Detecting Navigation Challenges for the Visually Impaired with mobile Monitoring of Biosignal

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A thesis submitted to the Department of Computer Science and Engineering
in partial fulfillment of the requirements for the degree of
B.Sc. in Computer Science and Engineering

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Declaration

It is hereby declared that

1. The thesis submitted is our own original work while completing degree at Brac University.
2. The thesis does not contain material previously published or written by a third party, except where this is appropriately cited through full and accurate referencing.
3. The thesis does not contain material which has been accepted, or submitted, for any other degree or diploma at a university or other institution.
4. We have acknowledged all main sources of help.

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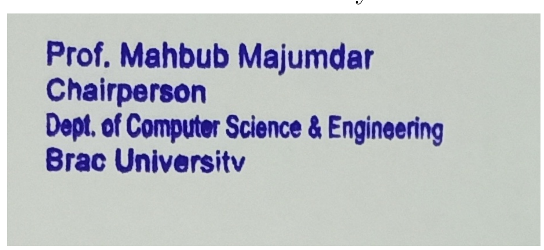

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Abstract

In recent years, mobile Brain Computer Interface (BCI) has gained much popularity in the design of navigation aids. This opens up the platform to build navigation aids based on the level of stress imposed on visually impaired people (VIPs). The goal is to build a bridge between different environments and the cognitive load on VIP navigating through those environments. In order to do that, the first step is to label the cognitive load each possible type of environment imposes on the VIPs. For the purposes of this study the stimuli have been narrowed down to indoor environments. Cognitive psychology defines cognitive load as the used amount of working memory resources. Working memory performance is measured by the spectral changes in the alpha frequency band in an Electroencephalography (EEG) report. This correlation provides a measurable quantity to determine the overall cognitive load associated with a task. Besides alpha bands, beta activity has also been linked to psychological and physiological stress, which in effect is imposed on cognition. The oscillations in another frequency band, gamma have also been observed to increase with memory load. Putting the above together, the bio signals in the alpha, beta and gamma frequency ranges are useful for detecting the cognitive load of the subject. The data set used in this study has been obtained from the European Union from one of their experiments for VIP. It constitutes of EEG signals taken from 9 visually impaired people as they navigated through various indoor environments. Features are extracted using Welch's Power Spectral Density (WPSD) from the relevant bands of the EEG signals. A Machine Learning algorithm is used for classification. The features are mapped onto different cognitive levels as labels and a Support Vector Machine (SVM) trained to classify the stress levels of the VIPs. The AUROC is around 90% for each environment analysed in this research.

Keywords:EEG, BCI, VIP, Cognitive Load, Machine Learning, SVM, WPSD

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Table of Contents

Declaration **i**

Approval **ii**

Abstract **iii**

Acknowledgment **iv**

Table of Contents **v**

List of Figures **viii**

List of Tables **ix**

Nomenclature **xi**

1 Introduction **1**

1.1 Thesis Overview 2

1.2 Thesis Contribution 3

1.3 Thesis Orientation 3

2 Literature Review **4**

3 Background Analysis **9**

3.1 Working Memory 9

3.2 CLT 9

3.2.1 Intrinsic Cognitive Load 10

3.2.2 Extraneous Cognitive Load 10

3.2.3 Germane Cognitive Load 10

3.3 Measuring Cognitive Load 10
3.4 Different Parts Of Brain 11
3.5 BCI 12
3.6 Non-invasive BCIs 14
3.6.1 MRI 14
3.6.2 fMRI 14
3.6.3 EEG 14
3.7 Biosignals 15
3.7.1 Gamma 16
3.7.2 Beta 16
3.7.3 Alpha 17
3.7.4 Theta 17
3.7.5 Delta 17
3.8 Feature Extraction 17
3.8.1 Fourier Transform 17
3.8.2 Wavelet Transform 18
3.8.3 PCA 18
3.8.4 ICA 19
3.8.5 LDA 19
3.8.6 Welch's method for finding Power Spectral Density 19
3.9 Classification Techniques 20
3.9.1 SVM 20
3.9.2 Random Forest Classifier 22
3.10 ERD/ERS calculation 22

4 Proposed Model **24**
4.1 Data Description 24
4.2 Feature Extraction 27
4.2.1 WPSD 27
4.3 Cognitive Load Measurement 27
4.4 Cognition Classification 28

5 Results and Discussion **29**

5.1 Analysis Of Results 29

5.2 Discussion 31

6 Conclusion **33**

Bibliography **34**

List of Figures

3.1 Different regions of Brain [2] 12
3.2 BCI workflow [8] 13
3.3 Acquiring EEG signals [22] 14
3.4 Travelling of brain waves in neurons [39] 15
3.5 Brain samples for the five different waveforms [3] 16
3.6 Illustration of record segmentation [61] 20
3.7 Optimal separating hyperplane in 2D SVM 21
3.8 Random Forest based Classification [31] 22
3.9 Calculation of ERD/ERS using Inter trial Variance method [62] . . . 23

4.1 10-20 Electrode Placement System [1] 25
4.2 Workflow Of the Proposed Model 26

5.1 The ROC Curves 32

List of Tables

4.1 Categories of Visual Impairment. 25

5.1 Descriptions and corresponding challenges for each environment . . . 31

5.2 Sensitivity, Specificity and Accuracy table 31

Nomenclature

The next list describes several symbols & abbreviation that will be later used within the body of the document

AUC Area Under Curve

BCI Brain Computer Interface

CLT Cognitive Load Theory

CNS Central Nervous System

$ECoG$ Electrocorticographic

EEG Electroencephalography

FFT Fast Fourier Transform

$fMRI$ Functional Magnetic Resonance Imaging

FN False Negative

FP False Positive

ICA Independant Component Analysis

LDA Linear Discriminant Analysis

MRI Magnetic Resonance Imaging

PCA Principal Component Analysis

RBF Radial Basis Function

ROC Receiver Operator Characteristics

SVM Support Vector Machine

TN True Negative

TP True Positive

$WPSD$ Welch's Power Spectral Density

Chapter 1

Introduction

Common existing mobility aids for the visually impaired include canes, service dogs and electronic mobility aids [41]. While all of these are effective aids to locate obstacles and help the visually impaired people (VIPs) with navigation, none of these take the user's mental state into consideration [43]. At first glance, visual impairment seems to be a small percentage of the population, but eye sight is observed to deteriorate with age [13]. Many of the elderly people tend to stay at home most of the time because they find outdoor environments stressful. Eyesight generally plays a factor in that stress. The aim of this study is to provide individual assessment of VIPs. However, different navigation techniques can also be compared by analysing EEG signals of individuals. Although user feedback can easily be used to compare different techniques, user or customer feedback is not always reliable. A quantitative comparison will be useful for companies when designing new navigation aids. A similar study can include analysing the EEG bands from a group with a different type of impairment, such as hearing impairment. The mapping of task to stress is also very relevant beyond impairment. For instance, a healthy subject will have a standard stress level during activities heavy on cognition such as interviews and exams. A stress level beyond that standard will indicate an extra factor in play. Probable factors can be depression or anxiety.

Invasive and partially invasive techniques, such as Electrocorticographic (ECoG), lead to complications of brain tissue depletion causing signals to recede with time. As a non-invasive measure, Electroencephalography(EEG) provides a safer and more efficient procedure to conduct experiments. Other non-invasive methods such as fMRI (functional Magnetic Resonance Imaging), MRI (Magnetic Resonance Imaging) provide higher resolution and better understanding of the brain. However, these methods call for machines that are not portable and require the subject to be in a specific posture. This means that both fMRI and MRI are not suitable for mobile experiments that are necessary for our study. Hence, we have chosen EEG to collect brain signals for analysing, classifying and labelling cognitive load.

1.1 Thesis Overview

A Brain Computer Interface (BCI), sometimes called a neural-control interface (NCI), or brain-machine interface (BMI), is a direct communication pathway between an enhanced or wired brain and an external device. BCI is often directed at researching, mapping, assisting, augmenting, or repairing human cognitive or sensory-motor functions [34]. Based on what has been found, noninvasive BCI techniques have helped pave a safe path for VIPs to perform regular tasks [49]. These help us perceive the issue tackling the physical disadvantage of the blind people more clearly.

Researches have suggested that technology has had great success in aiding VIPs [11]. In [46] the relevance of EEG to measure cognitive load is explained. EEG signals have been shown to be stable indicators of cognitive load in a variety of tasks performed in controlled laboratory settings such as learning to carry out tasks to navigate using hypertext and multimedia data [14][9], or learning to use complex navigating tools using hypermedia navigation [38].

A good measure for the user's state of mind at a given time is the cognitive load of the user obtained in real time. In cognitive psychology, the implication of cognitive load is the amount of working memory resources used in given time. The capacity and performance of the neural circuitry that implements working memory plays a vital role in cognitive activities and varies from person to person. In order to understand working memory better, it is useful to distinguish between working memory performance and task performance. Task performance is typified by a participant's external performance of a task; for example, the time it takes to complete the task or the ratio of incorrect responses to correct ones. As opposed to that,

working memory performance is measured by the spectral changes in the alpha, beta and gamma frequency bands in the EEG bio signal [36][8][60]. This provides a connection between the task and the resultant cognitive load.
The mental instability and the challenges of visual orientation the VIPs face have been studied in cognitive load theory (CLT) by John Sweller in [56]. It is the basis of what we want to achieve in the forthcoming future.
Research done by Saitis et al. in [48] and [47] with Machine Learning use Fast Fourier Transform (FFT) for feature extraction and Random Forest classifier algorithm for classification.

1.2 Thesis Contribution

Building on the above, we have based our work on helping the visually impaired to navigate in unfamiliar indoor environments. Some research has been done to analyse the mental state of the VIPs using EEG as they navigate through various environments [48][47]. We want to carry out similar research using a different approach and see if the results still hold and agree with the work done in existing studies. We use Welch's Power Spectral Density (WPSD) for feature extraction and Support Vector Machine (SVM) for classification. Collecting EEG signals, we assess the resulting cognitive load label for each participant in different indoor environments.

1.3 Thesis Orientation

The consequent chapters of the paper have been covered in the following order. Chapter 2 discusses similar work in the field corresponding to our work and existing methodologies with their limitations. Chapter 3 gives an in depth study and analysis of the topics preceding data and information associated with our work. Chapter 4 presents the proposed model in detail. Chapter 5 give the test results, analysis of the results and the interrelated discussions. The last chapter, Chapter 6 closes and outlines our study with future plans.

Chapter 2

Literature Review

The use of BCI to provide communication and control capabilities to people with severe motor disabilities has become more common in the last decade [50]. So a gradual rise in interest in this field can be expected in the future. Studies have been done to measure cognitive load using fMRI or MRI, for example by Callicot J. in [16]. This study finds that the prefrontal cortical signal decreases at highest working memory load which is also coincident with a significant decrement in performance. The paper also talks about a relationship between the pericingulate or the posterior cingulate region, and capacity-unconstrained response. This is because activation of this region is observed to be related to attention and effort related processes. The cingulate cortex is a part of the brain situated in the medial aspect of the cerebral cortex. All of this leads us to draw a strong connection between the level of stress and results obtained from BCI reports.
Previous work in extracting features from EEG uses different approaches, for instance, in [55] the ACSP (Adaptive Common Spatial Pattern) is conducted for feature extraction of EEG signals, which is validated of its efficacy and superiority over the SCSP (Stationary Common Spatial Pattern) and WCSP (Windowed Common Spatial Pattern) methods through classification experiments on multiple recordings sessions of three subjects.

The analysis of EEG signals have been gaining more popularity recently in different sectors including neuromarketing [63], for the detection of various diseases including epilepsy [5], Alzheimer's disease [19] and Parkinson's disease[40]. These various journals carry out feature extraction in different ways. Yadava et al in [63] uses Discrete Wavelet Transform (DWT). The wide range of various wavelets available when using DWT leads to unreliability if the wrong wavelet is chosen for a particular application.

Machine Learning is observed to be a common tool for classification among the existing biosignal analysing journals. U. R. Acharya et al in [5] uses the Gaussian Mixture Model (GMM) and support vector machine (SVM) to investigate the performance of the features they extract. Another journal in the biomedical disease detection field, Oh et al in [40] uses Convolutional Neural Network(CNN) as the classification algorithm. The Deep Learning algorithm has shown remarkable outcome in conjunction with the Artificial Neural Network to classify dataset accurately.

Using EDA (Electrodermal Activity) instead of EEG means that there is no way to differentiate between cognitive load and cognitive stress. Cognitive load does not always correspond to stress as shown by the recovery stage as stated by Setz et al in [51]. This is why it is important to analyse specific bands which do correspond to stress. The paper has laid the idea of concatenating the signals from the MIST (Montreal Imaging Stress Test) stress experiment and MIST cognitive load experiment. MIST is a standardized test which involves putting the subjects under arithmetic and social stress. Adding or concatenating signals from the time period when stress is applied with the signals from the time when the subjects are recovering (i.e. not facing any stress or relaxing) means that any noise which persists due to basic cognitive load which is not brought about from stress is not considered in the final feature. This makes it easier to analyse the curve only for stress indicators.

A study by Anderson et al. in [21] uses an alternative approach to visualization techniques evaluation using signals from EEG. Advanced studies have shown a connection between neural networks and human cognition. Posner et al [44] has cogently revived the notion that neural network models of attention can provide a common, unifying approach to theory and research on many aspects of human cognitive and emotional development. The study has drawn attention that a neural network like PDP (Parallel and Distributed Processing) model helps us to understand commonalities among developmental processes associated with social learning, symbolic thinking, social cognition and social motivation. Using Deep Learning in order to classify cognitive load shows promising outcomes with good accuracy over the data set.

Kumar et al. in [35] explains the importance of detecting and analysing frequency bands in EEG signals. Some waves are based on their shape, head distribution and symmetry property [8]. The familiar classification of such wave forms include the gamma, alpha, beta, theta, delta. The continuous rhythms of the brain or brain waves are categorized by frequency bands where brain wave frequency differs in correspondence to different behavior and mental state of the brain [12][23][32].

