduction: Brain is the most complex part of the entire human body. Researchers and doctors have dedicated a considerable amount of effort in decoding the human brain. However, only a small percentage of brain functioning theory has been established so far and still, there is a long way to go. In today's world, where technology has taken over every aspect of our day-to-day life, the study of mental/cognitive workload, its source of generation, measurement, etc. are becoming very important to build applications based on them and for the betterment of the human race. Mental workload measurement (CWM) has a great role to play in various fields like aviation, driving, critical military or space mission, safety at work and wellbeing of human resources.

The present study was conducted to investigate the potential value of Electroencephalography (EEG) data to decode the mental workload using signals for various types of the task performed by subjects to get a clear understanding of how a person handles a task and performs under certain planned conditions.

Motivation: Brain-Computer Interface (BCI) technology is a powerful communication tool between users and systems. It does not require any external devices or muscle intervention to issue commands and complete the interaction. The work on BCI data is done by extracting the important features and feeding them into a model. However, such computing procedures may associate with a heavy computational burden, which could render themselves unsuitable for certain tasks (e.g., online processing). Neural network methods adopt a different paradigm by combining feature extraction and classification into one pipeline. Unlike machine learning approach deep learning architectures are robust and work well even with noisy data. The training stage of the neural network may require a long period of time, but once the neural network has been trained, the resulted parameters could be directly applied to new data, which can be computationally more efficient and more suitable for certain problems (e.g., real-time learning of unlabeled EEG data)

Scope of work: Brain-Computer Interface technology is still to be utilized to its full potential. Although EEG signals depend on various aspects of the subject and his environment, an accurate and online method to classify cognitive mental load data will allow a platform of applications to be built using it as an interface between applications and user's brain.

To move forward with this goal we build an experimental setup to figure out the workload impressed upon a subject upon performing a particular task and using feature extraction and different feature selection techniques to understand the underlying importance of various features for the classification of the workload using various machine learning algorithms.

Limitations:
Technical challenges They are issues related to the recorded electrophysiological properties of the brain signals which include non-linearity, nonstationarity and noise, small training sets and the companying dimensionality curse.

• Non-linearity: The brain is a highly complex nonlinear system in which chaotic behavior of neural ensembles can be detected. Thus EEG signals can be better characterized by nonlinear dynamic methods than linear methods.

• Noise: Noise includes unwanted signals caused by alterations in electrode placement and environmental noise. A combination of movement artifacts, such as electrical activity produced by skeletal muscles and signals created by eye movements and blinking, is also reflected in the acquired signals resulting in difficulties in distinguishing the underlying pattern.

• Small training sets: The training sets are relatively small, since the training process is influenced by usability issues. Although heavily training sessions are considered time-consuming and demanding for the subjects, they provide the user with the necessary experience to deal with the system and learn to control his or her neurophysiological signals. Thus a significant challenge in building a classifier is to balance the trade-off between the technological complexity of interpreting the user's brain signals and the amount of training needed for the successful operation of the Interface.

Related Work
Since a few years, brain imaging has been used in HCI to deepen the understanding of users, thanks notably to the spread of affordable and lightweight devices. For instance, EEG and fNIRS are particularly well suited for mobile brain imaging.

Objective:
The objective of this project is the identification of Mental workload generated in an individual while performing different tasks using EEG Data signals with accurate predictions. This work focuses on the analysis of feature extraction, feature selection and classification of EEG signals.The objectives as part of the research study include:

• Collecting signals related to mental workload and signal preprocessing: The experiment is carried out to collect data of subjects trying to build models in the SolidWorks Software and then, the acquired raw EEG signals are processed.

Feature Engineering
(a) Signal Preprocessing
EEG data is generally contaminated with noise. Removal of various artifact is not only dicult but is lossy, as it may accidentally remove some features which could be otherwise important for calculation of Mental Workload. A very carefully designed algorithm should be considered for removing artifacts.

(b) Feature Extraction
Feature extraction is more of an 'Art' than just a 'Technique'. It is important to study and calculate various features and evaluate the results before deciding to make it a part of model.

(c) Feature Selection
To reduce the dimensionality of data to make the system real-time, it is important to select important features only. A very sound algorithm has to be considered for feature selection without loss of important features accidentally.

• Classification of the preprocessed mental load data in 3 classes :

Build a model to extract the important features from the data.
Perform feature selection using various models and understand the features which contribute most in classifying the data}

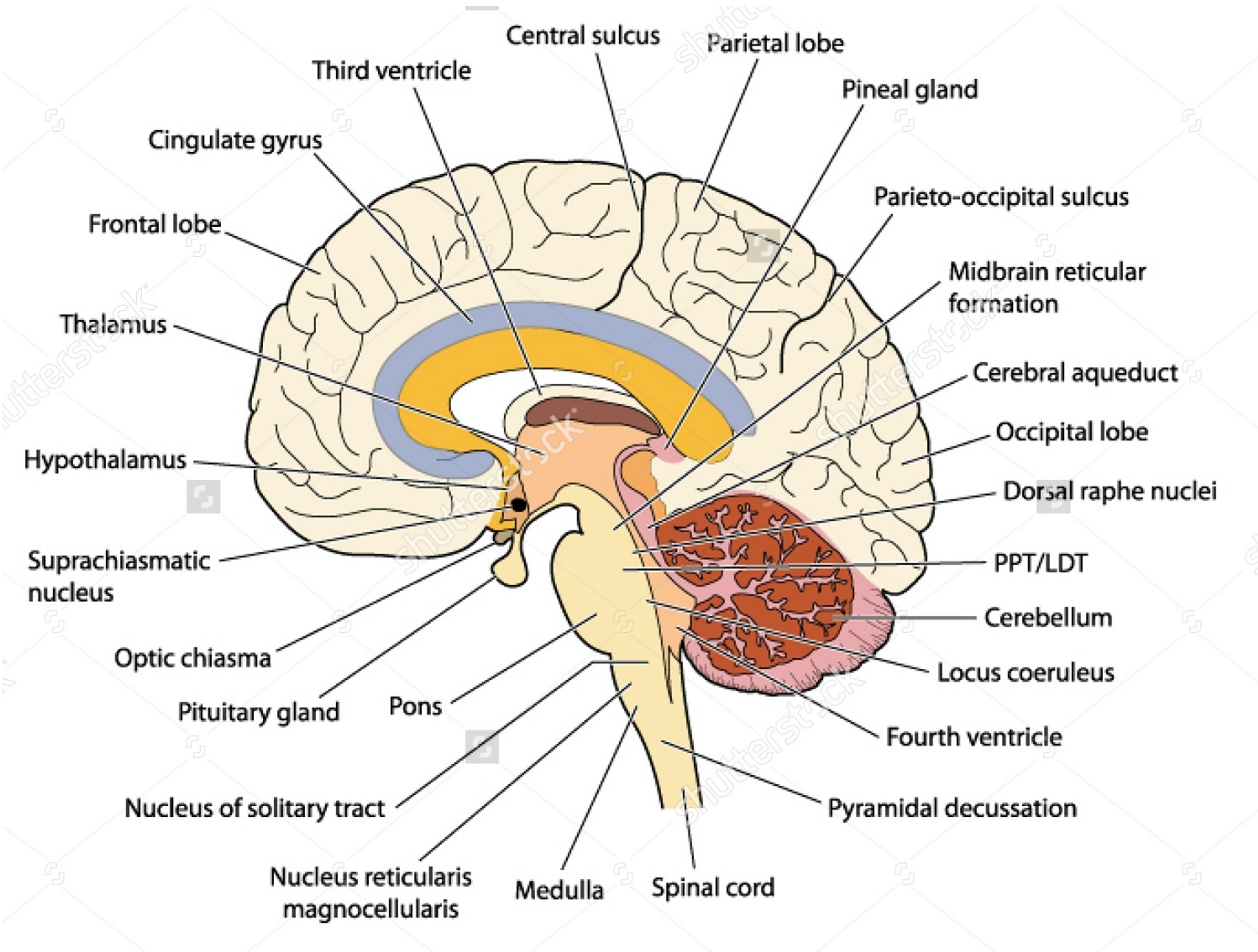
Through this study, we aim to eliminate the issues and challenges that are related to Mental load data classification.

Literature Survey

Biological Background

Human Brain

Human Brain is the most amazing part of the human body. An average human brain consists of approximately 100 billion neurons, interconnected via axons and neurons. A neuron has a cell body called Soma, a long axon and many dendrites. Neurons receive stimulus from other inter connected neurons(about 103 to 105) through synapses. This stimulus travel through axon as electrical impulses and helps controlling body movements, emotions and other aspects of body coordination.



Parts of Human Brain (according to position)

- **Forebrain** - consisting of the cerebrum, thalamus, and hypothalamus
- **Midbrain** - consisting of tectum and tegmentum
- **Hindbrain** - consisting of the cerebellum, pons, and medulla

Parts of Human Brain (according to functions) Human brain is the center for thinking, sensory activity and controlling other voluntary and involuntary actions of the body. Different regions of brain are responsible for different specific tasks, hence brain can be classified into various parts based on their functions. It can be classified into :

- Cerebrum - The cerebrum also called cortex, is found only in mammals, and is largest part of human brain. It is site for complex brain functions as thought and action. Cerebral cortex has large number of folding, that increase the surface area and the number of neurons within it.

• Cerebellum - The cerebellum, also known as "little brain", is divided into two hemispheres. It is responsible for regulation and coordination of movement, posture and balance. The cerebellum is also highly folded to increase the surface area and number of neurons in the area.