Abo-Zahhad et al in [4] talk about the relevance of signals obtained in different frequency bands or ranges. EEG waveform is classified into five different frequency bands. The slowest waves usually found in an EEG report are delta waves (up to 4Hz) which correspond to deep and unconscious sleep. At a slightly higher pitch are theta waves (4-8Hz) involved with quiet focus and light sleep. The next frequency band (8-14Hz), commonly known as alpha waves are observed during relaxation with eyes closed but the subject still awake. Beta (14-30Hz) arises during normal consciousness and active concentration. And the highest frequency band, gamma waves (over 30Hz) are known to be stronger electrical signals in response to visual stimulation [4][35].

A study conducted by Subasi et al in [54] uses and compares the three algorithms of feature extraction methods to classify if an individual is epileptic or not. The publicly available data as described by Andrzejack et al. in [7] is used. A versatile signal processing and analysis framework of EEG is suggested, where the features were decomposed into sub bands using DWT. The features are then extracted using PCA (Principal Component Analysis), LDA (Linear Discriminant Analysis) and ICA (Independant Component Analysis) to reduce dimensionality to increase the performance of the classifier. The classification process is carried out using a SVM kernel. The training process is carried out using RBF (Radial Basis Function) kernel to PCA+SVM, ICA+SVM and LDA+SVM which are then cross compared to the in terms of their accuracy relative to the observed epileptic/normal patterns. Scaler performance measures, sensitivity and specificity, are derived from the confusion matrix. The results show that SVM by feature extraction using PCA, ICA and LDA always perform better than that without feature extraction (98%). According to this result, the application of nonlinear feature extraction and SVMs can serve as a potential alternative for intelligent diagnosis systems.

The data set used in this study has been obtained from [27], research done by Kalemari et al. later used in [48] and [47]. This particular data set focuses on the electric potentials of signals obtained from the brains of visually impaired people via EEG. Using the data set we collect signals from fourteen channels in nine participants experiencing indoor challenges. Saitis et al. in [48] further labels frequency bands with different kinds of activity and level of stress in a the brain. This paper says that beta activity is associated with psychological and physical stress, whereas theta and alpha-1 (i.e. lower alpha) frequencies reflect response inhibition and attentional demands such as phasic alertness. Degutis in [20] defines phasic alertness as the rapid change in attention due to a brief event and says that it is the basis for operations such as orienting and selective attention, which leads to the possibility of relating lower alpha waves to extra attention required for orientation by the subjects in the experiment. Alpha-2 (i.e. higher alpha) is related to task performance in terms of speed, relevance, and difficulty [48][30]. This group of frequency ranges or bands therefore correspond to the difficulty level presented to the VIP as they navigate through the different circumstances. Gamma waves are involved in more complex cognitive functions such as multimodal processing or object representation[48][29]. So even though interpretation from visual stimulation is not a factor, gamma waves are still relevant to this study because interpretation from the other senses (touch, smell) might be involved in the navigation process.
The journal in [48] is based on data collected by the European Union in a University in Iceland. The ten VIPs of the experiment are made to navigate through circumstances with various levels of stress. They use the EMOTIV+ EPOC headset with

16 dry electrodes placed according to the 10-20 system with sampling rate 128Hz. The participants are familiarized with the route prior to the experiment. Unnecessary head movements and hand gestures as well as talking to their O&M instructor are avoided with the exception of emergency. Annotations (which circumstance corresponds to which brain wave) are made with the help of video and audio besides using GPS.

Any missing data resulting from connectivity issues are made up for using interpolation in the time domain using FFT. All signals are baseline-normalized by subtracting for each participant and for each channel the mean of resting state registrations.These are obtained during a series of laboratory studies with the same participants.

Features related to signal power and complexity are extracted using the PyEEG open source Python module. For each of the 14 EEG channels, they compute the Relative Intensity Ratio as an indicator of relative spectral power in each of the six frequency bands, namely delta (0.5–4 Hz), theta (4–7 Hz), alpha-1 (7–10 Hz),alpha-2 (10–13 Hz), beta (13–30 Hz), and gamma (30–60 Hz).

Next they estimate the event-related (de-)synchronization (ERD/ERS) index, a well-established measure of band power change in EEG originally proposed by Pfurtscheller and Aranibar in [42]. Slightly modifying the model, this paper [48] calculates ERD/ERS every second, where every time point expresses the synchronization or desynchronization according to the same baseline. The drawback for this paper is that the data set is made up of a small set of people, which makes the study susceptible to overfitting.The participants are also of various levels of visual impairment. Another limitation include the EMOTIV+ headset which recedes the quality of signal generated that has been recorded.

Chapter 3

Background Analysis

In this chapter, we give an in depth study and analysis of the topics preceding data and information associated with our work that includes cognition, CLT, EEG, the different methods for band extraction and the different classification algorithms used for such cases.

3.1 Working Memory

The working memory is a part of primary memory often referred to as short-term memory and has limited capacity. It holds the information temporarily required for processing instantaneous activities. It is responsible for logical analysis and for the decision making aspects of activities. As a result, it impacts behavior. For instance, it is responsible for instantaneous perception through the different senses and for the processes required for deciphering language.

3.2 CLT

Cognitive psychology defines cognitive load as the used amount of working memory resources. CLT divides cognitive load into three types: intrinsic, extraneous, and germane[58].

3.2.1 Intrinsic Cognitive Load

Intrinsic cognitive load is the load on working memory due to the complexity of the knowledge that is being gained as opposed to how that knowledge is gained. It can only be altered by changing what is learned or by changing the knowledge levels of learners. One of the key features of intrinsic cognitive load is that it is unchangeable for given information to be processed by learners with given levels of expertise[48].

3.2.2 Extraneous Cognitive Load

Some information imposes a heavy cognitive load not because of its intrinsic nature but rather because of the way it is presented. That load is referred to as extraneous cognitive load. It can be reduced by modifying the instructional procedures [57]. Element interactivity affects both intrinsic as well as extraneous cognitive load. Simultaneous processing imposes a heavy working memory load, while successive processing does not. Low element interactivity materials allow individual elements to be learned with minimal reference to other elements and so imposes a low working memory load. Whether information can be processed simultaneously or successively depends on element interactivity [57].

3.2.3 Germane Cognitive Load

Germane cognitive load does not depend on any one source of cognitive load. Instead, it refers to the working memory resources available to deal with the element interactivity associated with intrinsic cognitive load. If more working memory resources are used up in dealing with extraneous cognitive load, less will be available to deal with intrinsic cognitive load and so less will be devoted to germane cognitive load. [21]

3.3 Measuring Cognitive Load

Early stages of CLT using indirect methods such as error rates, time on task and computational method provide evidence that various instructional effects can be explained by fluctuations in cognitive load. Paas (1992) in [59] proposes a single-scale subjective measure of mental effort, which in effect made a significant move away from the early proposals. In most instances, the subjective measures have evidently provides collaborating support of all CLT effects. However, subjective rating scales do not provide real time concurrent data. An alternative measure that is able to provide concurrent data is the use of a secondary task. The method is seen to be easy and efficient in learning the cognitive load, and is also very unobtrusive. It has the most use and has been most successfully employed. Other methods include the eye tracking and physiological methods such as the use of EEG data have started to emerge as potential measures on ongoing research on CLT [8].

3.4 Different Parts Of Brain

The human brain is a complex organ. It is divided into three parts; the cerebrum, the cerebellum and the brain stem (which leads into the spinal cord). The cerebrum is the largest part of the brain. It is the principal and most anterior part of the brain in vertebrates, located in the front area of the skull. It is divided into two parts by a fissure- the right hemisphere and the left hemisphere. The right hemisphere controls the left side of the body, and the left hemisphere controls the right side of the body. The left hemisphere is also responsible for actions that require logic such as science and mathematics while the right is responsible for actions that have to do with creativity and art. The cerebrum controls the integration of complex sensory and neural functions, and hence the fine control of movement and the initiation and coordination of voluntary activity in the body. It also controls the performance of higher functions like the interpretation of touch, vision, hearing. Figure 3.1 shows the different parts of the brain.

The cerebellum receives information from the sensory systems, the spinal cord, and other parts of the brain and then regulates motor movements. The cerebellum co-ordinates voluntary movements such as posture, balance, coordination, and speech, resulting in smooth and balanced muscular activity.

Activities based on regions in the cerebrum:

Frontal - The front part of the brain which is responsible for motor function, self awareness,writing and speech, intelligence, problem solving.

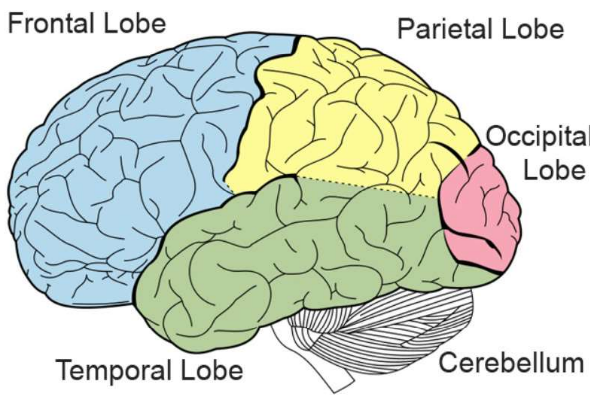

Figure 3.1: Different regions of Brain [2]

Temporal - Positioned on the side of the brain. Responsible for auditory processing, memory, learning/processing new language.

Occipital - Located at the back of the cerebrum. Plays a role in the processing of visual information. The information is processed to make decisions of color, depth and perception.

Parietal- Situated just behind the frontal lobe. It has somatosensory cortex and deals with processing sensory information to determine touch, sense of pain and temperature.

3.5 BCI

Human brain controls body function, such as heart activity, movement, speech, but also thinking itself. These activities are measured using the EEG which fundamentally captures the electrical potential in the brain. What BCI provides is a means of communication and independence, for instance if an individual has suffered damage in the Central Nervous System (CNS) causing blindness, BCI can used to give them artificial vision. Figure 3.2 depicts a simple model of BCI workflow.

Recent developments in BCI technology may see such hands-free control methods come into use. A BCI is a communication and control system in which the thoughts of the human mind are translated into real-world interaction without the use of the usual neural pathways and muscles. For example, utilising BCI, people with no limbs or damaged limbs or damaged sensors in the skin, can use artificial limbs which are

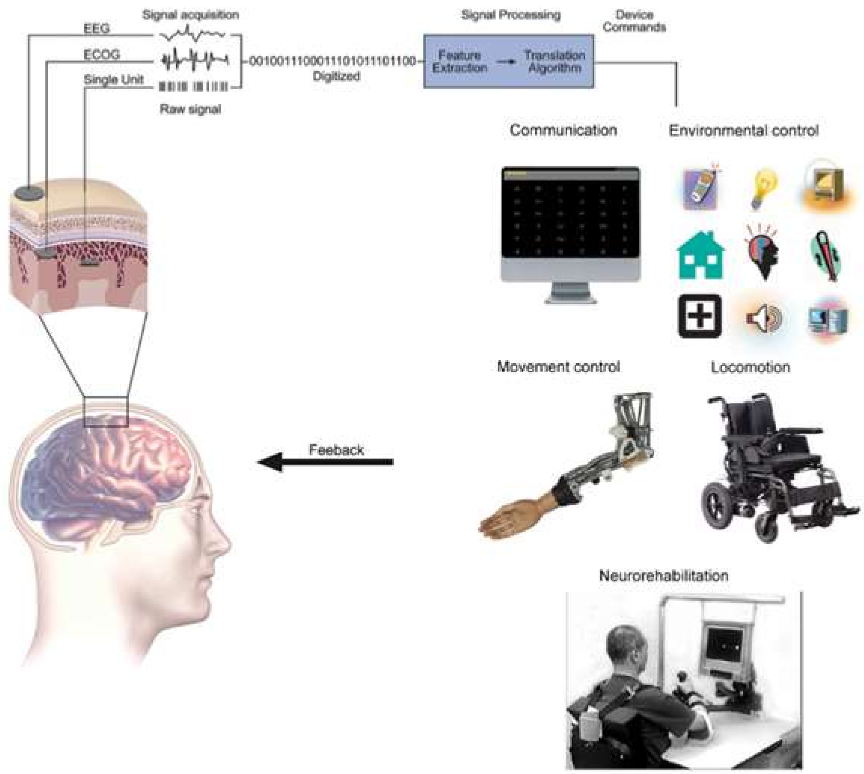

Figure 3.2: BCI workflow [8]

directly controlled by signals from their brain, thus allowing them to carry out their regular activities. Recent advances in the human brain and BCI research reveal that BCI-based devices and technologies can play a significant role in medicine [53] and can create an impact in future studies. There are three parts of BCIs. Invasive, Non-invasive and Partially invasive [32].

Invasive BCI- Requires surgery to position the sensors or stimulators in the cortical tissue. Complications may rise since the surgery may be prone to scar-tissue build up. Scar-tissue causes weak signal, which can even be lost.

Partially invasive BCI- Partially Invasive BCIs are implanted into the skull, but outside the brain. It uses a technology called the ECoG where electrodes are embedded in a thin plastic pad that is placed above the cortex, beneath the dura mater [32]. It produces good signal but is weaker than that of invasive BCI.

Non-invasive BCI- Non-Invasive BCI means electrodes are placed on the surface of the skull to record changes in EEG state. It is the easiest and safest way to record EEG.

3.6 Non-invasive BCIs

3.6.1 MRI

MRI provides a map of the brain in real time. The structural map helps to determine the location of any anomaly (for instance, tumours) that might be present in the brain or compare the sizes of the brain.

3.6.2 fMRI

fMRI provides a more detailed structure of the map. It shows the presence of oxygen in the brain due to different activities. The area with the more oxygenated blood in the brain becomes accentuated than the others and also the most active.

3.6.3 EEG

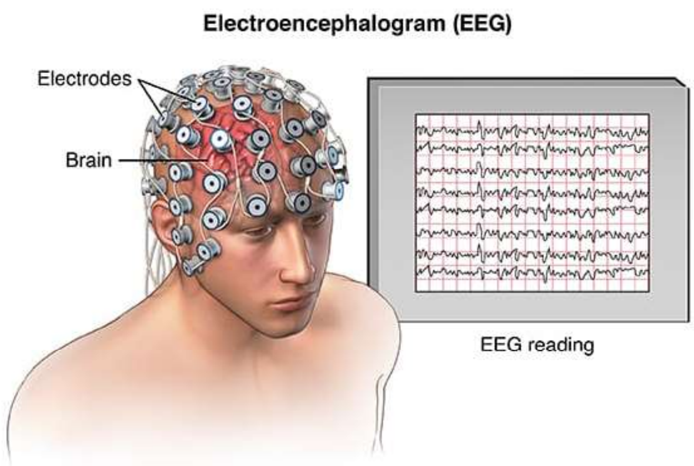

Figure 3.3: Acquiring EEG signals [22]

EEG is a non invasive technology used to record brain activity. Using EEG is the most prevalent method of signal acquisition for BCI. It is more accessible, can easily look in the brain activity, cost efficient and most optimum for research purposes. Metal electrodes are placed on the scalp according to standardized measurement systems and the relative electrical activity [54] recorded and analysed. A simple illustration is shown in Figure 3.3. In order to place the electrodes, a standard method used is the 10-20 method. The 10–20 system is an internationally recognized method to describe and apply the location of scalp electrodes in the context of an EEG exam. The measurements used in this system are explained as follows. The Nasion is the bridge of the nose and the Inion is the bony prominence at the back of the head. The two preauricular points are the points just anterior to each ear. The first measurement is made from nasion to inion. This is now divided into 10% and 20% increments. The next measurement is made from one preauricular point to the other. This is again divided into 10% and 20% increments. The next measurement made is the circumference of the head which is also divided into 10% increments. Parasagittal measurements are made, separated by 25% increments. Finally, transverse measurements are made. The intersections of these last two lines give the last electrode placement points. Electrode placement points are named in a manner that odd numbers are on the left and even numbers are on the right. Lower numbers are generally electrodes closer to the midline. Midline is represented by z which stands for zero. The letters are indicators of the position of the head. The F stands for frontal, C for Central, P for Parietal and O for Occipital [1]. Figure 4.1 illustrates the 10-20 system.

3.7 Biosignals

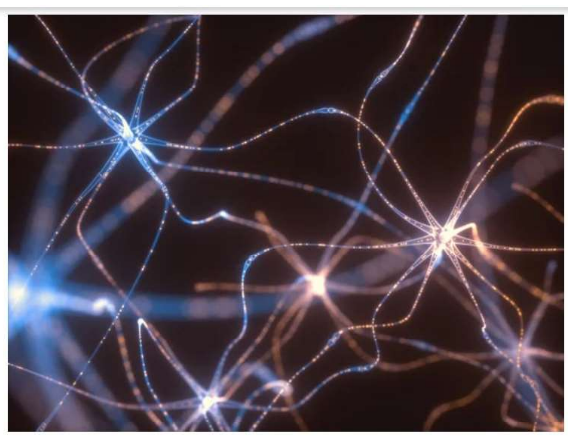

Figure 3.4: Travelling of brain waves in neurons [39]

Brainwaves are the short electrical pulses in the CNS with repetitive cycles over the period of time [32] (Figure- 3.4). These neural cycles are measured in Hertz. Pulses are generated from a single neuron or due to interactions between two neurons in the

CNS. The neurons in turn interchange information with the muscles via the nervous system to perform motor function, sensory interaction or have virtual information. The different functions of the brain emanates different frequencies of waves; for instance, high frequency waves are observed when a person is ecstatic while the low frequency waves can be seen when a person is bored or lazy. The different ranges can be detected and observed using the EEG. The different brain waves can be classified into five categories as the Figure 3.5 suggests.

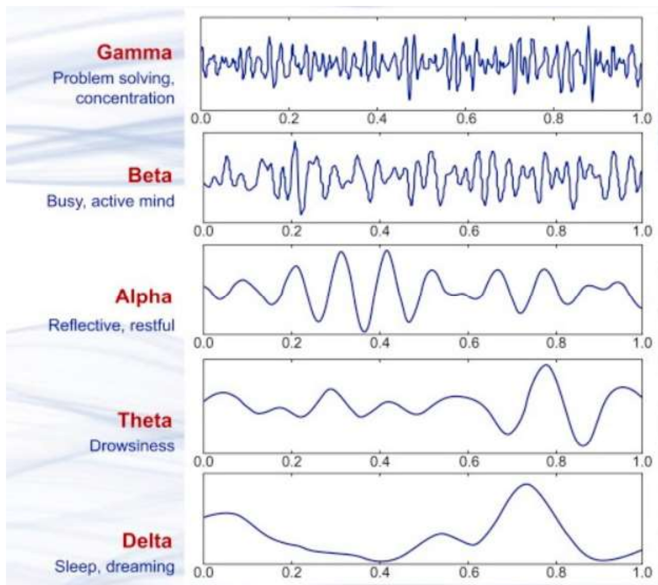

Figure 3.5: Brain samples for the five different waveforms [3]

3.7.1 Gamma

Gamma waves are important for learning, memory and information processing. This infers the working memory is responsible for this high frequency brain wave.

3.7.2 Beta

Beta waves are active in a waking state. This frequency is visible in logical-analytical reasoning. The cognitive tasks, problem solving, planning, self awareness can be observed using beta wave since the wave is mostly generated in the frontal lobe.

3.7.3 Alpha

Alpha waves connect the gap between our conscious thinking and subconscious mind. It helps us to calm down or it promotes a feeling of relaxation.

3.7.4 Theta

Theta waves are involved in sleep or daydreaming. While in this range, humans tap into their subconscious mind.

3.7.5 Delta

Delta waves occur during meditation, in a state of deep sleep or coma. Abnormal delta activity may occur if the person has learning disabilities or difficulties maintaining conscious awareness (such as in cases of brain injuries).

3.8 Feature Extraction

3.8.1 Fourier Transform

The Fourier Transform of an intensity versus time function like g(t) is a new function which does not have time as an input but instead takes in frequency. The common notation for this function is ĝ(f). The output of this function, ĝ(f) is a complex number, some point in the 2D plane that corresponds to the strength of a given frequency in the original function. As explained by Euler's formula, exponentials correspond to rotation. Multiplying that exponential by a function g(t) means drawing a wound up version of the function, g(t). An integral of the complex valued function can be interpreted in terms of a center of mass idea. Leading us to the final Fourier Transform in equation 3.1.

$$\widehat{g}(f) = \int_{t1}^{t2} g(t) e^{-2\pi i f t} dt \tag{3.1}$$

3.8.2 Wavelet Transform

Wavelet transform (WT) is suitable for analysis of sudden and transient signal changes. This method can pick up impulses at different time instances. WT plays an important role in the recognition and diagnostic field [28]; it compresses the time-varying biomedical signal, which is composed of many data points, into a small few parameters that represents the signal. As the EEG signal is non-stationary, a suitable way for feature extraction from the raw data is the use of the time-frequency domain methods like WT which is a spectral estimation technique in which any general function can be expressed as an infinite series of wavelets [6][49]. Real world data or signals frequently exhibit slowly changing trends or oscillations punctuated with transients. On the other hand images have smooth regions interrupted by edges and abrupt changes. These abrupt changes usually contain useful information and can be picked up by WT.

3.8.3 PCA

PCA is a dimensionality reduction technique used in feature extraction to find correlation by maximizing variance. From the 'm' independent variables in the dataset, PCA extracts $p \leq m$ new independent variables that explain the most variance of the dataset, regardless of the dependent variable. The basic approach in principal components is theoretically rather simple. Firstly the data is standardized. The Eigenvectors and eigenvalues are obtained from the covariance matrix or correlation matrix. The eigenvalues are sorted in descending order and the 'k' eigenvectors correspond to the k largest eigenvalues, where k is the number of dimensions of the new feature subspace ($k \leq d$). The projection matrix W is constructed from the selected k eigenvectors. Finally the original dataset X is transformed to k-dimensional feature subspace Y. A very high level of classification accuracy is obtained in the result of classification, which is based on reducing the feature dimension using PCA and deriving the support vectors using SVM [17].

3.8.4 ICA

ICA is a feature extraction method that transforms multivariate random signals into a signal having components that are mutually independent [54]. The ICA of a random vector consists of searching for a linear transformation that minimizes the statistical dependence between its components [18]. ICA finds independent projections which are almost not mutually orthogonal or not at all. It is one method used to identify temporally coherent networks [15].

3.8.5 LDA

The aim of LDA is to create a new variable that is a combination of the original predictors [54]. This is accomplished by maximizing the differences between the predefined groups, with respect to the new variable. The goal is to combine the predictor scores in such a way that, a single new composite variable, the discriminant score, is formed. LDA is used as a feature reduction technique for BCI systems in signal processing where all classification methods shows small classification errors [33].

3.8.6 Welch's method for finding Power Spectral Density

Welch's method, originally published in his journal in 1967 is an approach for spectral density estimation. It is an extension of the FFT. Signal nonstationarities make signals difficult to interpret visually. Welch's method is one of the solutions for dealing with signal nonstationarities since it gives smoother results. This method involves fewer computations and therefore is ideal for many non stationary tests [61]. The transformations have to be carried out on shorter signals since the original signal is split into segments. The segmentation is described in Figure 3.6. The FFT is carried out on each individual segment and the results of each averaged to obtain the final Welch's Power Spectral Density (WPSD). This makes the method more ideal for portable navigation aids with limited core storage. Mobile navigation aids call for fast systems with accurate outputs. A reduced number of computations is an essential part of that.

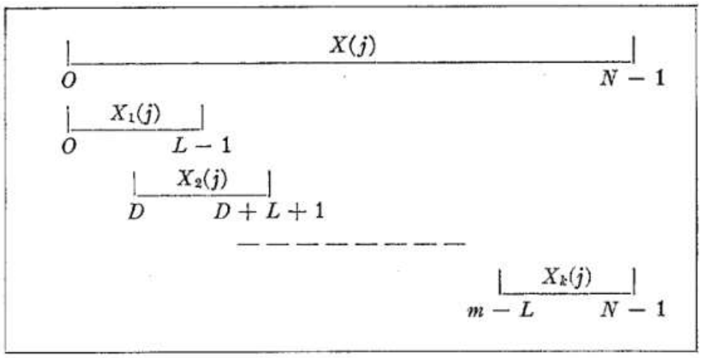

Figure 3.6: Illustration of record segmentation [61]

In order to carry out Welch's method, the Fourier Transform is calculated for each snippet and the power spectrum obtained. Each snippet is modified before carrying out the Fourier Transform on it. By having overlapping segments, attenuated data resulting from modification in the Fourier Transform of one snippet is made up for by the Fourier Transform of the next snippet. The final Welch's transform is obtained by averaging all the resulting power spectra together.

3.9 Classification Techniques

3.9.1 SVM

Generally speaking, SVM is a supervised machine learning model consisting of classification algorithms for binary division of data. Most real life data consists of too much overlapping for clear classification using simple classifiers like linear regression or logistic regression. The machine learning model, SVM has the ability to classify overlapping data with no clear linear classification by visualising the data in a higher dimension and using a hyper plane in the higher dimension as the classifier as mentioned in [37] and [54]. This hyper plane is referred to as the Support Vector Classifier. The paper further explains how the method's name, support vector machine is derived from the support vectors, which are data coordinates that lie closest to the decision boundary separating the classes. The support vector classifier is expressed in terms of the input vectors and dot products. Figure 3.7 illustrates how an SVM operates. It should be noted that the data are not actually being moved into a higher dimension but rather pictured in a higher dimension to come up with a classifier [10] [24]. This is done by using the dot product to find how individual points reflect in the feature subspace. The kernel function decides the dot product. The distances between these reflections on the new higher-dimension subspace can be calculated. It is also important to decide on a scale of impact for violating the soft margin between the classes. Therefore, it can be said that the goal of SVM is to find a hyper plane in an N-dimensional space, where N is the number of features, that distinctly classifies the data points. The SVM chooses the classifier which separates the classes with maximal margin, referred to as the optimal separating hyper plane in [10]. The margin is defined as the width of the largest 'tube' not containing samples that can be drawn around the decision boundary i.e. the solution with the highest generalization ability [54].

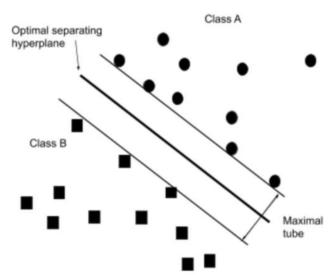

Figure 3.7: Optimal separating hyperplane in 2D SVM

The Polynomial Kernel is used to calculate the relationships between the observations in a higher dimension. The dimension which does provide a hyper plane with distinct classification is chosen.

Gaussian RBF can be considered as an extension of the Polynomial Kernel. In this case, the new subspace consists of infinite dimensions and the algorithm finds the hyper plane in the infinite dimension which can be used for binary classification.

The radial kernel behaves like a Weighted Nearest Neighbour model, that is, the closest data points have the highest influence on how we classify the new data point. A constant term determined by cross validation scales the influence. This model is useful for training data set with a lot of overlap. The radial kernel finds Support Vector Classifiers in infinite dimensions.

3.9.2 Random Forest Classifier

An ensemble learning method for classification that operates by creating multitude decision trees at training time and outputs the class that is the mode of the classes of the trees. The first algorithm for Random Forest was first developed by Tin Kam Ho [26].