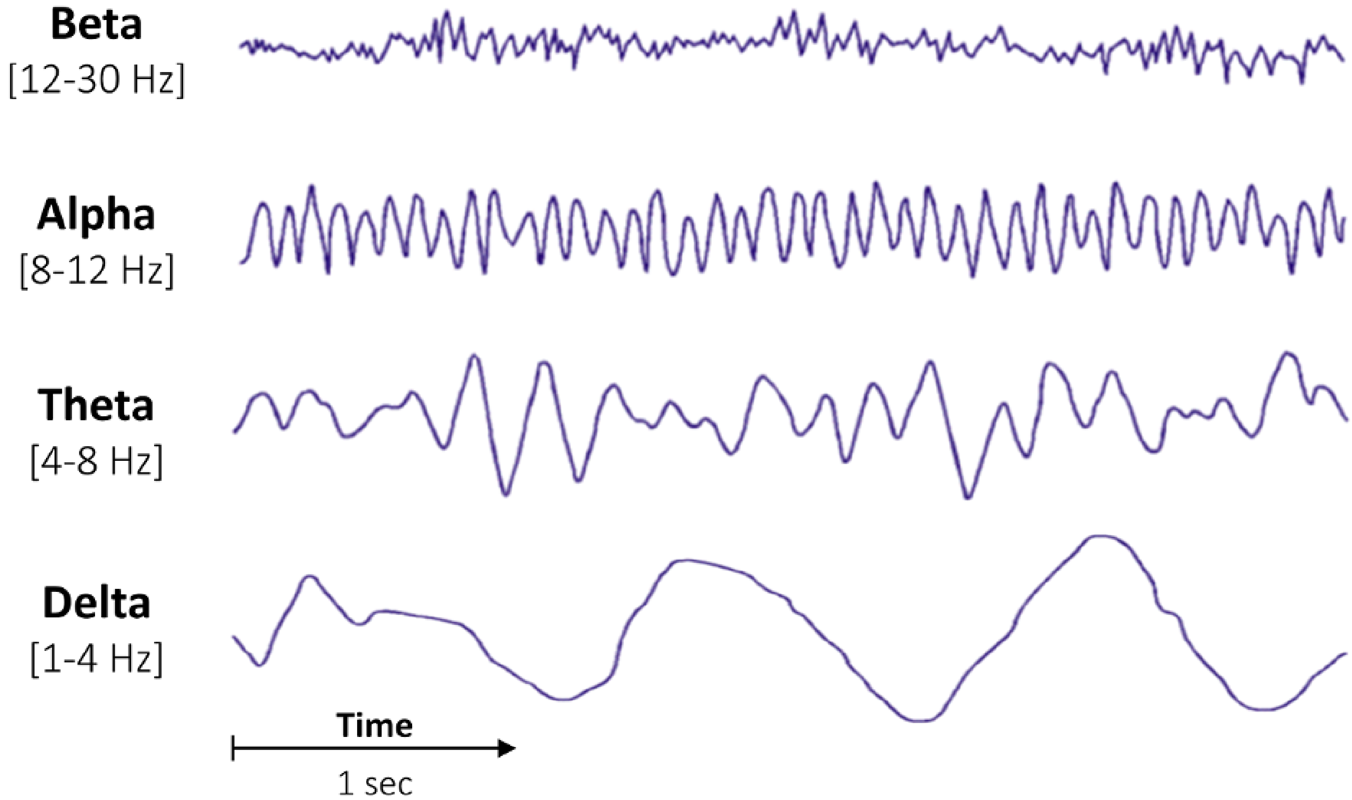
• Limbic System - The limbic system, also referred to as the "emotional brain", is found buried within the cerebrum. This system consists of the thalamus, hypothalamus, amygdala, and hippocampus.

• Brain Stem - The brain stem is underneath limbic system, and is responsible for basic functions like breathing, blood pressure, heartbeat. The brain stem is consists of the midbrain, pons, and medulla.

Brain Activity Patterns

The brain consists of large number of neurons, and when humans perform some activity, electric potential is developed and it travels across axons of neurons. Since, different parts of brain are associated to different functions, the electric signals generated due to neural activity widely differ in terms of their frequency, amplitude, shape and the position. These Brain waves, based on their frequency, amplitude, shape and the position are classified a

(a) Alpha Wave
(b) Beta Wave
(c) Delta Wave
(d) Gamma Wave
(e) MU Wave
(f) Theta Waves



• **Alpha Waves** - originate from occipital lobe and backside of the head, and have frequency range from 7.5 Hz to 12 Hz. They are associated with relaxed and calm states in awake humans.

• **Beta Waves** - originate from the central area of the brain and front side of head, and have frequency range from 13 to 30 Hz. They are associated with deep thinking, high concentration level and anxious state.

• **Theta Waves** - originate from central, temporal and parietal parts of head, and have frequency range from 3.5 to 7.5 Hz. They are associated with thinking, stressed and deep meditating state.

• **Gamma Waves** - they have frequency range above 30 Hz. They are associated with Motor functions, simultaneous work and while multitasking.

• **MU Waves** - originate from motor cortex of the head, and have frequency range from 9 Hz to 11 Hz. They are associated with motor activities,when there is actual movement or intent to move.

• **Delta Waves** - they have frequency range from 0.5 to 3.5 Hz. They are associated with deep sleep, and coma mental state.

Cognitive Load

In cognitive psychology, cognitive load refers to the effort being used in the working memory. The ability to process information differs from person to person. A person may not be comfortable with the structure and representation of the information and may face difficulty understanding it. Mental workload is a hypothetical construct that describes the extent to which the cognitive resources required to perform a task have been actively engaged by the operator. It has been widely demonstrated that neurophysiological measurements transcend both behavioral and subjective measures in discriminating cognitive demand fluctuation. Thus, the online neurophysiological measurements of the mental workload could become very important not only as monitoring techniques but mainly as support tools to the user during operative activities. In fact, as the changes in cognitive activity can be measured in real time, it should also be possible to manipulate the task demand in order to help the user in maintaining optimal levels of mental workload during the work.

Brain-Computer Interfaces

A BCI system allows humans to interact with their environment by translating their brain signals into control commands for a specific purpose device.

A typical BCI system functions as follows. Once brain activity has been detected, brain signals are digitally processed to separate those signals from artifacts. Then, brain signals are transformed into features that encode the user control task. This stage consists of a feature extractor and a feature selector. The feature extractor usually obtains values in time or frequency domain. The feature selector removes noisy data (useless features) reducing the dimensionality of the feature vectors. After generating useful features, these are converted into logical control signals by means of linear methods, such as classical statistical analyses, or nonlinear methods, such as neural networks. In both cases, the independent variables (features) will be translated into dependent variables (logical control commands). In addition, the post-processing method is sometimes used in order to reduce the number of false activations of the BCI system. Once logical control signals are available, a control interface stage provides feedback about the user performance (typically via a control display) and translates the logical control signals into semantic control signals. Finally, a device control module converts the semantic control signals into physical signals that regulate the overall behavior of the device of interest. BCIs are normally assessed according to the classification accuracy of the control tasks in use.

Signal Acquisition:
Translation of intent into action is dependent on expression of the intent in the form of a measurable signal. Proper acquisition of this signal is important for the functioning of any BCI. The goal of signal acquisition methods is to detect the voluntary neural activity generated by the user, whether the signals are acquired invasively or noninvasively. Each method of signal acquisition is
associated with an inherent spatial and temporal signal resolution. Choice of appropriate method to use in a particular circumstance depends on striking a balance between the feasibility of acquiring the signal in the operating environment and the resolution required for proper translation.
Invasive Techniques: Invasive acquisition of brain signals for use in BCIs is primarily accomplished by electrophysiologic recordings from electrodes that are neurosurgically implanted either inside the user's brain or over the surface of the brain.

Noninvasive Techniques: There are many methods of measuring brain activity through noninvasive means. Noninvasive techniques reduce risk for users since they do not require surgery or permanent attachment to the device. Techniques such as positron emission tomography (PET), functional magnetic resonance imaging (fMRI), functional near-infrared spectroscopy (fNIRS), magnetoencephalography (MEG), and EEG have been used to measure brain activity non-invasively.

Measuring Brain Activity using EEG

Brain activity produces electrical and magnetic activity. Therefore, sensors can detect different types of changes in electrical or magnetic activity, at different times over different areas of the brain, to study brain activity. Most BCIs rely on electrical measures of brain activity, and rely on sensors placed over the head to measure this activity. Electroencephalography (EEG) refers to recording electrical activity from the scalp with electrodes. It is a very well established method, which has been used in clinical and research settings for decades. EEG equipment is inexpensive, lightweight, and comparatively easy to apply. Temporal resolution, meaning the ability to detect changes within a certain time interval, is very good. However, the EEG is not without disadvantages: The spatial (topographic) resolution and the frequency range are limited. The EEG is susceptible to so-called artifacts, which are contaminations in the EEG caused by other electrical activities. Examples are bioelectrical activities caused by eye movements or eye blinks (electrooculographic activity, EOG) and from muscles (electromyographic activity, EMG) close to the recording sites. External electromagnetic sources such as the power line can also contaminate the EEG. Furthermore, although the EEG is not very technically demanding, the setup procedure can be cumbersome. To achieve adequate signal quality, the skin areas that are contacted by the electrodes have to be carefully prepared with special abrasive electrode gel. Because gel is required, these electrodes are also called wet electrodes. The number of electrodes required by current BCI systems range from only a few to more than 100 electrodes. Most groups try to minimize the number of electrodes to reduce setup time and hassle. Since electrode gel can dry out and wearing the EEG cap with electrodes is not convenient or fashionable, the setting up procedure usually has to be repeated before each session of BCI use. From a practical viewpoint, this is one of the largest drawbacks of EEG-based BCIs. A possible solution is a technology called dry electrodes. Dry electrodes do not require skin preparation nor electrode gel. This technology is currently being researched, but a practical solution that can provide signal quality comparable to wet electrodes is not in sight at the moment.

A BCI analyzes ongoing brain activity for brain patterns that originate from specific brain areas. To get consistent recordings from specific regions of the head, scientists rely on a standard system for accurately placing electrodes, which is called the International 10{20 System. It is widely used in clinical EEG recording and EEG research as well as BCI research. The name 10{20

indicates that the most commonly used electrodes are positioned 10, 20, 20, 20, 20, and 10 percent of the total nasion-inion distance. The other electrodes are placedat similar fractional distances. The inter-electrode distances are equal along any transverse (from left to right) and antero-posterior (from front to back)
line and the placement is symmetrical. The labels of the electrode positions are usually also the labels of the recorded channels. That is, if an electrode is placed at site C3, the recorded signal from this electrode is typically also denoted as C3. The first letters of the labels give a hint of the brain region over which the electrode is located: Fp-pre-frontal, F - frontal, C - central, P - parietal, O - occipital, T - temporal. The following figure depicts the electrode placement according to the 10-20 system.

Signal Processing

A BCI measures brain signals and processes them in real time to detect certain patterns that reflect the user's intent. This signal processing can have three stages: preprocessing, feature extraction, and detection and classification. A BCI application aims at simplifying subsequent processing operations without losing relevant information. An important goal of preprocessing is to improve signal quality by improving the so-called signal-to-noise ratio (SNR). A bad or small SNR means that the brain patterns are buried in the rest of the signal (e.g. background EEG), which makes relevant patterns hard to detect.