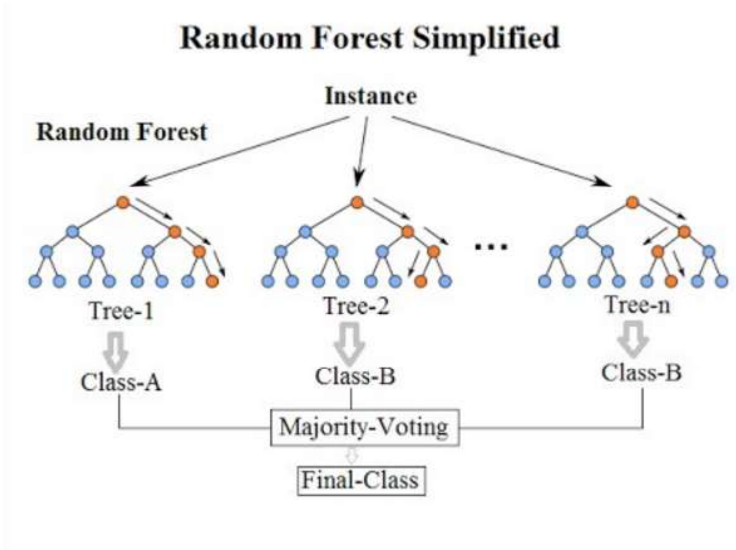

Figure 3.8: Random Forest based Classification [31]

The basic approach in Random Forest is theoretically rather simple. Firstly pick 'n' data points from the training set randomly. Build the decision tree associated with these n data points. Choose the number of Ntree you want to build and repeat the first two steps. For a new data point, make each of the Ntree predict the value of Y for the data point in question and assign the new data point the average across all of the predicted Y values. Finally the accuracy of the Random Forest is estimated from which 'out of the bag' error is used to optimize the number of variables that should be used in the classifier. Figure 3.8 illustrates a simplified random forest.

3.10 ERD/ERS calculation

The term ERD refers to an event related localized amplitude attenuation whereas ERS refers to event-related localized amplitude enhancement within mu and beta frequency bands [52].

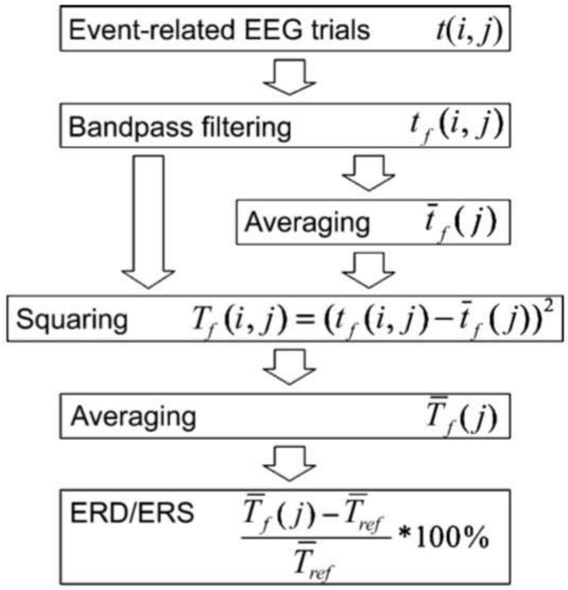

Figure 3.9: Calculation of ERD/ERS using Inter trial Variance method [62]

The common ERD/ERS detection can be processed in four steps, which contains band pass filtering of the EEG signal, squaring of amplitude of the signal and averaging of their power within all experiments in order to smooth the data [52]. Figure 3.9 depicts the several steps taken to calculate the ERD/ERS using the Intertrial Variance method.

As study in [62] shows, short red light flashes of 10 ms duration were presented on patients for visual stimulation at intervals of at least 2s using alpha power in the 7 to 13 Hz band. This stimulation resulted in an ERD followed by resynchronization. Trials were controlled for artifacts, averaged offline, and the amount of ERD/ERS was calculated.

Chapter 4

Proposed Model

In this chapter, we present our proposed model, an overview of the steps carried out in our study. EEG is the non-invasive BCI used for detecting the cognitive load in VIPs. Initially signals have noise and gaps due to connectivity issues. Preprocessing is done to reduce deviations, noises and inconsistent signals. The preprocessed signals are then further refined and features extracted using WPSD. The features are labelled with corresponding cognitive loads based on recordings and post experiment interviews. Finally these features are fed into RBF SVM and classified accordingly. Figure 4.2 represents our proposed model.

4.1 Data Description

The data used in our study has been obtained from an experiment conducted in the indoor environments of the University of Iceland, Reykjavik [48].
The project was funded by the European Union to aid VIP for their navigation. The data set they collected [48] has been used in our study.
The EMOTIV EPOC+ EEG headset is used to collect EEG signals from 9 healthy participants as they navigate through indoor environments [48]. EPOC+ is chosen because it provides a good compromise between performance and usability with respect to other wireless EEG recording devices available. Participants of various levels of visual impairment (VI-2, VI-3, VI-4), have been described in Table 4.1. Indoor environments are divided into 6 types (Door, Narrow Space, Open Space, Elevator, Stairs, Moving Objects). The EEG signals from the subjects at each of

these labels are recorded.

Table 4.1: Categories of Visual Impairment.

Category	Description	Participant Gender
VI-2	Vision less than 10% and more than 5%	2(F,M)
VI-3	Vision less than 5%	4 (F, F, M, F)
VI-4	Not being able to count fingers less than one meter away	3 (F, M, F)

Electrodes Placement:

In order to place the electrodes, a standard method , the 10-20 system with probes at AF3, F7, F3, FC5, T7, P3 , P7, O1, O2, P8, P4 , T8, FC6, F4, F8, and FC is used as shown in the figure 4.1.

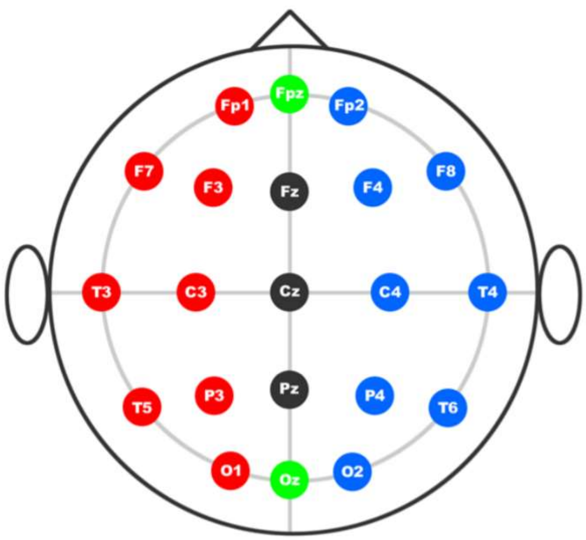

Figure 4.1: 10-20 Electrode Placement System [1]

Different bands such as Delta (up to 4 Hz), Theta (4-8 Hz), Alpha (8 -15 Hz), Beta (15-32 Hz), and Gamma (above 32 Hz) can be extracted from EEG signals. The ones relevant to our study are Alpha (8 -15 Hz), Beta (15-32 Hz) waves, and Gamma (above 32 Hz) waves.

The cognitive tasks, problem solving, planning, self awareness can be observed using beta waves [45]. The results conducted shows a relationship between cognitive load

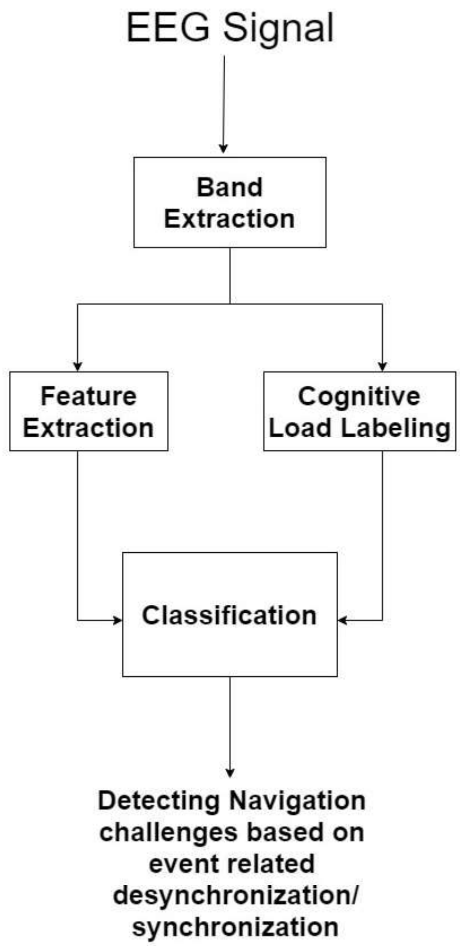

Figure 4.2: Workflow Of the Proposed Model

and beta frequency [36]. This leads to the conclusion that beta waves should be taken into consideration for our research.
Similarly, gamma band activity participates in various cerebral functions, such as perception, attention, memory, consciousness, and motor control [60]. Therefore, it shows the significance of gamma frequency to detect cognitive load.
Cognition has shown association with alpha frequency when the frequency is detected in the visual cortex of the brain. Repeated observations from experiments show that signals in the alpha band tend to correspond to brain activity associated with cognitive load, for instance, alpha activity is observed to fall in magnitude with higher task difficulty [8].

The comprehensive sources contribute the indispensable information and data to conduct our research for navigation of VIPs.

4.2 Feature Extraction

In the dataset collected from the European Union, EEG signals are recorded using the Emotiv EPOC+, a mobile headset with 16 dry electrodes registering over the 10-20 system locations. A sampling rate of 128 Hz is used. In this experiment there are 9 participants each of whom are stimulated to 6 different indoor environments and EEG signals are recorded from 14 different channels
When extracting features, three frequency bands are taken into consideration, aforementioned in Section 4.1, namely, alpha (8 -15 Hz) waves, beta (15-32 Hz) waves, and gamma (above 32 Hz) waves. The following passage demonstrates how feature extraction is carried out on the relevant bands.

4.2.1 WPSD

Welch's method is an approach for spectral density estimation. It uses FT to compute a smoother signal. Welch had the idea to split the entire signal into segments before carrying out the FT on each individual segment. This reduces computation time and complexity and thus makes the process much more appropriate for devices involving mobility [61]. Since we are trying to build a navigation aid which provides real time classification, this is a useful property for the logic involved in our backend computation. The FT of each separate segment are then averaged to obtain the final WPSD. The segments are intentionally taken in a manner that they overlap with each other. This is done so that any data attenuated as a result of modifying the segments before FT are made up for by adjacent overlapping segments.The method is ideal for portable navigation aids with limited core storage.

4.3 Cognitive Load Measurement

The definition used in our study to measure band power change in EEG is based on the technique first developed by Pfurtscheller and Aranibar[42]. It is defined as follows:

$$ERD/ERS(\%) = \frac{baselineIBP - testIBP}{baselineIBP} \tag{4.1}$$

, where IBP stands for interval band power. The baseline IBP refers to a prestimulus time period without any task demands, which in our case is the resting state, while the testIBP is the band power obtained during the time frames when the different stimuli are presented to each participant.

The ERD/ERS is calculated using beta band. From the estimation of the ERD/ERS the cognitive load is found. The value of the cognitive load represents the level of mental difficulty a participant faces due to the combination of parameters that lead to the cognitive label.

4.4 Cognition Classification

Our data, like most real life data, consists of too much overlapping for clear classification using simple classifiers like linear regression or logistic regression. The machine learning model, SVM has the ability to classify overlapping data with no clear linear classification by visualising the data in a higher dimension and estimating the classifier better than any linear model.

The extracted features were fed into a SVM kernel for classification. The higher dimension in a SVM is chosen based on which one provides a hyperplane for clear classification [10]. RBF in particular maps the data points in the existing dimension into an infinite dimensions subspace. SVM with 5 fold cross validation and grid search is implemented. That is, the data set is divided into five parts. The first section is used to train the algorithm and the remaining 4 sets are used for testing. In its existing dimensions, our data is difficult to differentiate. So visualising it in the infinite dimension subspace makes it easier to classify the data. Grid search is used as an approach for hyper-parameter tuning to build the SVM model for each combination of parameters specified in our data.

Chapter 5

Results and Discussion

EEG signals are captured from 9 VIP as they navigate through the indoor environments in a university. Features are extracted per second with a sampling rate of 128 Hz. ERD/ERS is calculated using beta bands. From the calculation, the measurement for the cognitive load is found and labelled accordingly. These labels are used to train the RBF kernel of SVM using 5 fold cross-validation. In this section, the results and its corresponding ROC (Receiver Operator Characteristics) curve is described and analyzed.

5.1 Analysis Of Results

In medical diagnosis, test sensitivity is the ability of a test to correctly identify those with the disease (true positive rate), whereas test specificity is the ability of the test to correctly identify those without the disease (true negative rate)[54]. A graph of the sensitivity by 1-specificity plotted at different cut off points for classification is called the ROC curve. This curve is useful for analysing the efficiency of a model.
The ROC curve can be used to pick the cut off point that optimises sensitivity and specificity for a given curve. Common criteria for picking the cut off point include the point on ROC curve where the sensitivity and specificity of the test are equal, or the point on the curve with minimum distance from the left-upper corner of the unit square[25]. The area under the ROC curve gives the accuracy. This area under the curve is commonly referred to as the AUC (Area Under Curve). The best test is the one with the ROC curve that clusters up to the left.

In our experiment, ROC curves are plotted with pairs of sensitivity and specificity obtained at each hyper plane. The hyper planes are exponential functions discovered by the RBF kernel of the SVM. As more iterations are carried out, the kernel learns better and the hyper plane obtained provides a new value of sensitivity and specificity, that is, the ratio of true positive and the ratio of true negative change with respect to total predictions made. So each classifier gives a unique set of sensitivity and specificity values.
The sensitivity, specificity, and accuracy are calculated from confusion matrix defined as:

$$Sensitivity = \frac{TP}{TP + FN} \tag{5.1}$$

$$Specificity = \frac{TN}{TN + FP} \tag{5.2}$$

$$Accuracy = \frac{TP + TN}{TP + FN + TN + FP} \tag{5.3}$$

where TP is the number of true positive, TN is the number of true negative, FP is the number of false positive,FN is the number of false negative.

In this paper, the cognitive load, labelled as stress, has been classified based on features extracted from the EEG signals of nine healthy participants of various levels of visual impairments in different indoor environments. Features were extracted from three frequency bands alpha, beta and gamma for all 14 channels using the WPSD. The environments can be divided into 6 different types, each subjecting the VIP to a unique set of challenges. Environment A is the annotation for any door that the subject faces in their route and the corresponding challenges they may face, for instance a rotating door can be a potential obstacle for a physically disadvantaged individual. The Table 5.1 shows corresponding challenges for each environment for the VIPs.

Table 5.1: Descriptions and corresponding challenges for each environment

ID	Environment	Challenges
A	Door	Rotating door, Bumping into closed doors
B	Narrow space	People, Chairs, Table, Furniture, Walls, Shelves
C	Open Space	People, Crowd, Losing direction
D	Elevator	Finding button, Selecting floor, People, Elevator door close
E	Stairs	Steps starting, Steps ending, Finding railing, Slippery
F	Moving Object	Avoiding people, Trolleys

5.2 Discussion

5 fold cross validation was carried out for each environment based on the features extracted from alpha, beta and gamma bands and ROC curves were plotted to analyze the classification for each environment, shown in Figure- 5.1. The ROC curve for environment A has an AUC of 0.91, B of 0.89, C of 0.96, D of 0.86, E of 0.88 and F of 0.90. Table 5.2 shows this in details. From the AUC values, we can see that the classification in environment C is done the most efficiently as it has the highest AUC. On the other hand, environment D has the least effective classification. However, the classification of stress for all environments using the RBF from SVM is very valid because the AUC for all shows a significant improvement compared to paper [27]. This proves that the algorithm picked is appropriate for this experiment.

Table 5.2: Sensitivity, Specificity and Accuracy table

Environment	Sensitivity%	Specificity%	Accuracy%
A	96.17	82.14	90.77
B	94.04	72.37	89.26
C	95.74	76.92	96.41
D	90.57	83.33	86.42
E	97.55	92.31	88.46
F	93.05	83.67	90.17

Aforementioned, the ROC curve can also be used to pick the hyper plane that

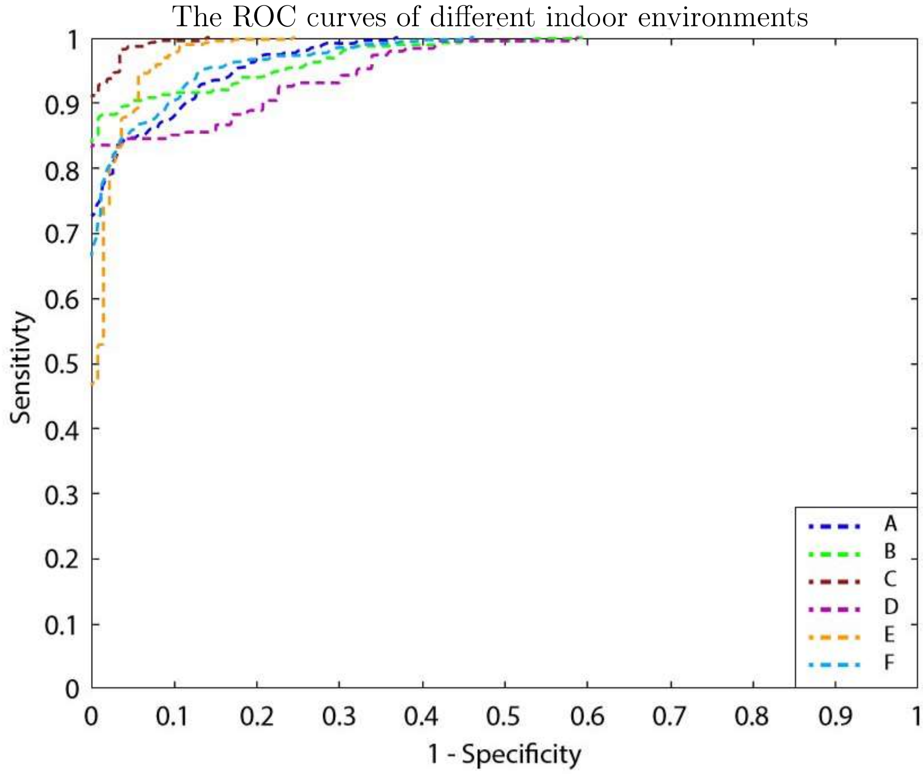

Figure 5.1: The ROC Curves

optimises sensitivity and specificity.

The ROC curves can be observed to find the point where the specificity and sensitivity match. This is also the point at minimum distance from the left upper corner of the unit square. Mapping this pair of sensitivity and specificity to the obtained hyper plane at the iteration which provides us with this pair of specificity and sensitivity values gives us the best classifier for that environment. The function of the hyper plane divides the new test subjects into two categories- high cognitive load or stressed, or low cognitive load or not stressed.

Chapter 6

Conclusion

This paper highlights how real time cognitive load assessment is done as the VIPs navigate their way through indoor environments. The main objective is to reflect the viability of the challenging tasks and find their corresponding cognition level by extracting features from the frequency bands. Our study describes the design of the user study performed, the extraction of cognitive load measured from EEG signals, and how those measures can be used to quantitatively evaluate the effectiveness of navigation aids with the use of features extracted from certain frequency bands. What we have achieved in this research is an effective way to label the cognitive load using WPSD and RBF SVM with an AUROC of above or around 0.9 for each environment.

Since our work agrees with papers[27][48] to say that EEG signals are a stable visualisation technique for cognitive load, further work can include using EEG signals to compare the effectiveness of different visual aids as opposed to individual assessment of people. So research can be done to decide which mobility aids are the most comfortable for impaired users. The work done in this paper opens opportunities for research in a variety of fields. The usability of EEG to detect stress can be applied on non impaired participants during tasks with probable high cognitive loads. Anyone facing cognitive load beyond normal levels can have extra factors like stress, anxiety or illness into play.

Bibliography

[1] *10/20 System Positioning MANUAL.* URL: https://www.scientificamerican.com/article/traveling-brain-waves-may-be-critical-for-cognition/. (accessed: 28.03.2020).

[2] *5 Important Brain Parts and Its Functions - ControlMind.* URL: https://controlmind.info/brain-parts-and-functions. (accessed: 28.03.2020).

[3] P. Abhang, B. Gawali, and S. Mehrotra. *Introduction to EEG- and Speech-Based Emotion Recognition.* 1st ed. Academic Press, 2016. ISBN: 978-0-12-804490-2.

[4] M. Abo-Zahhad, S. Ahmed, and S. Abbas. "A New EEG Acquisition Protocol for Biometric Identification Using Eye Blinking Signals". In: *International Journal of Intelligent Systems and Applications* 7.6 (2015), pp. 48–54.

[5] U. Acharya et al. "Automatic Identification Of Epileptic Eeg Signals Using Nonlinear Parameters". In: *Journal of Mechanics in Medicine and Biology* 9.4 (2009), pp. 539–533. DOI: 10.1142/s0219519409003152.

[6] A. Al-Fahoum and A. Al-Fraihat. "Methods of EEG Signal Features Extraction Using Linear Analysis in Frequency and Time-Frequency Domains". In: *ISRN Neuroscience* 2014 (2014). DOI: 10.1155/2014/730218.

[7] R. Andrzejak et al. "Indications of nonlinear deterministic and finite-dimensional structures in time series of brain electrical activity: Dependence on recording region and brain state". In: *Physical Review E* 64.6 (2001). DOI: 10.1103/physreve.64.061907.

[8] P. Antonenko et al. "Using Electroencephalography to Measure Cognitive Load". In: *Educational Psychology Review* 22.4 (2010), pp. 425–438. DOI: 10.1007/s10648-010-9130-y.

[9] C. Berka et al. “EEG correlates of task engagement and mental workload in vigilance, learning, and memory tasks”. In: *Viation, space, and environmental medicine* 78.5 (2007). PMID: 17547324.

[10] H. Bhavsar and M. Panchal. “A Review on Support Vector Machine for Data Classification”. In: *International Journal of Advanced Research in Computer Engineering Technology (IJARCET)* 1 (2012).

[11] A. Bhowmick and H. Shyamanta. “An Insight into Assistive Technology for the Visually Impaired and Blind People: State-of-the-Art and Future Trends”. In: *Multimodal User Interfaces* 11.2 (2017), 149–172. DOI: 10.1007/s12193-016-0235-6.

[12] N. Birbaumer et al. “Slow potentials of the cerebral cortex and behavior”. In: *Educational Psychology Review* 70.1 (1990), pp. 1–41. DOI: 10.1152/physrev.1990.70.1.1.

[13] *Blindness and vision impairment*. URL: https://www.who.int/news-room/fact-sheets/detail/blindness-and-visual-impairment. (accessed: 31.03.2020).

[14] D. Bos. “Eeg-based emotion recognition”. In: *The Influence of Visual and Auditory Stimuli* 56.3 (2006), 1–17.

[15] V. Calhoun, K. Kiehl, and G. Pearlson. “Modulation of Temporally Coherent Brain Networks Estimated Using ICA at Rest and during Cognitive Tasks”. In: *Human Brain Mapping* 29.7 (2008), pp. 828–838. DOI: 10.1002/hbm.20581.

[16] J. Callicott. “Physiological Characteristics of Capacity Constraints in Working Memory as Revealed by Functional MRI”. In: *Cerebral Cortex* 9.1 (1999), pp. 20–26. DOI: 10.1093/cercor/9.1.20.

[17] M. Chandani. “Statistical Wavelet Features, PCA, MLPNN, SVM and K-NN Based Approach for the Classification of EEG Physiological Signal”. In: *International Journal of Industrial and Manufacturing Systems Engineering* 2.5 (2017), p. 57. DOI: 10.11648/j.ijimse.20170205.12.

[18] P. Comon. “Independent Component Analysis, A New Concept?” In: *Signal Processing* 36.3 (1994), pp. 287–314. DOI: 10.1016/0165-1684(94)90029-9.

[19] J. Dauwels, F. Vialatte, and A. Cichocki. "Diagnosis of Alzheimers Disease from EEG Signals: Where Are We Standing?" In: *Current Alzheimer Research* 7.6 (2010), pp. 487–505. DOI: 10.2174/156720510792231720.

[20] J. Degutis. "Tonic and Phasic Alertness Training: a Novel Behavioral Therapy to Improve Spatial and Non-Spatial Attention in Patients with Hemispatial Neglect". In: *Frontiers in Human Neuroscience* 4 (2010). DOI: 10.3389/fnhum.2010.00060..

[21] Anderson E. et al. "A User Study of Visualization Effectiveness Using EEG and Cognitive Load". In: *Computer Graphics Forum* 30.3 (2011), 791–800. DOI: 10.1111/j.1467-8659.2011.01928.x.

[22] *EEG Measures of Cognition: H.V.M.N. Biohacker Guide*. URL: blog.hvmn.com/biohacker-guide/cognition/eeg-measures-of-cognition. (28.03.2020).

[23] J. Fell, N. Axmacher, and S. Haupt. "From alpha to gamma: Electrophysiological correlates of meditation-related states of consciousness". In: *Medical Hypotheses* 75.2 (2010), pp. 218–224. DOI: 10.1016/j.mehy.2010.02.025.

[24] L. Guo et al. "Classification of Mental Task From EEG Signals Using Immune Feature Weighted Support Vector Machines". In: *IEEE Transactions on Magnetics* 47.5 (2011), pp. 866–869.

[25] P. Yadollahie M. Habibzadeh F. Habibzadeh. "On determining the most appropriate test cut-off value: the case of tests with continuous results". In: *Biochemia Medica* 34.7 (2016, doi = 10.11613/BM.2016.034, note =, URL = , eprint =), 838–848.

[26] K. Ho. "Random Decision Forests". In: *Proceedings of 3rd International Conference on Document Analysis and Recognition* (1995). DOI: 10.1109/icdar.1995.598994..

[27] K. Kalimeri and C. Saitis. "Exploring Multimodal Biosignal Features for Stress Detection during Indoor Mobility". In: *Proceedings of the 18th ACM International Conference on Multimodal Interaction- ICMI* (2016). DOI: 10.1145/2993148.2993159.

[28] S. Karim and B. Karim. “Wavelet Transform and Fast Fourier Transform for Signal Compression:A Comparative Study”. In: *2011 International Conference on Electronic Devices, Systems and Applications (ICEDSA)* (2013).

[29] A. Keil et al. “Human Gamma Band Activity and Perception of a Gestalt”. In: *International Journal of Intelligent Systems and Applications* 19.16 (1999), pp. 7152–7161. DOI: 10.1523/jneurosci.19-16-07152.1999.

[30] W. Klimesch. “EEG alpha and theta oscillations reflect cognitive and memory performance: a review and analysis”. In: *Brain Research Reviews* 29.2-3 (1999), pp. 169–195.

[31] W. Koehrsen. *Random Forest Simple Explanation.* URL: https://www.medium.com/@williamkoehrsen/random-forest-simple-explanation-377895a60d2d. (accessed: 28.03.2020).

[32] Z. Koudelková and M. Strmiska. “Introduction to the identification of brain waves based on their frequency”. In: *MATEC Web Of Conferences* 210.2 (2018), p. 05012. DOI: 10.1051/matecconf/201821005012.

[33] M. Kołodziej, A. Majkowski, and R. Rak. “Linear discriminant analysis as EEG features reduction technique for brain-computer interfaces”. In: *Przeglad Elektrotechniczny* (Jan. 2012).

[34] Rahimpour S. Krucoff M. et al. “Enhancing Nervous System Recovery through Neurobiologics, Neural Interface Training, and Neurorehabilitation”. In: *Frontiers In Neuroscience* 10 (2016). DOI: 10.3389/fnins.2016.00584.

[35] J. Kumar and P. Bhuvaneswari. “Analysis of Electroencephalography (EEG) Signals and Its Categorization–A Study”. In: *Procedia Engineering* 38 (2012), pp. 2525–2536. DOI: 10.1016/j.proeng.2012.06.298.

[36] H. Lee. “Measuring Cognitive Load with Electroencephalography and Self-Report: Focus on the Effect of English-Medium Learning for Korean Students”. In: *Educational Psychology* 34.7 (2013), 838–848. DOI: 10.1080/01443410.2013.860217.