A good or large SNR, on the other hand,simplifies the BCI's detection and classification task. Transformations combined with filtering techniques are often employed during preprocessing in a BCI.
The brain patterns used in BCIs are characterized by certain features or properties. For instance, amplitudes and frequencies are essential features of sensorimotor rhythms. The feature extraction algorithms of a BCI calculate (extract) these features. Feature extraction can be seen as another step in preparing the signals to facilitate the subsequent and last signal processing stage, detection and classification. Detection and classification of brain patterns is the core signal processing task in BCIs. The user elicits certain brain patterns by performing mental tasks according to mental strategies, and the BCI detects and classifies these patterns and translates them into appropriate commands for BCI applications.
This detection and classification process can be simplified when the user communicates with the BCI only in well defined time frames. Such a time frame is indicated by the BCI by visual or acoustic cues. For example, a beep informs the user that s/he could send a command during the upcoming time frame, which might last 2seconds - 1minute(depending on the experiment).During this time, the user is supposed to perform a specific mental task. The BCI tries to classify the brain signals recorded in this time frame. This mode of operation is called synchronous or cue-paced.Correspondingly, a BCI employing this mode of operation is called a synchronous BCI or a cue-paced BCI.

Although these BCIs are relatively easy to develop and use, they are impractical in many real-world settings. A cue-pased BCI is somewhat like a keyboard that can only be used at certain times. In an asynchronous or selfpaced BCI, users can interact with a BCI at their leisure, without worrying about well defined time frames. Users may send a signal, or choose not to use a BCI, whenever they want. Therefore, asynchronous BCIs or self-paced BCIs have to analyse the brain signals continuously. This mode of operation is technically more demanding, but it offers a more natural and convenient form of interaction with a BCI

Applications of BCI

Brain computer interfaces have contributed in various fields of research. As briefed in below, they are involved in medical, neuroergonomics and smart environment, neuromarketing and advertisement, educational and selfregulation, games and entertainment, and Security and authentication fields.

Medical applications: Health care field has a variety of applications that could take advantage of brain signals in all associated phases including prevention, detection, diagnosis, rehabilitation and restoration.

Prevention: Traffic accidents are considered the main cause for death or some serious injuries. Analyzing their causes for later prevention has been a concern for researches in various fields. Thus concentration level for those suffer from motion sickness, especially drivers, has been studied. A prediction of motion sickness could contribute in a driver-state monitoring and alertness system using a set of EEG power indicators.

Detection and diagnosis: Mental state monitoring function of BCI systems has also contributed in forecasting and detecting health issues such as abnormal brain structure (such as brain tumor), Seizure disorder (such as epilepsy), Sleep disorder (such as narcolepsy), and brain swelling (such as encephalitis).

Rehabilitation and restoration: Mobility rehabilitation is a form of physical rehabilitation used with patients who have mobility issues, to restore their lost functions and regain previous levels of mobility or at least help them adapt to their acquired disabilities.

Security and authentication: Cognitive Biometrics or electrophysiology, where only modalities using biosignals (such as brain signals) are used as sources of identity information, gives a solution for vulnerabilities. The motivation behind exploring the feasibility of electrophysiology is that biosignals cannot be casually acquired by external observers. They also can be of great value for disabled patients or users missing the associated physical trait. This makes such signals difficult to synthesize and therefore improves the resistance of biometric systems to spoofing attacks.

Challenges faced by current EEG signal classification methods

Ten years ago, most classifiers explored for BCI were rather standard classifiers used in multiple machine learning problems. Since then, research efforts have focused on identifying and designing classification methods dedicated to the specificities of EEG-based BCIs. In particular, the main challenges faced by classification methods for BCI are the low signal-to-noise ratio of EEG signals their non- stationarity over time, within or between users, where same user EEG signals varying between or even within runs and the overall low reliability and performance of current BCIs.

Dataset Description

The dataset that is used to carry out the classification of EEG data was collected in the at IIT Kharagpur.The experiments were conducted in a controlled environment, the details of the experiment are given below

Experimental Design and Setup

We collected the mental workload data from 8 different subjects during the time they were building models on the software - Solidworks. They had to build the models that had varying levels of complexity and difficulty and they had to use various tools and methods to build them. Participants declared having no history of Solidworks usage and no previous experience with BCIs. Each participant agreed with the terms and conditions of the study. Each participant was given an introductory hands-on experience with the tools and whole software environment.

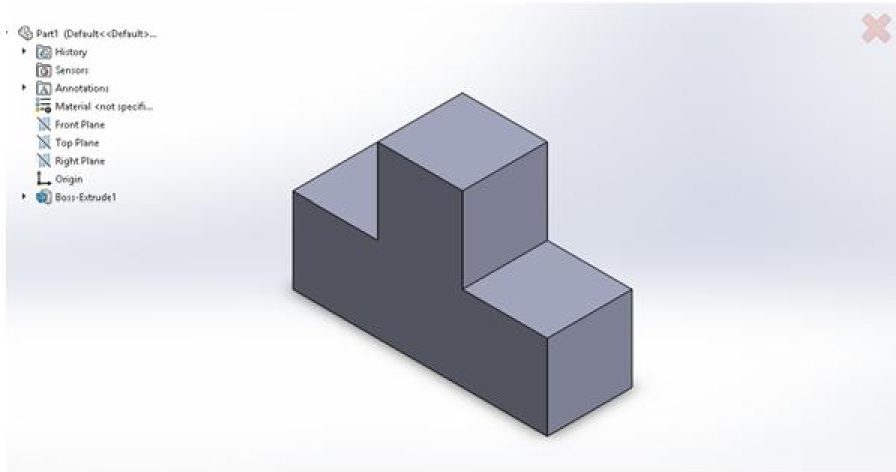
Three different levels of models were given to each participant in any order and the experiments were conducted at three different times of the day - Morning, Afternoon and Evening, without any selective association of the time of the day with the level of complexity of the models.

There were three levels of models complexity, Level 1, Level 2 and Level 3. The models were shuffled before giving to the subjects for the experiment.

Below include the details of the experiment and the models.

Level 1

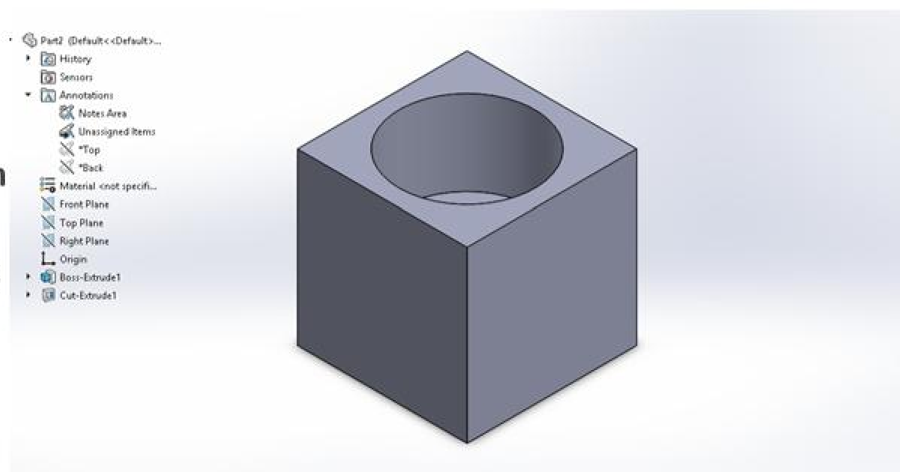
- Complexity type : **Easy**
- No. of tools used : **2***
- Time taken : **50 seconds**



* Sketch and Extrude tools were used.

Level 2

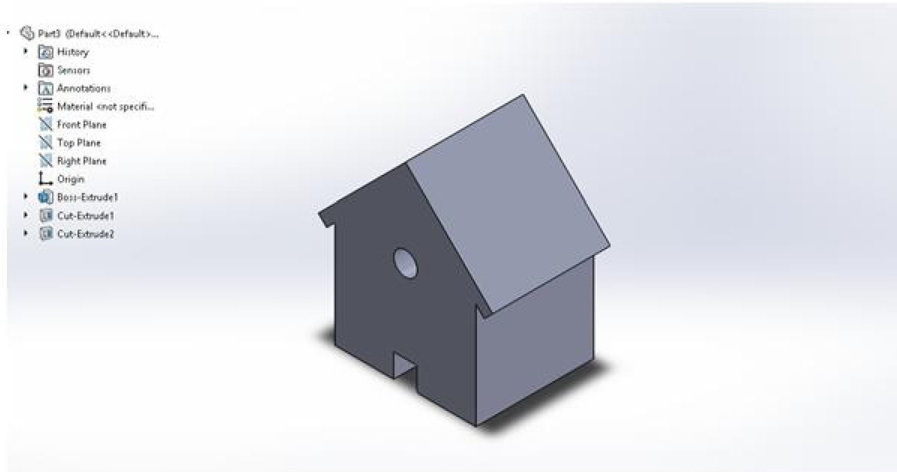
- Complexity type : **Medium**
- No. of tools used : **3***
- Time taken : **110 seconds**



* Sketch, Extrude and Extrude cut tools were used

Level 3

- Complexity type : **Hard**
- No. of tools used : **4***
- Time taken : **170** seconds



*Sketch, Extrude, Extrude cut and mirror transform

The subjects were asked to wear the EEG device on their scalp and gel was applied to get a better contact of electrodes with the scalp. To minimize any of the artifacts generated, the subjects were asked to avoid any unnecessary physical movements and their hands were placed in a fixed position. Subjects were requested to refrain from excessive blinking of the eye lid.

- Each subject build a model same as shown above using the software.
- Each subject underwent 3 trials.
- Each Trial Included the following step -
    - The first 5 seconds of procedure was quite, the subject was Idle
    - At the beginning of the 6th second, the subject started building the model.
    - Finally, after a given time limit and 5s, idle time after the experiment indicates the end of the trial

One Trial

First Idle Period	Experiment time(seconds)	Last Idle Period
5 seconds	40(Lvl 1)/100(Lvl 2)/160(Lvl 3)	5 seconds

Trials

Metadata Eight healthy male volunteers engaged in the graduate study participated in the experiment with age ranging between 20 to 25 years. All subjects had normal or corrected to normal eye-sight. All subjects were given adequate practice and idea of the experiments. Room temperature was controlled to ensure adequate comfort during the experiments.

Participant	Gender	Age	Medically Fit?	Time of 1st exp. Data collection	Time of 2nd exp. Data collection	Time of 3rd exp. Data collection
S01	Male	21	Yes	AF	EV	EV
S02	Male	22	Yes	MN	AF	MN
S03	Male	19	Yes	AF	MN	AF
S04	Male	24	Yes	EV	AF	MN
S05	Male	23	Yes	EV	AF	MN
S06	Male	22	Yes	EV	MN	EV
S07	Male	21	Yes	AF	MN	EV
S08	Male	20	Yes	MN	EV	AF

The total of 24 trials was split into training and test for each subject having only a small amount of training samples poses a problem. Following table shows the respective number of training and test trials for each subject.