[37] Y. Lin et al. “Support vector machine for EEG signal classification during listening to emotional music”. In: *2008 IEEE 10th Workshop on Multimedia Signal Processing* (2008). DOI: 10.1109/mmsp.2008.4665061..

[38] S. Macgregor. “Hypermedia Navigation Profiles: Cognitive Characteristics and Information Processing Strategies”. In: *Journal Of Educational Computing Research* (1999), pp. 189–206. DOI: 10.2190/1mec-c0w6-111h-yq6a.

[39] S. Makin. *"Traveling" Brain Waves May Be Critical for Cognition.* URL: https://www.scientificamerican.com/article/traveling-brain-waves-may-be-critical-for-cognition/. (accessed: 28.03.2020).

[40] S. Oh et al. “A Deep Learning Approach for Parkinson’s Disease Diagnosis from EEG Signals”. In: *Neural Computing and Applications* 5 (2018), pp. 866–869. DOI: 10.1007/s00521-018-3689-5.

[41] W. Penrod, M. Corbett, and B. Blasch. “Practice Report: A Master Trainer Class for Professionals in Teaching the UltraCane Electronic Travel Device”. In: *Journal of Visual Impairment Blindness* 99.11 (2005), pp. 711–715. DOI: 10.1177/0145482x0509901110.

[42] G. Pfurtscheller and A. Aranibar. “Event-related cortical desynchronization detected by power measurements of scalp EEG”. In: *Electroencephalography and Clinical Neurophysiology* 42.6 (1977), pp. 817–826.

[43] H. Pham, T. Le, and N. Vuillerme. “Real-Time Obstacle Detection System in Indoor Environment for the Visually Impaired Using Microsoft Kinect Sensor”. In: *Journal of Sensors* 2014 (2016), pp. 1–13. DOI: 10.1155/2016/3754918..

[44] Michael I Posner and Mary K Rothbart. *Educating the human brain.* American Psychological Association, 2007.

[45] W. Ray and H. Cole. “EEG Alpha Activity Reflects Attentional Demands, and Beta Activity Reflects Emotional and Cognitive Processes”. In: *Science* 228.4700 (1985), 750–752. DOI: 10.1126/science.3992243.

[46] R. Roy et al. “Mental Fatigue and Working Memory Load Estimation: Interaction and Implications for EEG-Based Passive BCI”. In: *2013 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)* (2013). DOI: 10.1109/embc.2013.6611070..

[47] C. Saitis and K. Kalimeri. “Multimodal Classification of Stressful Environments in Visually Impaired Mobility Using EEG and Peripheral Biosignals”. In: *IEEE Transactions on Affective Computing* (2019), pp. 1–1.

[48] C. Saitis, M. Parvez, and K. Kalimeri. "Cognitive Load Assessment from EEG and Peripheral Biosignals for the Design of Visually Impaired Mobility Aids". In: *Wireless Communications and Mobile Computing,* (2018). PMID: 27442303, pp. 1–9. DOI: 10.1155/2018/8971206.

[49] S. Sarwar et al. "Noninvasive imaging system for visually impaired people". In: *2010 3Rd International Conference On Computer Science And Information Technology* (2010). DOI: 10.1109/iccsit.2010.5564650.

[50] G. Schalk et al. "BCI2000: a general-purpose brain-computer interface (BCI) system". In: *IEEE Transactions on Biomedical Engineering* 51.6 (2004), pp. 1034–1043. DOI: 10.1109/tbme.2004.827072.

[51] C. Setz et al. "Discriminating Stress From Cognitive Load Using a Wearable EDA Device". In: *IEEE Transactions on Information Technology in Biomedicine* 14.2 (2010), pp. 410–417. DOI: 10.1109/TITB.2009.2036164.

[52] F. Shahlaei et al. "Classification of Motor Imagery Tasks Using Inter Trial Variance In The Brain Computer Interface". In: *2018 IEEE International Symposium on Medical Measurements and Applications (MeMeA)* (2018), pp. 1–6.

[53] J. Shih, D. Krusienski, and J. Wolpaw. "Brain-Computer Interfaces in Medicine". In: *Mayo Clinic Proceedings* 87.3 (2012), pp. 268–279. DOI: 10.1016/j.mayocp.2011.12.008.

[54] A. Subasi and M. Gursoy. "EEG Signal Classification Using PCA, ICA, LDA and Support Vector Machines". In: *Expert Systems with Applications* 37.12 (2010), 8659–8666. DOI: 10.1016/j.eswa.2010.06.065.

[55] S. Sun and C. Zhang. "Adaptive Feature Extraction for EEG Signal Classification". In: *Medical & Biological Engineering & Computing* 44.10 (2006), pp. 931–935. DOI: 10.1007/s11517-006-0107-4.

[56] J. Sweller. "Cognitive Load During Problem Solving: Effects on Learning". In: *Cognitive Science* 12.2 (1998), pp. 257–285. DOI: 10.1207/s15516709cog1202_4.

[57] J. Sweller. "Cognitive Load Theory". In: *Psychology of Learning and Motivation* (2011), 37–76. DOI: 10.1016/b978-0-12-387691-1.00002-8.

[58] J. Sweller. "Element Interactivity and Intrinsic, Extraneous and Germane Cognitive Load". In: *Educational Psychology Review* 22.2 (2010), pp. 123–138. DOI: 10.1007/s10648-010-9128-5.

[59] J. Sweller, P. Ayres, and S. Kalyuga. *Cognitive Load Theory*. 1st ed. Springer New York, 2011. ISBN: 978-1-4419-8125-7.

[60] P. Uhlhaas et al. "The Role of Oscillations and Synchrony in Cortical Networks and Their Putative Relevance for the Pathophysiology of Schizophrenia". In: *Schizophrenia Bulletin* 34.5 (2008), pp. 927–943.

[61] P. Welch. "The use of fast Fourier transform for the estimation of power spectra: A method based on time averaging over short, modified periodograms". In: *IEEE Transactions on Audio and Electroacoustics* (1967), pp. 70–73.

[62] M. Woertz, G. Pfurtscheller, and W. Klimesch. "Alpha power dependent light stimulation: dynamics of event-related (de)synchronization in human electroencephalogram". In: *Cognitive Brain Research* 20(2) (2004), pp. 256–260. DOI: 10.1016/j.cogbrainres.2004.03.014.

[63] M. Yadava et al. "Analysis of EEG Signals and Its Application to Neuromarketing". In: *Multi76media Tools and Applications* 76.18 (2017), pp. 19087–19111. DOI: 10.1007/s11042-017-4580-6.

Chapter 1

Introduction

Common existing mobility aids for the visually impaired include canes, service dogs and electronic mobility aids [41]. While all of these are effective aids to locate obstacles and help the visually impaired people (VIPs) with navigation, none of these take the user's mental state into consideration [43]. At first glance, visual impairment seems to be a small percentage of the population, but eye sight is observed to deteriorate with age [13]. Many of the elderly people tend to stay at home most of the time because they find outdoor environments stressful. Eyesight generally plays a factor in that stress. The aim of this study is to provide individual assessment of VIPs. However, different navigation techniques can also be compared by analysing EEG signals of individuals. Although user feedback can easily be used to compare different techniques, user or customer feedback is not always reliable. A quantitative comparison will be useful for companies when designing new navigation aids. A similar study can include analysing the EEG bands from a group with a different type of impairment, such as hearing impairment. The mapping of task to stress is also very relevant beyond impairment. For instance, a healthy subject will have a standard stress level during activities heavy on cognition such as interviews and exams. A stress level beyond that standard will indicate an extra factor in play. Probable factors can be depression or anxiety.

Invasive and partially invasive techniques, such as Electrocorticographic (ECoG), lead to complications of brain tissue depletion causing signals to recede with time. As a non-invasive measure, Electroencephalography(EEG) provides a safer and more efficient procedure to conduct experiments. Other non-invasive methods such as fMRI (functional Magnetic Resonance Imaging), MRI (Magnetic Resonance Imaging) provide higher resolution and better understanding of the brain. However, these methods call for machines that are not portable and require the subject to be in a specific posture. This means that both fMRI and MRI are not suitable for mobile experiments that are necessary for our study. Hence, we have chosen EEG to collect brain signals for analysing, classifying and labelling cognitive load.

1.1 Thesis Overview

A Brain Computer Interface (BCI), sometimes called a neural-control interface (NCI), or brain-machine interface (BMI), is a direct communication pathway between an enhanced or wired brain and an external device. BCI is often directed at researching, mapping, assisting, augmenting, or repairing human cognitive or sensory-motor functions [34]. Based on what has been found, noninvasive BCI techniques have helped pave a safe path for VIPs to perform regular tasks [49]. These help us perceive the issue tackling the physical disadvantage of the blind people more clearly.

Researches have suggested that technology has had great success in aiding VIPs [11]. In [46] the relevance of EEG to measure cognitive load is explained. EEG signals have been shown to be stable indicators of cognitive load in a variety of tasks performed in controlled laboratory settings such as learning to carry out tasks to navigate using hypertext and multimedia data [14][9], or learning to use complex navigating tools using hypermedia navigation [38].

A good measure for the user's state of mind at a given time is the cognitive load of the user obtained in real time. In cognitive psychology, the implication of cognitive load is the amount of working memory resources used in given time. The capacity and performance of the neural circuitry that implements working memory plays a vital role in cognitive activities and varies from person to person. In order to understand working memory better, it is useful to distinguish between working memory performance and task performance. Task performance is typified by a participant's external performance of a task; for example, the time it takes to complete the task or the ratio of incorrect responses to correct ones. As opposed to that,

working memory performance is measured by the spectral changes in the alpha, beta and gamma frequency bands in the EEG bio signal [36][8][60]. This provides a connection between the task and the resultant cognitive load.
The mental instability and the challenges of visual orientation the VIPs face have been studied in cognitive load theory (CLT) by John Sweller in [56]. It is the basis of what we want to achieve in the forthcoming future.
Research done by Saitis et al. in [48] and [47] with Machine Learning use Fast Fourier Transform (FFT) for feature extraction and Random Forest classifier algorithm for classification.

1.2 Thesis Contribution

Building on the above, we have based our work on helping the visually impaired to navigate in unfamiliar indoor environments. Some research has been done to analyse the mental state of the VIPs using EEG as they navigate through various environments [48][47]. We want to carry out similar research using a different approach and see if the results still hold and agree with the work done in existing studies. We use Welch's Power Spectral Density (WPSD) for feature extraction and Support Vector Machine (SVM) for classification. Collecting EEG signals, we assess the resulting cognitive load label for each participant in different indoor environments.

1.3 Thesis Orientation

The consequent chapters of the paper have been covered in the following order. Chapter 2 discusses similar work in the field corresponding to our work and existing methodologies with their limitations. Chapter 3 gives an in depth study and analysis of the topics preceding data and information associated with our work. Chapter 4 presents the proposed model in detail. Chapter 5 give the test results, analysis of the results and the interrelated discussions. The last chapter, Chapter 6 closes and outlines our study with future plans.

Chapter 2

Literature Review

The use of BCI to provide communication and control capabilities to people with severe motor disabilities has become more common in the last decade [50]. So a gradual rise in interest in this field can be expected in the future. Studies have been done to measure cognitive load using fMRI or MRI, for example by Callicot J. in [16]. This study finds that the prefrontal cortical signal decreases at highest working memory load which is also coincident with a significant decrement in performance. The paper also talks about a relationship between the pericingulate or the posterior cingulate region, and capacity-unconstrained response. This is because activation of this region is observed to be related to attention and effort related processes. The cingulate cortex is a part of the brain situated in the medial aspect of the cerebral cortex. All of this leads us to draw a strong connection between the level of stress and results obtained from BCI reports.
Previous work in extracting features from EEG uses different approaches, for instance, in [55] the ACSP (Adaptive Common Spatial Pattern) is conducted for feature extraction of EEG signals, which is validated of its efficacy and superiority over the SCSP (Stationary Common Spatial Pattern) and WCSP (Windowed Common Spatial Pattern) methods through classification experiments on multiple recordings sessions of three subjects.

The analysis of EEG signals have been gaining more popularity recently in different sectors including neuromarketing [63], for the detection of various diseases including epilepsy [5], Alzheimer's disease [19] and Parkinson's disease[40]. These various journals carry out feature extraction in different ways. Yadava et al in [63] uses Discrete Wavelet Transform (DWT). The wide range of various wavelets available when using DWT leads to unreliability if the wrong wavelet is chosen for a particular application.

Machine Learning is observed to be a common tool for classification among the existing biosignal analysing journals. U. R. Acharya et al in [5] uses the Gaussian Mixture Model (GMM) and support vector machine (SVM) to investigate the performance of the features they extract. Another journal in the biomedical disease detection field, Oh et al in [40] uses Convolutional Neural Network(CNN) as the classification algorithm. The Deep Learning algorithm has shown remarkable outcome in conjunction with the Artificial Neural Network to classify dataset accurately.

Using EDA (Electrodermal Activity) instead of EEG means that there is no way to differentiate between cognitive load and cognitive stress. Cognitive load does not always correspond to stress as shown by the recovery stage as stated by Setz et al in [51]. This is why it is important to analyse specific bands which do correspond to stress. The paper has laid the idea of concatenating the signals from the MIST (Montreal Imaging Stress Test) stress experiment and MIST cognitive load experiment. MIST is a standardized test which involves putting the subjects under arithmetic and social stress. Adding or concatenating signals from the time period when stress is applied with the signals from the time when the subjects are recovering (i.e. not facing any stress or relaxing) means that any noise which persists due to basic cognitive load which is not brought about from stress is not considered in the final feature. This makes it easier to analyse the curve only for stress indicators.

A study by Anderson et al. in [21] uses an alternative approach to visualization techniques evaluation using signals from EEG. Advanced studies have shown a connection between neural networks and human cognition. Posner et al [44] has cogently revived the notion that neural network models of attention can provide a common, unifying approach to theory and research on many aspects of human cognitive and emotional development. The study has drawn attention that a neural network like PDP (Parallel and Distributed Processing) model helps us to understand commonalities among developmental processes associated with social learning, symbolic thinking, social cognition and social motivation. Using Deep Learning in order to classify cognitive load shows promising outcomes with good accuracy over the data set.