Metadata details

The data collected from each subject with 14 EEG channels for
Easy level of mental workload is - 89600 samples
For medium level of mental workload - 197120 samples
For hard level of mental workload - 304640 samples.

As explained below:- Let $A_{m \times n}$ be a matrix of size $m \times n$ representing data from each
channel. Where,

m = number of samples
n = number of EEG channels
m = time × sampling rate
= 50(level 1) / 110(level 2) / 170s(level 3) × 128Hz
= 6400 / 14080 / 21760
n = 14
m × n = 6400 / 14080 / 21760 × 14
= 89600(level 1) / 197120 (level 2)/ 304640 (level 3) samples

`Hardware and Software Interface

Device used for this research work is EMOTIV Epoc+. It uses international 10-20 standards for locations of electrodes. This device uses 14 Channels for data collection from various part of brain. This device is comparatively cheap and has been used by many researchers in their work. EMOTIV Epoc+ is an EEG headset as shown in gure below, build by Australian company Emotiv Systems. EMOTIV Epoc+ captures data in high resolution using 14 EEG channels plus 2 references for accurate spatial resolution, at sample rates of 128 samples per seconds (SPS). The device operates at a resolution of 14 bits per channel and frequency response between 0:16 – 43 Hz

Software Interface

SolidWorks is a solid modeling computer-aided design (CAD) and computer-aided engineering (CAE) computer program that runs on Microsoft Windows. SolidWorks is published by Dassault Systèmes.

It contains tools and features to create 3D objects from scratch and make sure that those 3D objects can be seen as real objects with a lot of information embedded into it. For our experiment we restricted ourselves to very limited and fixed tools and features to make sure that it doesnt add a lot of complexity in out experiment design.

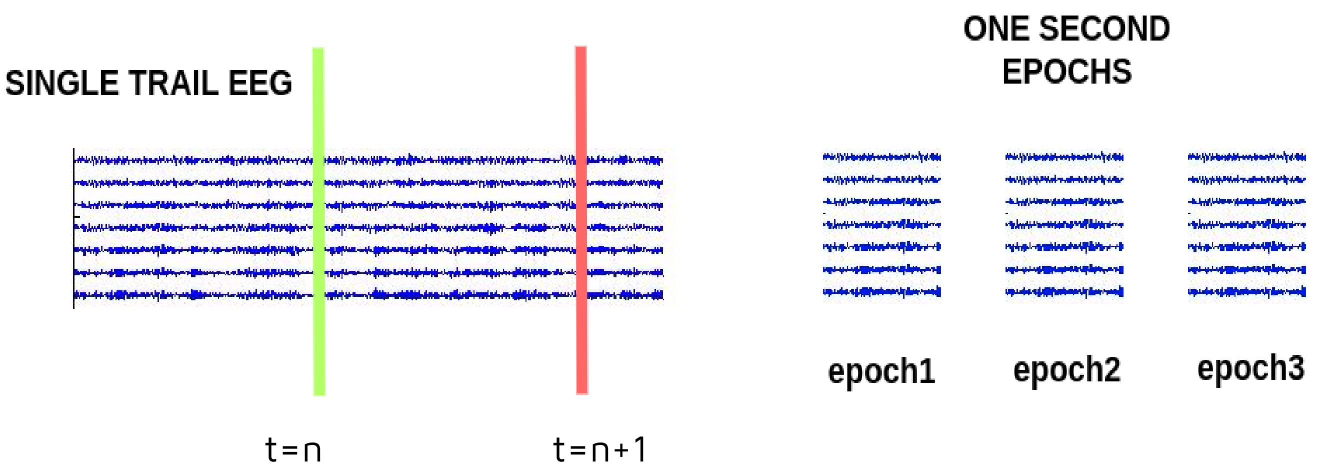
We used the SolidWorks version 2017 in our experiment.

Data Preprocessing

The signals obtained by the signal acquisition step are usually very noisy and contains a lot of artifacts including high-frequency noise due to electrical interference and physiological artifacts such as EOGs and EMGs. Apart from the noise, there is the issue of volume conduction in EEG due to the distance between the scalp and the neurons which makes it difficult to pinpoint the exact location of where an activation took place. Preprocessing these signals is a necessary step for our experiment.

Data Segmentation

From the description of the trails, the readings corresponding to the respective mental load were divided accordingly. Since there was sufficient time gap between two successive trials the readings of the two levels don't overlap. Three trials were taken for each individual for each level of mental workload and Each of these are further divided into 1 second epochs as shown in the figure below. The sampling frequency of the device used is 128, so for an epoch of 1 second we get 128samples.



Signal Preprocessing and Feature Engineering

Signal Preprocessing
EEG devices are capable of recording electrical activities other than the brain signals. Recorded EEG signal which is not originated from brain is termed as artifact

Artifact Removal
Artifact removing ia an approach of recognizing, identifying source and removing of EEG artifacts and is an important process to ensure good quality of recorded signal. There are many varieties of artifacts present in EEG signal. Few of the artifacts as

captured during our experiments are described below along with the 14-Channel EEG streams

Cardiac artifacts - Heart gives two kinds of artifacts, mechanical and electrical. Both gets generated due to cardiac contractions and are easy to identify.
Electrical artifact is due to ECG and mechanical is due to the circulatory pulse.
(a) Electrical - Electrical artifact is due to ECG.
(b) Mechanical - Mechanical is due to the circulatory pulse.

Electrode Artifacts
(a) Electrode pop - They are due to electrode and skin interface which act as a capacitor and store electrical charge across the electrolyte around the Electrode.

(b) Electrode Movement - This happens due to movement of electrodes bacause of muscular movement in scalp.

(c) Electrode Lead Movement - Electrode lead movement causes artifact due to varying voltages at electrodes due to movement.
(d) Perspiration (Sweat) - Sweat causes artifacts due to unwanted electrical connection between electrodes and skin.

External device artifacts
(a) 50/60 Hz Ambient Electrical Noise - These artifacts are caused due to noise in 50/60 Hz electrical lines in the vicinity.

(b) Electrical Motor - Electric motor may produce high amplitude, irregular, poly-spike or spike artifact due to the switching magnetic elds within the Motor.

(c) Phone - Mechanical telephone bells causes sinusoidal form of artifact.

Muscle artifacts
(a) Electromyography (scalp/facial muscle) - They are caused due to muscle activity and it could last for less than a second to an entire EEG record.

(b) Photomyogenic - These artifacts are due to the eect of light. The endeavor is to keep the lights to bare minimum in the EEG recording room.

(c) Glossokenetic(Chewing) - Chewing or jaw clinching causes the worst possible noise called Glossokenetic across all EEG channels.

5. Ocular artifacts
(a) Blink - Due to rapid movement of the eyes in up and down direction during blink causes this artifact.

(b) Lateral Eye Movement - This artifact may persist for a very long duration corrupting the signal during lateral eye

FORCe Algorithm

We have employed FORCe: Fully Online and Automated Artifact Removal for BrainComputer Interfacing (FORCe) an automatic ICA-based algorithm FORCe. FORCe applies stereotyped artifact-specic spatial and temporal features to identify independent components of artifacts automatically. Without aecting the activity of neural sources, this algorithm removes the artifacts eciently
The FORCe algorithm works on a novel combination of wavelet decomposition, independent component analysis and thresholding of EEG signals. FORCe does not require additional signals (e.g., electro-oculogram or electro-myogram signals, which is generally recorded with EEG signals separately) and it works on small Epoch of EEG data. This algorithm outperforms the state-of the-art automated artifact removal methods, Fully Automated Statistical Thresholding for EEG artifact Rejection (FASTER) and Lagged Auto-Mutual Information Clustering (LAMIC). FORCe can remove a wide range of artifact as described in the previous subsection.

Algorithm Steps:-

1. Decompose EEG signal from each channel into a set of approximation and detail coefficients with wavelet decomposition. Denote Cji 2 C and jth coecient set from the set of all coecients, from channel i. Wavelets decomposes the signal by convolving it with a mother wavelet function at a range of dierent frequency and time locations. Then it measures the strength of the signal as a coecient of the wavelet function. FORCe uses discrete wavelet transform (DWT)as this scales to the signal at a discrete set of frequencies and times. Mathematically, WT may be defined as:-

$$\omega(t,f) = \int_{-\infty}^{\infty} x(t) * \psi_{s,r}(t)dt$$

$$\psi_{s,r}(t) = \frac{1}{\sqrt{s}}\psi(\frac{t-\tau}{s})$$

where x(t) is the original signal and * denotes its complex conjugation. !(t; f) shows how the signal x(t) is translated into a set of wavelet basis functions s;r(t) at scale and translation dimensions s and τ. is the mother wavelet function with which the signal is convolved

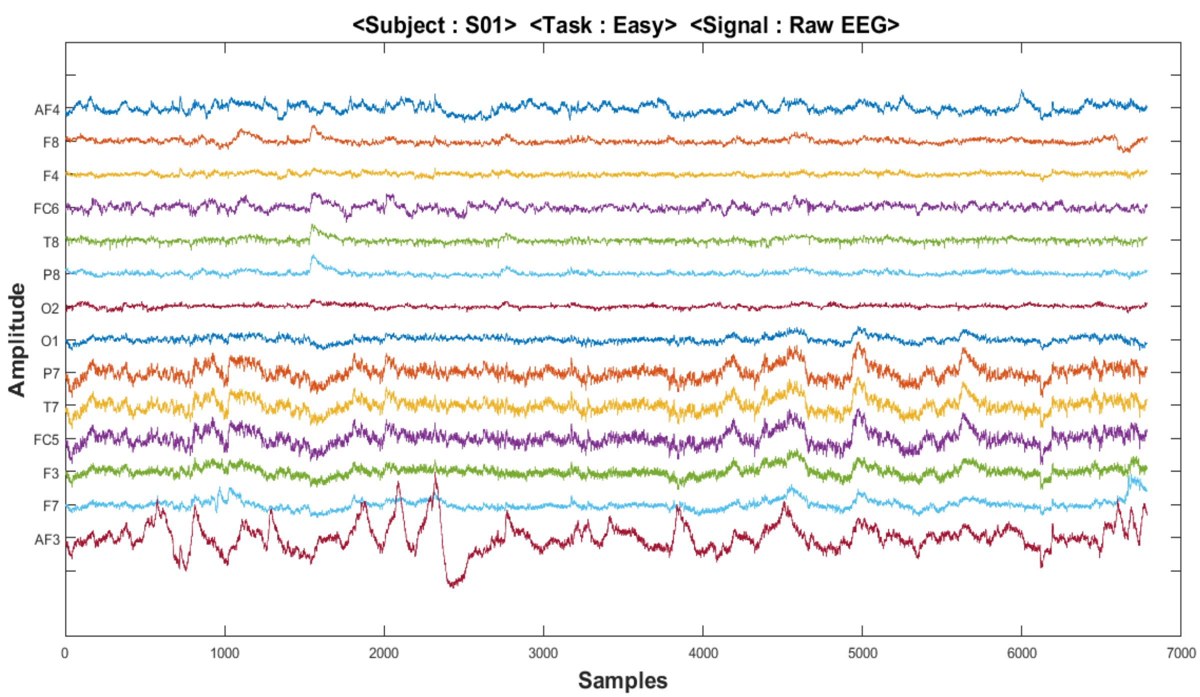
3. Estimate an ICA demixing matrix to separate the coecients into maximally statistically independent components (ICs) from the set of approximation coef- cients (Ai).

4. Multiply demixing matrix with the set of approximation coecients.

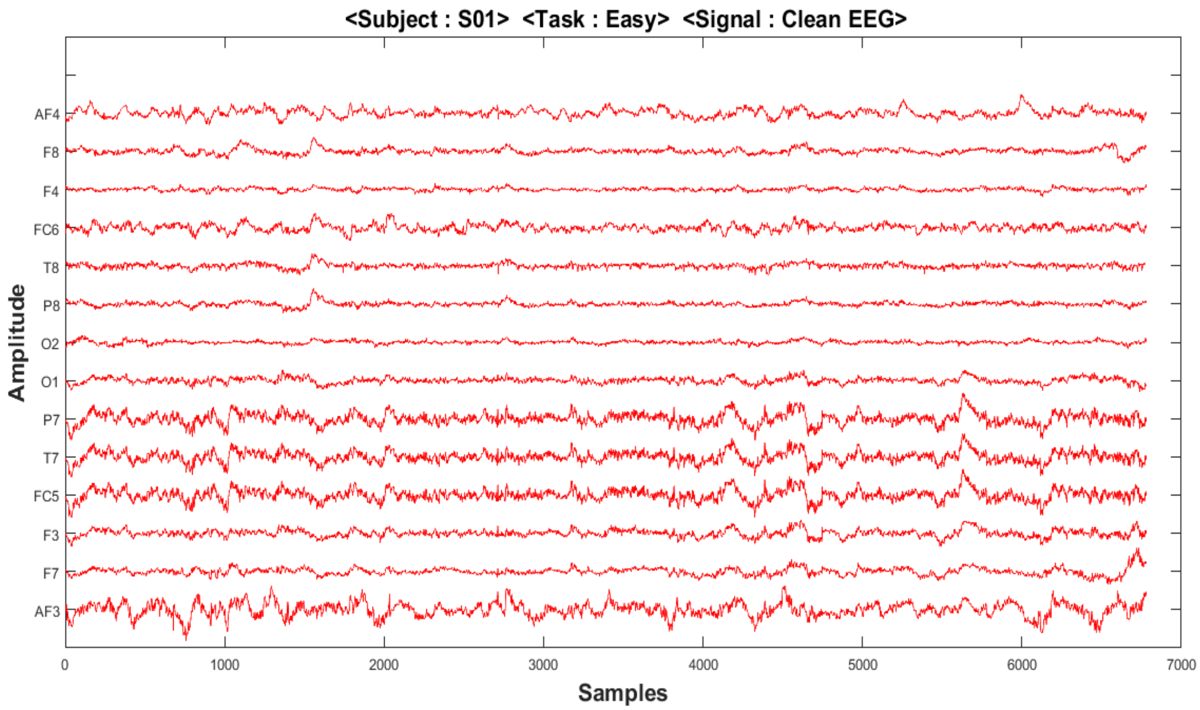
5. Identify ICs with artifacts and remove them.
6. To obtain an estimate of the cleaned approximation coecient set, invert the ICA decomposition.
7. Identify spike zones in both the approximation and detail coecient sets and then apply soft thresholding to reduce magnitude.
8. Reconstruct the cleaned EEG from the wavelet approximation and detail coecient sets.

Sample 14 Channel Raw and Clean EEG signal after application of FORCe algorithm is shown in Fig 4.3 and Fig 4.4. It can be seen clearly that the atrifacts present in the 14 Channel Raw EEG signal has been eliminated after application of this novel algorithm.

Raw EEG Data



Clean data after applying FORCe



Feature Extraction

After signal preprocessing and channel selection, the information needed for classication into individual load levels is extracted. This process is called feature extraction,
and represents an important step in EEG data processing. Feature extraction can be dened as automated recognition of various descriptive features of signals. Each segment obtained by signal segmentation can be represented by its extracted features. A good feature should remain unchanged if variations take place within a class, and it should reveal important dierences when discriminating between patterns of dierent classes. It is necessary not only to compute appropriate features but also to save them into a unied data structure. In our case, we store a list of computed features and the matrix of their values into the .csv le structure on a local linux machine. Various types and categories of features calculated in this thesis are discussed below in brief:-

Statistical Features

Statistical features are best suited for a time-series signal like EEG. An EEG signal can be characterized by the distribution of the amplitude and its moments. For each epoch of an EEG signal, following features were calculated.

FEATURE	DESCRIPTION
MEAN	Mean value
STD	Standard deviation
MAX_VALUE	Maximum positive amplitudes
MIN_VALUE	Maximum negative amplitudes
SKEWNESS	A measure of asymmetry of the distribution
KURTOSIS	A measure of flatness of the distribution
MEDIAN	The middle value of a set of ordered data
FD	Fractal Dimension
AR	Auto Regression

Derivative Features

Calculating the first and second derivative of mean and max of series signals gives a very meaningful feature value.

FEATURE	DESCRIPTION
1^{st} DIFF_MEAN	Mean value of the first derivative of the signal
1^{st} DIFF_MAX	Maximum value of the first derivative of the signal
2^{nd} DIFF_MEAN	Mean value of the second derivative of the signal
2^{nd} DIFF MAX	Maximum value of the second derivative of the signal

Interval or Period Features

EEG signals can also be analyzed based on measurement of distribution of the intervals between zero and other level crossings or between maximum and minimum. We have calculated the following features

FEATURE	DESCRIPTION
LINE_LENGTH	Line length
MEAN_VV_AMPL	Mean of vertex to vertex amplitudes
VAR_VV_AMPL	Variance of vertex to vertex amplitudes
MEAN_VV_TIME	Mean of vertex to vertex times
VAR_VV_TIME	Variance of vertex to vertex times
MEAN_VV_SLOPE	Mean of vertex to vertex slope
VAR_VV_SLOPE	Variance of vertex to vertex slope
ZERO_CROSSING	Number of zero crossings in a signal
MIN_MAX_NUMBER	Number of local minima and maxima
COEFF_OF_VARIATION	A statistical measure of the deviation of a variable from its mean, standard deviation divided by mean
AMPL_RANGE	The difference between the maximum positive and maximum negative Amplitude values

Hjorth Parameters
Hjorth parameters gives the complexity of a time-series EEG signal. These values are vary useful in EEG analysis and are a very useful tools for the its quantitative description.

FEATURE	DESCRIPTION
HJORTH1	Ability
HJORTH2	Mobility $(\sigma_{x'}/\sigma_x)$
HJORTH3	Complexity $(\frac{\sigma_{x''}/\sigma_{x'}}{\sigma_{x'}/\sigma_x})$

Frequency Features
These features are the most important features for analysis of EEG Signal. Based on the frequency content of EEG signals, following variations of EEG signals frequency features were calculated. Fast Fourier Transform was applied to various EEG wave bands to obtain values. We also calculate useful ratios of FFT in various bands. These are the most promising features of EEG signal.

FEATURE	DESCRIPTION
FFT_DELTA	0.1 - 4 Hz
FFT_THETA	4 - 8 Hz
FFT_ALPHA	8 - 13 Hz
FFT_BETA	13 - 30 Hz
FFT_GAMMA	30 - 40 Hz
FFT_WHOLE	0.1 - 40 Hz
FFT_DT_RATIO	DELTA / THETA
FFT_DA_RATIO	DELTA / ALPHA
FFT_TA_RATIO	THETA / ALPHA
FFT_DTA_RATIO	(DELTA + THETA) / ALPHA
FFT_SEF	Spectral edge frequency
FFT_SP-ROLL_OFF	Below which 85 % of the total spectral power resides

Wavelet Features

The wavelet transform (WT) is capable of distinguishing very small and delicate differences between time-series signals even from short epoch of signal. It can describe highly irregular and non-stationary signals easily. WT based methods can localize the signal components in time-frequency space better than FFT.

FEATURE	DESCRIPTION
MIN_WAV_VALUE	Minimum value
MAX_WAV_VALUE	Maximum value
MEAN_WAV_VALUE	Mean value
MEDIAN_WAV_VALUE	Median value
STD_WAV_VALUE	Standard deviation
SKEWNESS_WAV_VALUE	Skewness
KURTOSIS_WAV_VALUE	Kurtosis
WAV_BAND	Relative energy
ENTROPY_SPECTRAL_WAV	The spectral entropy
1st DIFF_WAV_MEAN	Mean value of the 1st derivative
1^{st}_DIFF_WAV_MAX	Maximum value of the 1^{st} derivative
2^{nd}_DIFF_WAV_MEAN	Mean value of the 2nd derivative
2^{nd}_DIFF_WAV_MAX	Maximum value of the 2nd derivative
ENERGY_PERCENT_WAV	Percentage of the total energy of a detail/approximation
WAV_ZERO_CROSSING	Zero crossing
WAV_COEFF_OF_VARIATION	Coefficient of variation
WAV_TOTAL_ENERGY	Total Energy

Features Selection and Optimization

Feature selection is important because

- It decreases the number of features that have to be measured and processed.
- It improves computational speed in lower dimensional feature spaces
- It may increase in the accuracy of the classification algorithms.

Feature Selection Method Used:

- Tree-based feature selection (Extra Trees Classifier)
- Extreme Gradient Boosting (XGBoost)
- Correlation Matrix

Extra Trees Classifier

The Extra-Tree method (standing for extremely randomized trees) was proposed, with the main objective of further randomizing tree building in the context of numerical input features, where the choice of the optimal cut-point is responsible for a large proportion of the variance of the induced tree.

With respect to random forests, the method drops the idea of using bootstrap copies of the learning sample, and instead of trying to find an optimal cut-point for each one of the K randomly chosen features at each node, it selects a cut-point at random.