Kumar et al. in [35] explains the importance of detecting and analysing frequency bands in EEG signals. Some waves are based on their shape, head distribution and symmetry property [8]. The familiar classification of such wave forms include the gamma, alpha, beta, theta, delta. The continuous rhythms of the brain or brain waves are categorized by frequency bands where brain wave frequency differs in correspondence to different behavior and mental state of the brain [12][23][32].

Abo-Zahhad et al in [4] talk about the relevance of signals obtained in different frequency bands or ranges. EEG waveform is classified into five different frequency bands. The slowest waves usually found in an EEG report are delta waves (up to 4Hz) which correspond to deep and unconscious sleep. At a slightly higher pitch are theta waves (4-8Hz) involved with quiet focus and light sleep. The next frequency band (8-14Hz), commonly known as alpha waves are observed during relaxation with eyes closed but the subject still awake. Beta (14-30Hz) arises during normal consciousness and active concentration. And the highest frequency band, gamma waves (over 30Hz) are known to be stronger electrical signals in response to visual stimulation [4][35].

A study conducted by Subasi et al in [54] uses and compares the three algorithms of feature extraction methods to classify if an individual is epileptic or not. The publicly available data as described by Andrzejack et al. in [7] is used. A versatile signal processing and analysis framework of EEG is suggested, where the features were decomposed into sub bands using DWT. The features are then extracted using PCA (Principal Component Analysis), LDA (Linear Discriminant Analysis) and ICA (Independant Component Analysis) to reduce dimensionality to increase the performance of the classifier. The classification process is carried out using a SVM kernel. The training process is carried out using RBF (Radial Basis Function) kernel to PCA+SVM, ICA+SVM and LDA+SVM which are then cross compared to the in terms of their accuracy relative to the observed epileptic/normal patterns. Scaler performance measures, sensitivity and specificity, are derived from the confusion matrix. The results show that SVM by feature extraction using PCA, ICA and LDA always perform better than that without feature extraction (98%). According to this result, the application of nonlinear feature extraction and SVMs can serve as a potential alternative for intelligent diagnosis systems.

The data set used in this study has been obtained from [27], research done by Kalemari et al. later used in [48] and [47]. This particular data set focuses on the electric potentials of signals obtained from the brains of visually impaired people via EEG. Using the data set we collect signals from fourteen channels in nine participants experiencing indoor challenges. Saitis et al. in [48] further labels frequency bands with different kinds of activity and level of stress in a the brain. This paper says that beta activity is associated with psychological and physical stress, whereas theta and alpha-1 (i.e. lower alpha) frequencies reflect response inhibition and attentional demands such as phasic alertness. Degutis in [20] defines phasic alertness as the rapid change in attention due to a brief event and says that it is the basis for operations such as orienting and selective attention, which leads to the possibility of relating lower alpha waves to extra attention required for orientation by the subjects in the experiment. Alpha-2 (i.e. higher alpha) is related to task performance in terms of speed, relevance, and difficulty [48][30]. This group of frequency ranges or bands therefore correspond to the difficulty level presented to the VIP as they navigate through the different circumstances. Gamma waves are involved in more complex cognitive functions such as multimodal processing or object representation[48][29]. So even though interpretation from visual stimulation is not a factor, gamma waves are still relevant to this study because interpretation from the other senses (touch, smell) might be involved in the navigation process.
The journal in [48] is based on data collected by the European Union in a University in Iceland. The ten VIPs of the experiment are made to navigate through circumstances with various levels of stress. They use the EMOTIV+ EPOC headset with

16 dry electrodes placed according to the 10-20 system with sampling rate 128Hz. The participants are familiarized with the route prior to the experiment. Unnecessary head movements and hand gestures as well as talking to their O&M instructor are avoided with the exception of emergency. Annotations (which circumstance corresponds to which brain wave) are made with the help of video and audio besides using GPS.

Any missing data resulting from connectivity issues are made up for using interpolation in the time domain using FFT. All signals are baseline-normalized by subtracting for each participant and for each channel the mean of resting state registrations.These are obtained during a series of laboratory studies with the same participants.

Features related to signal power and complexity are extracted using the PyEEG open source Python module. For each of the 14 EEG channels, they compute the Relative Intensity Ratio as an indicator of relative spectral power in each of the six frequency bands, namely delta (0.5–4 Hz), theta (4–7 Hz), alpha-1 (7–10 Hz),alpha-2 (10–13 Hz), beta (13–30 Hz), and gamma (30–60 Hz).

Next they estimate the event-related (de-)synchronization (ERD/ERS) index, a well-established measure of band power change in EEG originally proposed by Pfurtscheller and Aranibar in [42]. Slightly modifying the model, this paper [48] calculates ERD/ERS every second, where every time point expresses the synchronization or desynchronization according to the same baseline. The drawback for this paper is that the data set is made up of a small set of people, which makes the study susceptible to overfitting.The participants are also of various levels of visual impairment. Another limitation include the EMOTIV+ headset which recedes the quality of signal generated that has been recorded.

Chapter 3

Background Analysis

In this chapter, we give an in depth study and analysis of the topics preceding data and information associated with our work that includes cognition, CLT, EEG, the different methods for band extraction and the different classification algorithms used for such cases.

3.1 Working Memory

The working memory is a part of primary memory often referred to as short-term memory and has limited capacity. It holds the information temporarily required for processing instantaneous activities. It is responsible for logical analysis and for the decision making aspects of activities. As a result, it impacts behavior. For instance, it is responsible for instantaneous perception through the different senses and for the processes required for deciphering language.

3.2 CLT

Cognitive psychology defines cognitive load as the used amount of working memory resources. CLT divides cognitive load into three types: intrinsic, extraneous, and germane[58].

3.2.1 Intrinsic Cognitive Load

Intrinsic cognitive load is the load on working memory due to the complexity of the knowledge that is being gained as opposed to how that knowledge is gained. It can only be altered by changing what is learned or by changing the knowledge levels of learners. One of the key features of intrinsic cognitive load is that it is unchangeable for given information to be processed by learners with given levels of expertise[48].

3.2.2 Extraneous Cognitive Load

Some information imposes a heavy cognitive load not because of its intrinsic nature but rather because of the way it is presented. That load is referred to as extraneous cognitive load. It can be reduced by modifying the instructional procedures [57]. Element interactivity affects both intrinsic as well as extraneous cognitive load. Simultaneous processing imposes a heavy working memory load, while successive processing does not. Low element interactivity materials allow individual elements to be learned with minimal reference to other elements and so imposes a low working memory load. Whether information can be processed simultaneously or successively depends on element interactivity [57].

3.2.3 Germane Cognitive Load

Germane cognitive load does not depend on any one source of cognitive load. Instead, it refers to the working memory resources available to deal with the element interactivity associated with intrinsic cognitive load. If more working memory resources are used up in dealing with extraneous cognitive load, less will be available to deal with intrinsic cognitive load and so less will be devoted to germane cognitive load. [21]

3.3 Measuring Cognitive Load

Early stages of CLT using indirect methods such as error rates, time on task and computational method provide evidence that various instructional effects can be explained by fluctuations in cognitive load. Paas (1992) in [59] proposes a single-scale subjective measure of mental effort, which in effect made a significant move away from the early proposals. In most instances, the subjective measures have evidently provides collaborating support of all CLT effects. However, subjective rating scales do not provide real time concurrent data. An alternative measure that is able to provide concurrent data is the use of a secondary task. The method is seen to be easy and efficient in learning the cognitive load, and is also very unobtrusive. It has the most use and has been most successfully employed. Other methods include the eye tracking and physiological methods such as the use of EEG data have started to emerge as potential measures on ongoing research on CLT [8].

3.4 Different Parts Of Brain

The human brain is a complex organ. It is divided into three parts; the cerebrum, the cerebellum and the brain stem (which leads into the spinal cord). The cerebrum is the largest part of the brain. It is the principal and most anterior part of the brain in vertebrates, located in the front area of the skull. It is divided into two parts by a fissure- the right hemisphere and the left hemisphere. The right hemisphere controls the left side of the body, and the left hemisphere controls the right side of the body. The left hemisphere is also responsible for actions that require logic such as science and mathematics while the right is responsible for actions that have to do with creativity and art. The cerebrum controls the integration of complex sensory and neural functions, and hence the fine control of movement and the initiation and coordination of voluntary activity in the body. It also controls the performance of higher functions like the interpretation of touch, vision, hearing. Figure 3.1 shows the different parts of the brain.

The cerebellum receives information from the sensory systems, the spinal cord, and other parts of the brain and then regulates motor movements. The cerebellum co-ordinates voluntary movements such as posture, balance, coordination, and speech, resulting in smooth and balanced muscular activity.

Activities based on regions in the cerebrum:

Frontal - The front part of the brain which is responsible for motor function, self awareness,writing and speech, intelligence, problem solving.

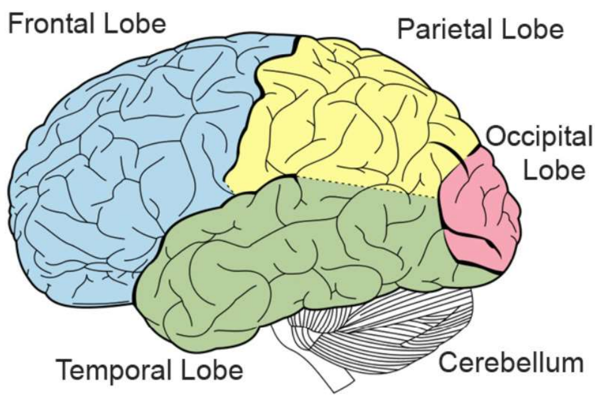

Figure 3.1: Different regions of Brain [2]

Temporal - Positioned on the side of the brain. Responsible for auditory processing, memory, learning/processing new language.
Occipital - Located at the back of the cerebrum. Plays a role in the processing of visual information. The information is processed to make decisions of color, depth and perception.
Parietal- Situated just behind the frontal lobe. It has somatosensory cortex and deals with processing sensory information to determine touch, sense of pain and temperature.

3.5 BCI

Human brain controls body function, such as heart activity, movement, speech, but also thinking itself. These activities are measured using the EEG which fundamentally captures the electrical potential in the brain. What BCI provides is a means of communication and independence, for instance if an individual has suffered damage in the Central Nervous System (CNS) causing blindness, BCI can used to give them artificial vision. Figure 3.2 depicts a simple model of BCI workflow.
Recent developments in BCI technology may see such hands-free control methods come into use. A BCI is a communication and control system in which the thoughts of the human mind are translated into real-world interaction without the use of the usual neural pathways and muscles. For example, utilising BCI, people with no limbs or damaged limbs or damaged sensors in the skin, can use artificial limbs which are

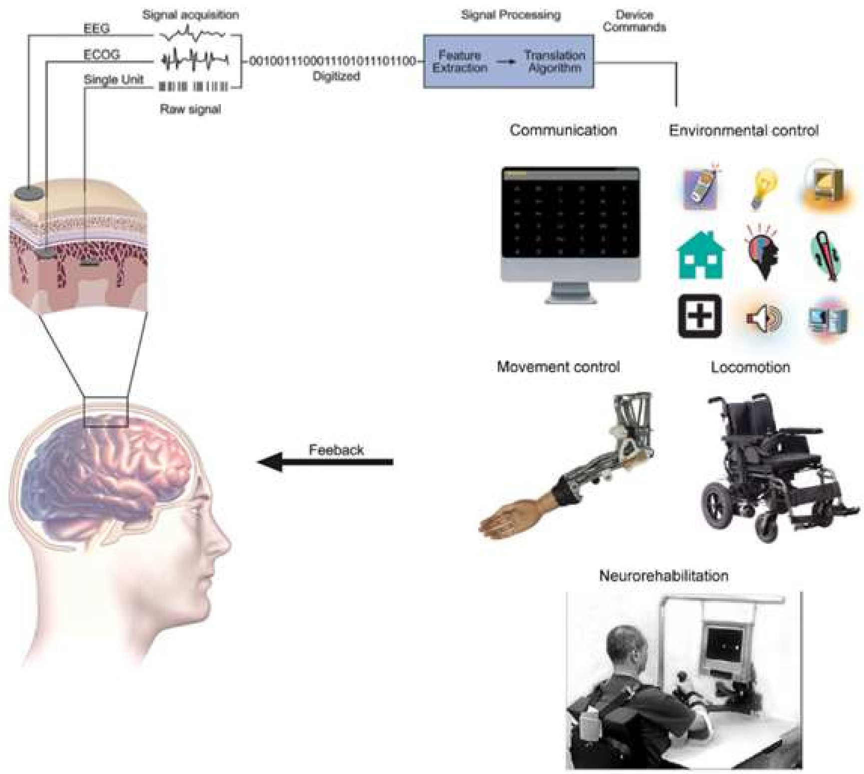

Figure 3.2: BCI workflow [8]

directly controlled by signals from their brain, thus allowing them to carry out their regular activities. Recent advances in the human brain and BCI research reveal that BCI-based devices and technologies can play a significant role in medicine [53] and can create an impact in future studies. There are three parts of BCIs. Invasive, Non-invasive and Partially invasive [32].

Invasive BCI- Requires surgery to position the sensors or stimulators in the cortical tissue. Complications may rise since the surgery may be prone to scar-tissue build up. Scar-tissue causes weak signal, which can even be lost.

Partially invasive BCI- Partially Invasive BCIs are implanted into the skull, but outside the brain. It uses a technology called the ECoG where electrodes are embedded in a thin plastic pad that is placed above the cortex, beneath the dura mater [32]. It produces good signal but is weaker than that of invasive BCI.

Non-invasive BCI- Non-Invasive BCI means electrodes are placed on the surface of the skull to record changes in EEG state. It is the easiest and safest way to record EEG.

3.6 Non-invasive BCIs

3.6.1 MRI

MRI provides a map of the brain in real time. The structural map helps to determine the location of any anomaly (for instance, tumours) that might be present in the brain or compare the sizes of the brain.