This idea is rather productive in the context of many problems characterized by a large number of numerical features varying more or less continuously: it leads often to increased accuracy thanks to its soothing and at the same time significantly reduces computational burdens linked to the determination of optimal cut-points in standard trees and in random forests.

From a statistical point of view, dropping the bootstrapping idea leads to an advantage in terms of bias, whereas the cut-point randomization has often an excellent variance reduction effect. This method has yielded state-of-the-art results in several high-dimensional complex problems.

From a functional point of view, the Extra-Tree method produces piece-wise multilinear approximations, rather than the piece-wise constant ones of random forests.

This class implements a meta estimator that fits a number of randomized decision trees (a.k.a. extra-trees) on various sub-samples of the dataset and uses averaging to improve the predictive accuracy and control over-fitting.

XGBoost (Extreme Gradient Boosting)

A benefit of using gradient boosting is that after the boosted trees are constructed, it is relatively straightforward to retrieve importance scores for each attribute.

Generally, importance provides a score that indicates how useful or valuable each feature was in the construction of the boosted decision trees within the model. The more an attribute is used to make key decisions with decision trees, the higher its relative importance.

This importance is calculated explicitly for each attribute in the dataset, allowing attributes to be ranked and compared to each other.

The importance is calculated for a single decision tree by the amount that each attribute split point improves the performance measure, weighted by the number of observations the node is responsible for. The performance measure may be the purity (Gini index) used to select the split points or another more specific error function.

The feature importance is then averaged across all of the decision trees within the model.

Correlation Feature Selection

The Correlation Feature Selection (CFS) measure evaluates subsets of features on the basis of the following hypothesis: "Good feature subsets contain features highly correlated with the classification, yet uncorrelated to each other. The following equation gives the merit of a feature subset S consisting of k features:

$$\mathrm{Merit}_{S_k} = \frac{k\overline{r_{cf}}}{\sqrt{k + k(k-1)\overline{r_{ff}}}}.$$

Here, kr_{cf} is the average value of all feature-classification correlations, and r_{ff} is the average value of all feature-feature correlations. The CFS criterion is defined as follows:

$$\text{CFS} = \max_{S_k}\left[\frac{r_{cf_1} + r_{cf_2} + \cdots + r_{cf_k}}{\sqrt{k + 2(r_{f_1 f_2} + \cdots + r_{f_i f_j} + \cdots + r_{f_k f_1})}}\right].$$

The rcf , rff variables are referred to as correlations, but are not necessarily Pearson's correlation coefficient or Spearman's ρ. Dr. Mark Hall's dissertation uses neither of these, but uses three different measures of relatedness, minimum description length (MDL), symmetrical uncertainty, and relief.

Let xi be the set membership indicator function for feature fi; then the above can be rewritten as an optimization problem:

$$\text{CFS} = \max_{x \in \{0,1\}^n}\left[\frac{(\sum_{i=1}^{n} a_i x_i)^2}{\sum_{i=1}^{n} x_i + \sum_{i \neq j} 2 b_{ij} x_i x_j}\right].$$

The combinatorial problems above are, in fact, mixed 0–1 linear programming problems that can be solved by using branch-and-bound algorithms.

Modeling for Mental Workload Measurement

Machine Learning

Machine learning is a branch of computer science that deals with the design of machines that learn to make predictions on data without being explicitly programmed. The formal denition of machine learning due to Mitchell 1998 is "A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P if its performance at tasks in T, as measured by P, improves with experience E". Machine learning algorithms are divided into three categories; supervised, semisupervised and un-supervised. We have explored following machine learning algorithms for CWM estimation in our report:

Models used

- k-Nearest Neighbors (k-NN)
- Decision Tree Classifier
- Support Vector Machine (SVM)
- Multi-Layer Perceptron (MLP)
- GaussianNB

- XGBoost Classifier

k-Nearest Neighbors (k-NN)

k-NN is a simple and robust classier. The classier works by comparing testing data with training data. The classier and the K neighborhood in the training data and assigns the class that appears most frequently in the neighbourhood of k. The default value of k is 1, and the default neighborhood object similarity setting is the Euclidean distance. In this experiment, the value of k is set to 5.

$$d(X_i, X_j) = \sqrt{\sum_i (X_i - X_j)^2}$$

Decision Tree Classier- Decision tree learning is one of the most widely used and practical inductive inference method. The decision tree classier is a method for approximating discrete-valued functions, in which the learned function is represented by a decision tree. Learned trees can also be represented as sets of if-then rules that may improve human readability. In addition, the results of decision tree classifiers can be directly compared with the rules used by physicians when evaluating EEG.

Support Vector Machine (SVM)

SVMs, also called support vector networks are supervised learning models with associated learning algorithms that analyze data used for classication and regression analysis. Given a set of training examples, each marked as belonging to one or the other of two categories, an SVM training algorithm builds a model that assigns new examples to one category or the other, making it a non-probabilistic binary linear classier. An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall on. We have used both linear and RBF kernel in our algorithm.

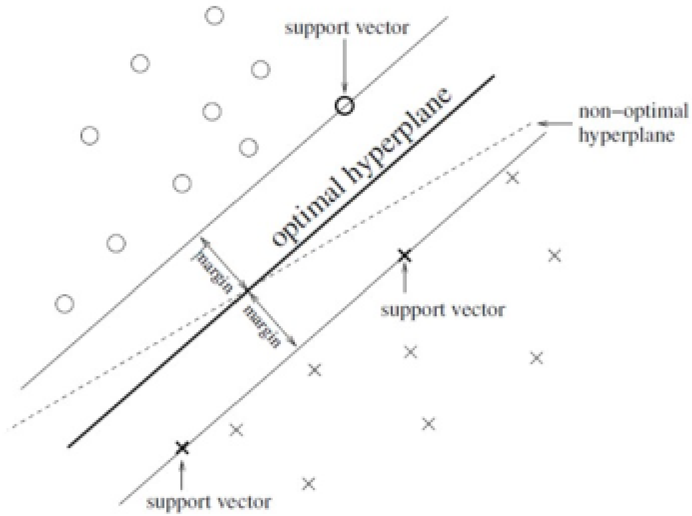


Figure 5.1: Support vector machine.

Multi Layer Perceptron (MLP)

The most commonly used representative of ANNs (Articial Neural Network) is the MLP. MLP is the most commonly used feedforward ANN, due to ease of implementation and smaller training set requirements. The MLP model maps sets of input data on to a set of appropriate output. MLP can solve complex classication tasks, but it risks overtting the training data and it takes a lot of time. The diagram shown in Fig illustrates a MLP network with hidden layers. Neural Networks and thus MLP, are universal approximators, i.e., when composed of enough neurons and layers, they can approximate any continuous function. Added to the fact that they can classify any number of classes, this makes NN very exible classiers that can adapt to a great variety of problems. A MLP without hidden layers is known as a perceptron. Interestingly enough, a perceptron is equivalent to LDA and, as such, has been sometimes used for BCI applications.

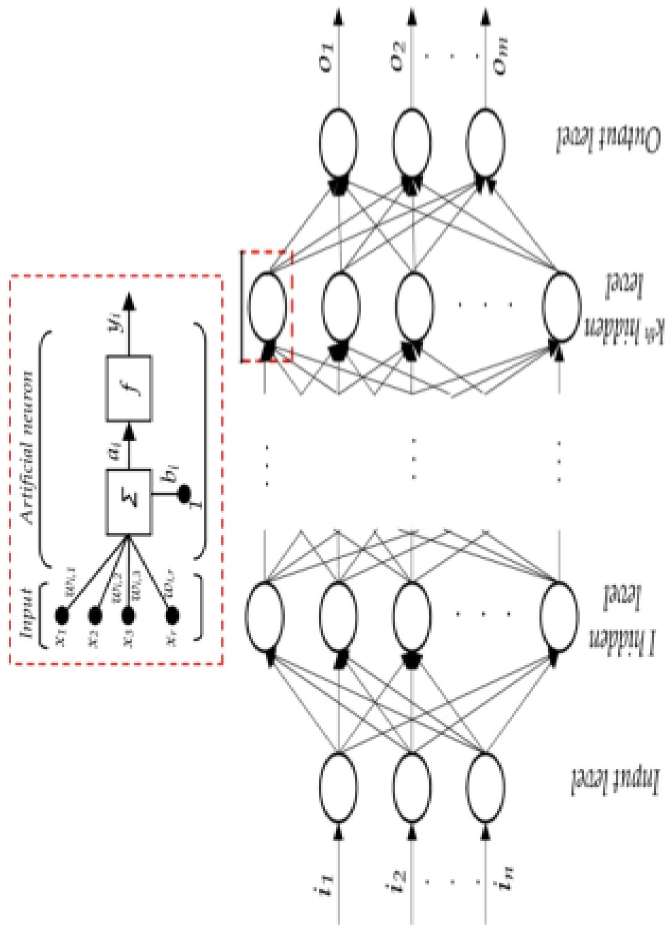


Figure 5.2: Multi layer perceptron.

Gaussian NB

Naive Bayes methods are a set of supervised learning algorithms based on applying Bayes’ theorem with the “naive” assumption of conditional independence between every pair of features given the value of the class variable.

Naive Bayes learners and classifiers can be extremely fast compared to more sophisticated methods. The decoupling of the class conditional feature distributions means that each distribution can be independently estimated as a one dimensional distribution. This in turn helps to alleviate problems stemming from the curse of dimensionality.

XGBoost Classifier

XGBoost is a popular and efficient open-source implementation of the gradient boosted trees algorithm. Gradient boosting is a supervised learning algorithm, which attempts to accurately predict a target variable by combining the estimates of a set of simpler, weaker models.

When using gradient boosting for regression, the weak learners are regression trees, and each regression tree maps an input data point to one of its leafs that contains a continuous score. XGBoost minimizes a regularized (L1 and L2) objective function that combines a convex loss function (based on the difference between the predicted and target outputs) and a penalty term for model complexity (in other words, the regression tree functions). The training proceeds iteratively, adding new trees that predict the residuals or errors of prior trees that are then combined with previous trees to make the final prediction. It's called gradient boosting because it uses a gradient descent algorithm to minimize the loss when adding new models.

`Results

We used the three different types of feature selection techniques ie. Trees Based Feature Selection (Extra Trees Classifier), XGBoost Feature Selection and Correlation based Feature Selection.

We were able to get the most important features for each specific feature selection and feature important techniques. Based on the features we selected top 10 features for each selection technique.

The results for each of them are as follows:

Extra Trees	***XGBoost***	***Correlation Heatmap***
Wavelet Detailed STD	AR	Wavelet App. Entropy
Wavelet Detailed Energy	Wavelet Detailed STD	Hjorth_activity
Wavelet App. Entropy	Variance of Vertex to vertex slope	Variance of Vertex to vertex slope
Auto Regressor	Wavelet Appx. STD	Wavelet Detailed Energy
Wavelet Appx. STD	Kurtosis	Wavelet Appx. STD
Variance of Vertex to vertex slope	Hjorth_mobility	FFT Beta Max Power
Delta/ Theta	Wavelet App. Entropy	1st Difference Max
Wavelet Appx. mean	Delta/ Theta	FFT Alpha Max Power
FFT Delta Max Power	Wavelet App. Energy	Coefficent of Variation
Delta / Alpha	Wavelet Appx. Mean	FFT Theta Max Power

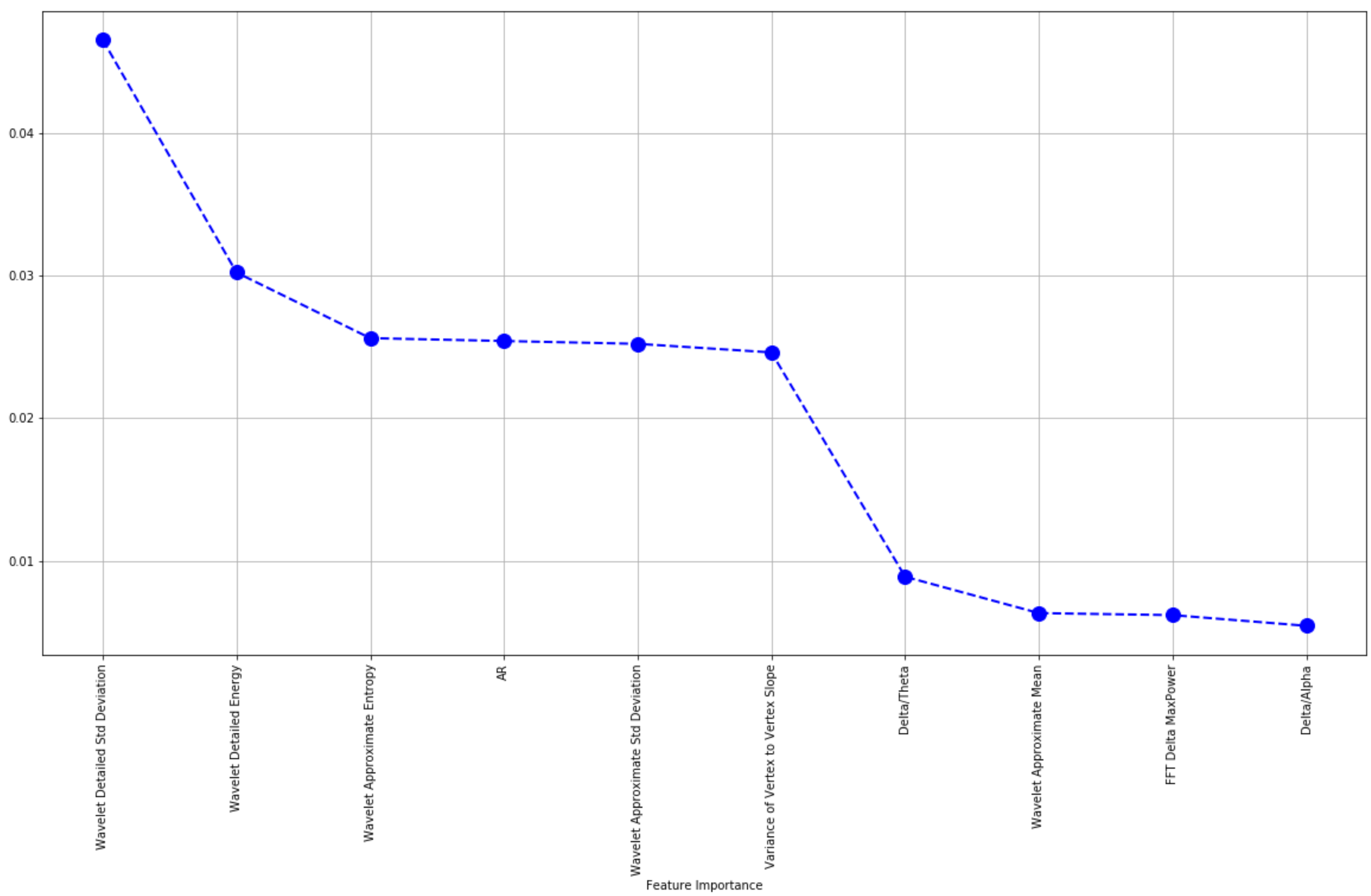
Each of them had some common features and were very relevant to our experiment.

It proved that some set of features were very likely to predict the outcome of the classification problem.

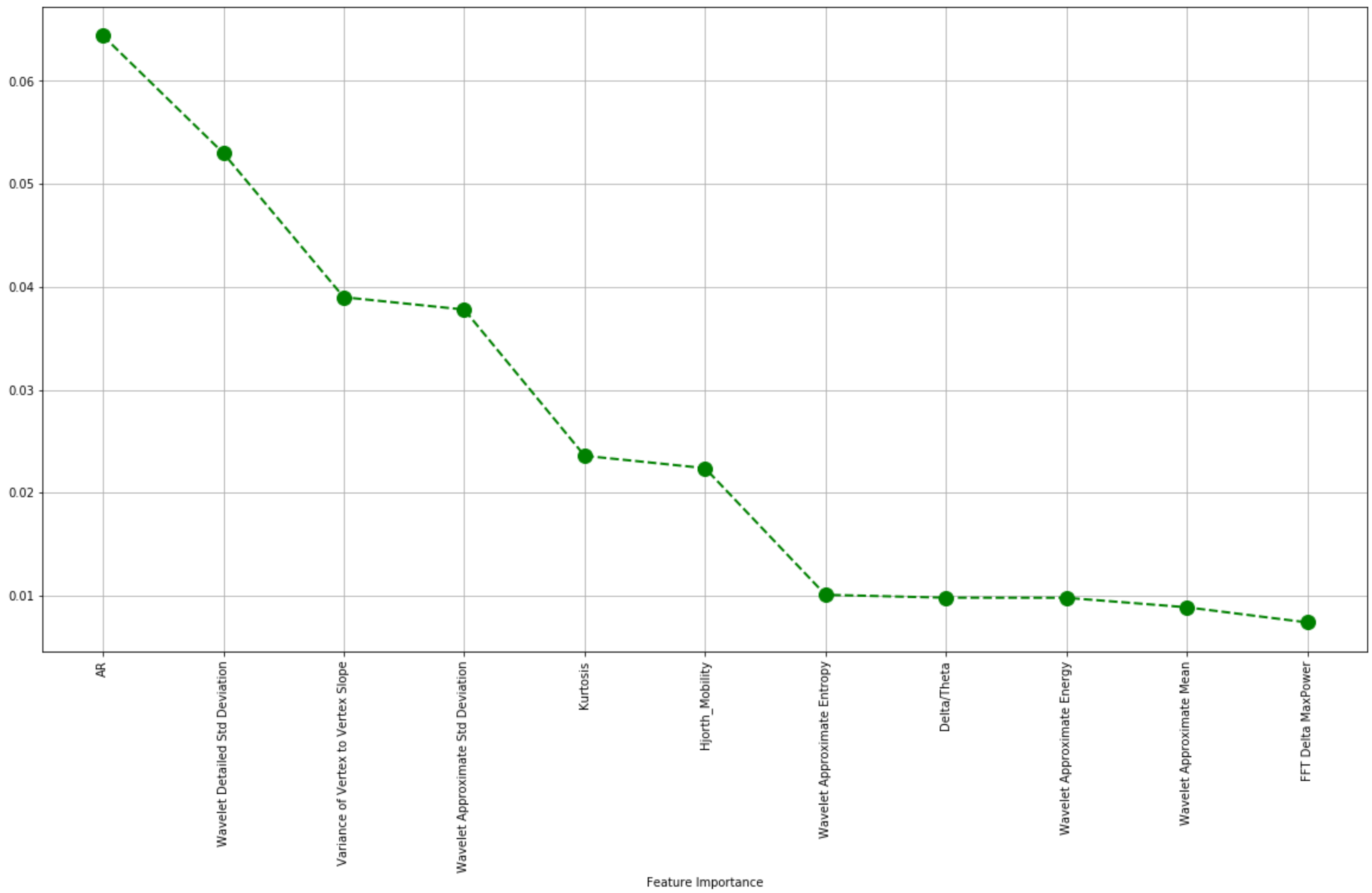
Based on the features selected we were able to rank them in order of their relevance.

Here are the results.:

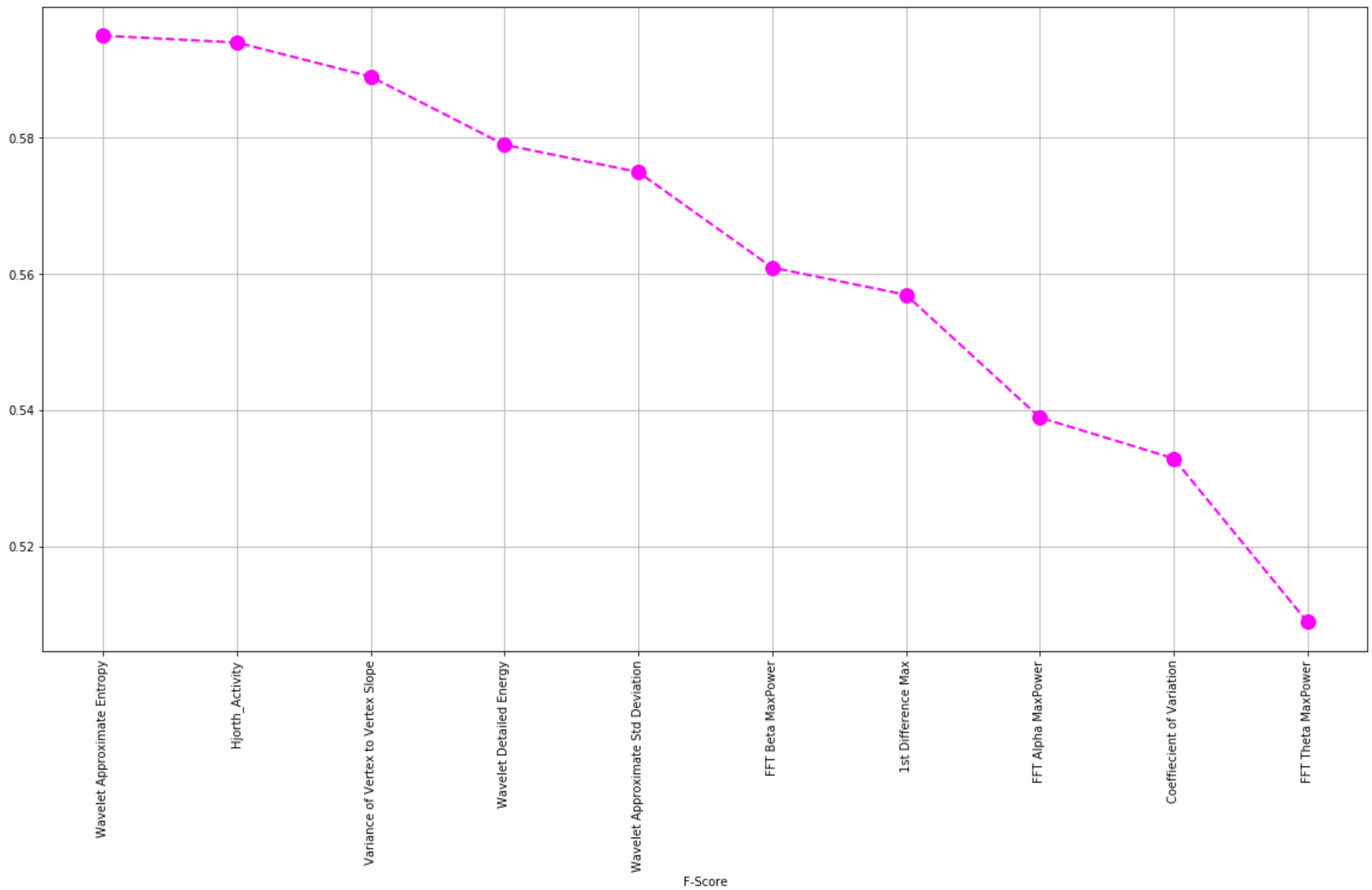
Feature Importance using Extra Trees Method.



Feature Importance using XGBoost method.



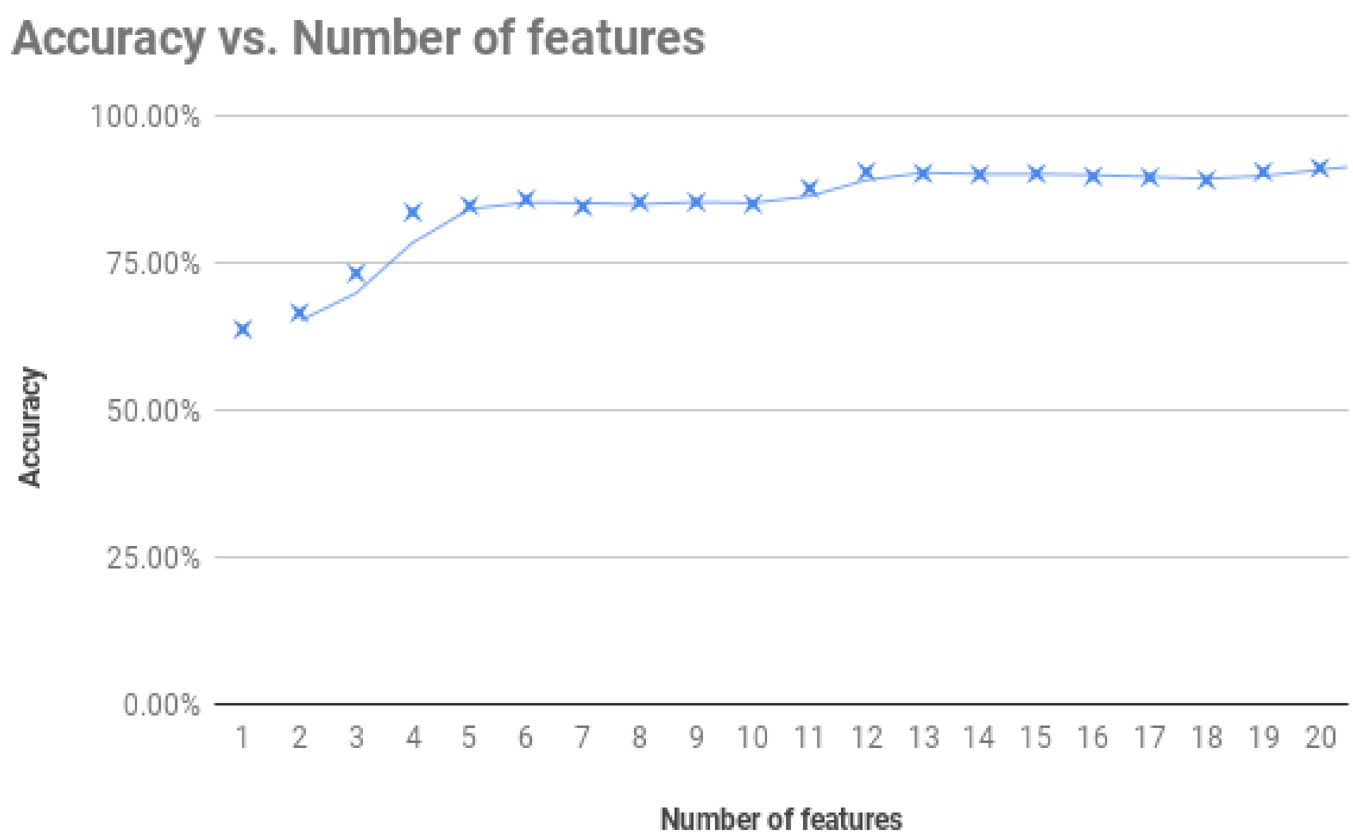
Feature Importance using Correlation



Additionally, XGBoost provided us a unique way to see how different features were relevant in predicting the correct output. For a different number of features, the predicting power of the classifier showed the following relationship. The accuracy increased on increasing the number of features while on further increasing the features the accuracy was lost a bit.

The relationship can be seen using this scatter plot.

XGBoost Accuracy vs/ Number of features used for classifying the target values.



Finally, we were able to select a selected few features from the top best features from the feature selection methods.

Optimized Selected Features.

Here are the finally optimized selected features:

Kurtosis	**Hjorth_Mobility**
Wavelet Detailed Std Deviation	**Wavelet Approximate Entropy**
Variance of Vertex to Vertex Slope	**Wavelet Approximate Std Deviation**
Delta/Theta	**Coefficient of Variation**
Delta/Alpha	**FFT Alpha MaxPower**
1st Difference Max	**Wavelet Approximate Energy**
Wavelet Detailed Energy	**FFT Beta MaxPower**

Various machine learning models were used to classify the target variables.

They were classification models and included.

- k-Nearest Neighbors (k-NN)
- Decision Tree Classifier
- Support Vector Machine (SVM)
- Multi-Layer Perceptron (MLP)
- GaussianNB

Comparisons were done in the classification of the target variable using all features and only the selected features. We found that although the selected features were comparatively less accurate but they proved to classify the target value to a great extent.Below is the table containing the overall accuracy of different machine learning models when all features were used and when an only limited number of selected features were used.

Classifier	Accuracy using all features	Time taken with all features	Accuracy using selected features	Time taken using selected features
Gaussian NB	57.32%	0.019 s	53.74%	0.007 s
Decision Tree	79.44%	0.121 s	73.21%	0.018 s
SVM	82.24%	1.041 s	70.56%	0.198 s
KNN	86.13%	0.456 s	75.08%	0.044 s
MLP	84.73%	1.937 s	71.81%	1.339 s
XGBoost	**88.01%**	**0.359 s**	**83.33%**	**0.046 s**

Confusion Matrix

In ML, a confusion matrix, also known as an error matrix, is a specific table layout that allows visualization of the performance of an algorithm, typically a supervised learning one. Each column of the matrix represents the instances in a predicted class while each row represents the instances in an actual class (or vice versa). The diagonal elements represent the number of points for which the predicted label is equal to the true label, while o-diagonal elements are those that are mislabeled by the classier. The higher the diagonal values of the confusion matrix the better, indicating many correct predictions.

Confusion matrix before feature selection using XGBoost Classifier

	Level 1 Actual	Level 2 Actual	Level 3 Actual
Level 1 Predicted	93	03	08
Level 2 Predicted	0	188	41
Level 3 Predicted	0	25	284

Accuracy(test) : **88.01%**

Confusion matrix after feature selection using XGBoost Classifier

	Level 1 Actual	Level 2 Actual	Level 3 Actual
Level 1 Predicted	93	04	07

Level 2 Predicted	**0**	**170**	**59**
Level 3 Predicted	**0**	**37**	**272**

Accuracy(test) : 83.33%

`

Conclusion

Exhaustive results, both in form of tables and charts, as shown in the previous section gives us a detailed intuition of mental workload and how it increases as the demand of mental resources increases as we migrate from Level 1 task to Level 3 task. Our experiment has successfully established the mental workload load theory by measuring mental load generated in various experiments done around in the BCI community.

This study marks a humble step in understanding human mental load. Considering the task demand in terms of cognitive resources is gaining importance in various critical mission related to Armed Forces and Space technologies. We have studied the gradual increase in mental workload as per the experiment designed. However, we can extend the research, by replacing the experiments conducted in controlled laboratory condition with practical tasks. For example, we can expose a combatant to practical military training and have the EEG signal recorded through EEG enabled helmets. We can do the online analysis of the mental workload, which can be very useful for various kinds of applications as discussed next.

Proposed Applications for Mental Workload Measurement for task evaluation Following are few important militaries and non-military applications which can use CWM study in this report.

Military Applications

- Selection of Combatant tools for Critical Mission
- Monitoring Combatant adaptability in Critical Mission
- Mental Workload Management of Pilot

Non-Military Applications

🏂 HR Management using EEG

🏂 Improving working Environment based on Mental Measurement

🏂 Monitoring Employees Tools and Softwares in a Company

Proposal for Future Work

In the field of Deep Learning (DL), Convolutional Neural Network (CNN) has proved it's worth in image recognition. We propose to use DL for MWM. Since CNN can handle two dimensional images precisely, it is proposed to convert the time-series EEG signal to two dimensional EEG images.

We can plot 2D colored heat map of the brain by calculating the Power Spectral Density (PSD) in various bands for every channel. This way, we can convert 14 channel EEG data into plenty of images. After this, the database of 2D EEG images can be fed to CNN directly without calculating the features and hence saving eort and time to calculate features and then do optimization. RNNs has memory and hence they may be used in conjunction with CNN to retain the time dependence of continuous EEG signal. Of course, the nal layer consists of the fully connected layer as per the class of cognitive workload desired.

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