3.6.2 fMRI

fMRI provides a more detailed structure of the map. It shows the presence of oxygen in the brain due to different activities. The area with the more oxygenated blood in the brain becomes accentuated than the others and also the most active.

3.6.3 EEG

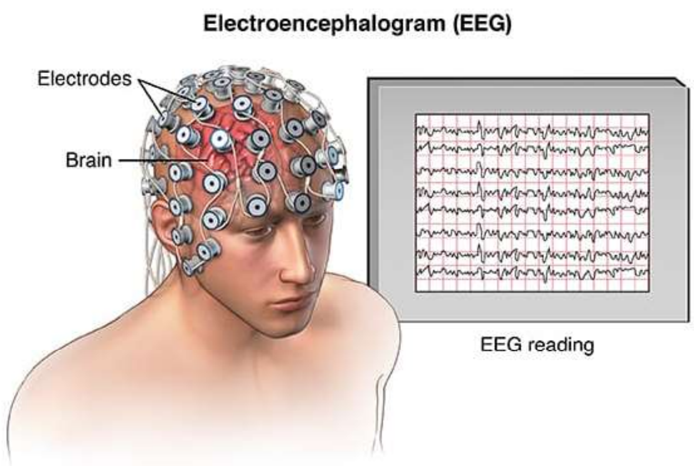

Figure 3.3: Acquiring EEG signals [22]

EEG is a non invasive technology used to record brain activity. Using EEG is the most prevalent method of signal acquisition for BCI. It is more accessible, can easily look in the brain activity, cost efficient and most optimum for research purposes. Metal electrodes are placed on the scalp according to standardized measurement systems and the relative electrical activity [54] recorded and analysed. A simple illustration is shown in Figure 3.3. In order to place the electrodes, a standard method used is the 10-20 method. The 10–20 system is an internationally recognized method to describe and apply the location of scalp electrodes in the context of an EEG exam. The measurements used in this system are explained as follows. The Nasion is the bridge of the nose and the Inion is the bony prominence at the back of the head. The two preauricular points are the points just anterior to each ear. The first measurement is made from nasion to inion. This is now divided into 10% and 20% increments. The next measurement is made from one preauricular point to the other. This is again divided into 10% and 20% increments. The next measurement made is the circumference of the head which is also divided into 10% increments. Parasagittal measurements are made, separated by 25% increments. Finally, transverse measurements are made. The intersections of these last two lines give the last electrode placement points. Electrode placement points are named in a manner that odd numbers are on the left and even numbers are on the right. Lower numbers are generally electrodes closer to the midline. Midline is represented by z which stands for zero. The letters are indicators of the position of the head. The F stands for frontal, C for Central, P for Parietal and O for Occipital [1]. Figure 4.1 illustrates the 10-20 system.

3.7 Biosignals

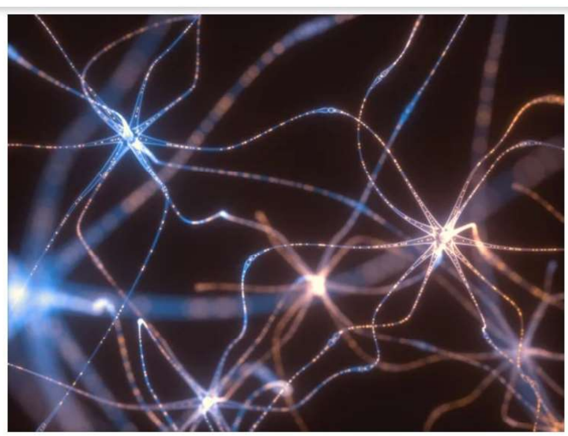

Figure 3.4: Travelling of brain waves in neurons [39]

Brainwaves are the short electrical pulses in the CNS with repetitive cycles over the period of time [32] (Figure- 3.4). These neural cycles are measured in Hertz. Pulses are generated from a single neuron or due to interactions between two neurons in the

CNS. The neurons in turn interchange information with the muscles via the nervous system to perform motor function, sensory interaction or have virtual information. The different functions of the brain emanates different frequencies of waves; for instance, high frequency waves are observed when a person is ecstatic while the low frequency waves can be seen when a person is bored or lazy. The different ranges can be detected and observed using the EEG. The different brain waves can be classified into five categories as the Figure 3.5 suggests.

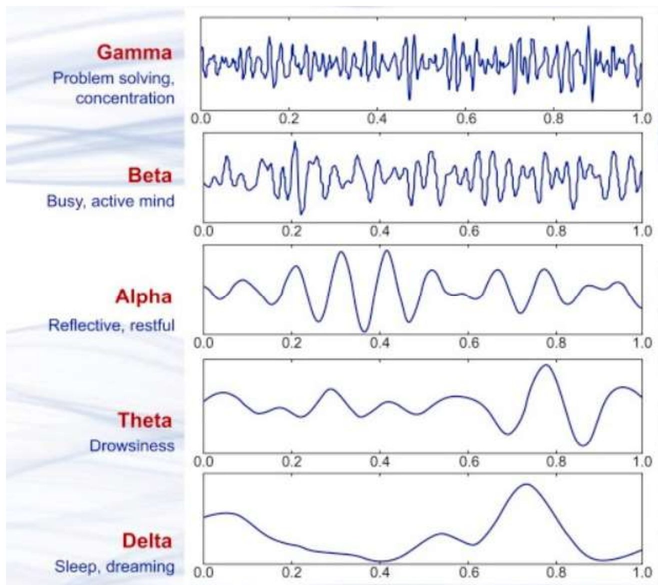

Figure 3.5: Brain samples for the five different waveforms [3]

3.7.1 Gamma

Gamma waves are important for learning, memory and information processing. This infers the working memory is responsible for this high frequency brain wave.

3.7.2 Beta

Beta waves are active in a waking state. This frequency is visible in logical-analytical reasoning. The cognitive tasks, problem solving, planning, self awareness can be observed using beta wave since the wave is mostly generated in the frontal lobe.

3.7.3 Alpha

Alpha waves connect the gap between our conscious thinking and subconscious mind. It helps us to calm down or it promotes a feeling of relaxation.

3.7.4 Theta

Theta waves are involved in sleep or daydreaming. While in this range, humans tap into their subconscious mind.

3.7.5 Delta

Delta waves occur during meditation, in a state of deep sleep or coma. Abnormal delta activity may occur if the person has learning disabilities or difficulties maintaining conscious awareness (such as in cases of brain injuries).

3.8 Feature Extraction

3.8.1 Fourier Transform

The Fourier Transform of an intensity versus time function like g(t) is a new function which does not have time as an input but instead takes in frequency. The common notation for this function is ĝ(f). The output of this function, ĝ(f) is a complex number, some point in the 2D plane that corresponds to the strength of a given frequency in the original function. As explained by Euler's formula, exponentials correspond to rotation. Multiplying that exponential by a function g(t) means drawing a wound up version of the function, g(t). An integral of the complex valued function can be interpreted in terms of a center of mass idea. Leading us to the final Fourier Transform in equation 3.1.

$$\widehat{g}(f) = \int_{t1}^{t2} g(t)e^{-2\pi ift}dt \tag{3.1}$$

3.8.2 Wavelet Transform

Wavelet transform (WT) is suitable for analysis of sudden and transient signal changes. This method can pick up impulses at different time instances. WT plays an important role in the recognition and diagnostic field [28]; it compresses the time-varying biomedical signal, which is composed of many data points, into a small few parameters that represents the signal. As the EEG signal is non-stationary, a suitable way for feature extraction from the raw data is the use of the time-frequency domain methods like WT which is a spectral estimation technique in which any general function can be expressed as an infinite series of wavelets [6][49]. Real world data or signals frequently exhibit slowly changing trends or oscillations punctuated with transients. On the other hand images have smooth regions interrupted by edges and abrupt changes. These abrupt changes usually contain useful information and can be picked up by WT.

3.8.3 PCA

PCA is a dimensionality reduction technique used in feature extraction to find correlation by maximizing variance. From the 'm' independent variables in the dataset, PCA extracts $p \leq m$ new independent variables that explain the most variance of the dataset, regardless of the dependent variable. The basic approach in principal components is theoretically rather simple. Firstly the data is standardized. The Eigenvectors and eigenvalues are obtained from the covariance matrix or correlation matrix. The eigenvalues are sorted in descending order and the 'k' eigenvectors correspond to the k largest eigenvalues, where k is the number of dimensions of the new feature subspace ($k \leq d$). The projection matrix W is constructed from the selected k eigenvectors. Finally the original dataset X is transformed to k-dimensional feature subspace Y. A very high level of classification accuracy is obtained in the result of classification, which is based on reducing the feature dimension using PCA and deriving the support vectors using SVM [17].

3.8.4 ICA

ICA is a feature extraction method that transforms multivariate random signals into a signal having components that are mutually independent [54]. The ICA of a random vector consists of searching for a linear transformation that minimizes the statistical dependence between its components [18]. ICA finds independent projections which are almost not mutually orthogonal or not at all. It is one method used to identify temporally coherent networks [15].

3.8.5 LDA

The aim of LDA is to create a new variable that is a combination of the original predictors [54]. This is accomplished by maximizing the differences between the predefined groups, with respect to the new variable. The goal is to combine the predictor scores in such a way that, a single new composite variable, the discriminant score, is formed. LDA is used as a feature reduction technique for BCI systems in signal processing where all classification methods shows small classification errors [33].

3.8.6 Welch's method for finding Power Spectral Density

Welch's method, originally published in his journal in 1967 is an approach for spectral density estimation. It is an extension of the FFT. Signal nonstationarities make signals difficult to interpret visually. Welch's method is one of the solutions for dealing with signal nonstationarities since it gives smoother results. This method involves fewer computations and therefore is ideal for many non stationary tests [61]. The transformations have to be carried out on shorter signals since the original signal is split into segments. The segmentation is described in Figure 3.6. The FFT is carried out on each individual segment and the results of each averaged to obtain the final Welch's Power Spectral Density (WPSD). This makes the method more ideal for portable navigation aids with limited core storage. Mobile navigation aids call for fast systems with accurate outputs. A reduced number of computations is an essential part of that.

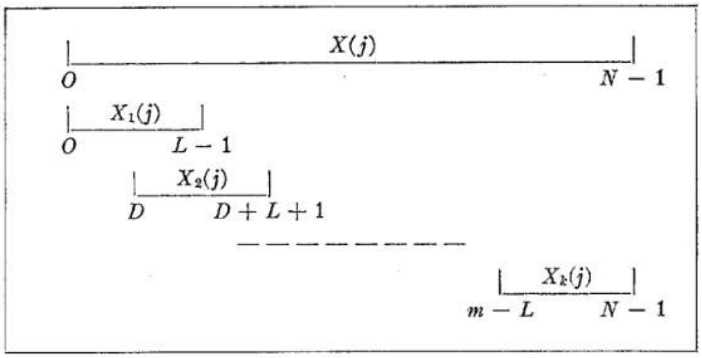

Figure 3.6: Illustration of record segmentation [61]

In order to carry out Welch's method, the Fourier Transform is calculated for each snippet and the power spectrum obtained. Each snippet is modified before carrying out the Fourier Transform on it. By having overlapping segments, attenuated data resulting from modification in the Fourier Transform of one snippet is made up for by the Fourier Transform of the next snippet. The final Welch's transform is obtained by averaging all the resulting power spectra together.

3.9 Classification Techniques

3.9.1 SVM

Generally speaking, SVM is a supervised machine learning model consisting of classification algorithms for binary division of data. Most real life data consists of too much overlapping for clear classification using simple classifiers like linear regression or logistic regression. The machine learning model, SVM has the ability to classify overlapping data with no clear linear classification by visualising the data in a higher dimension and using a hyper plane in the higher dimension as the classifier as mentioned in [37] and [54]. This hyper plane is referred to as the Support Vector Classifier. The paper further explains how the method's name, support vector machine is derived from the support vectors, which are data coordinates that lie closest to the decision boundary separating the classes. The support vector classifier is expressed in terms of the input vectors and dot products. Figure 3.7 illustrates how an SVM operates. It should be noted that the data are not actually being moved into a higher dimension but rather pictured in a higher dimension to come up with a classifier [10] [24]. This is done by using the dot product to find how individual points reflect in the feature subspace. The kernel function decides the dot product. The distances between these reflections on the new higher-dimension subspace can be calculated. It is also important to decide on a scale of impact for violating the soft margin between the classes. Therefore, it can be said that the goal of SVM is to find a hyper plane in an N-dimensional space, where N is the number of features, that distinctly classifies the data points. The SVM chooses the classifier which separates the classes with maximal margin, referred to as the optimal separating hyper plane in [10]. The margin is defined as the width of the largest 'tube' not containing samples that can be drawn around the decision boundary i.e. the solution with the highest generalization ability [54].

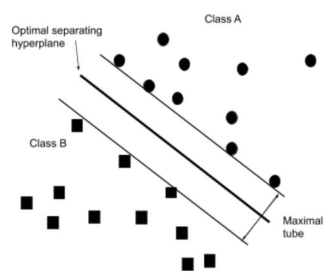

Figure 3.7: Optimal separating hyperplane in 2D SVM

The Polynomial Kernel is used to calculate the relationships between the observations in a higher dimension. The dimension which does provide a hyper plane with distinct classification is chosen.

Gaussian RBF can be considered as an extension of the Polynomial Kernel. In this case, the new subspace consists of infinite dimensions and the algorithm finds the hyper plane in the infinite dimension which can be used for binary classification.

The radial kernel behaves like a Weighted Nearest Neighbour model, that is, the closest data points have the highest influence on how we classify the new data point. A constant term determined by cross validation scales the influence. This model is useful for training data set with a lot of overlap. The radial kernel finds Support Vector Classifiers in infinite dimensions.

3.9.2 Random Forest Classifier

An ensemble learning method for classification that operates by creating multitude decision trees at training time and outputs the class that is the mode of the classes of the trees. The first algorithm for Random Forest was first developed by Tin Kam Ho [26].

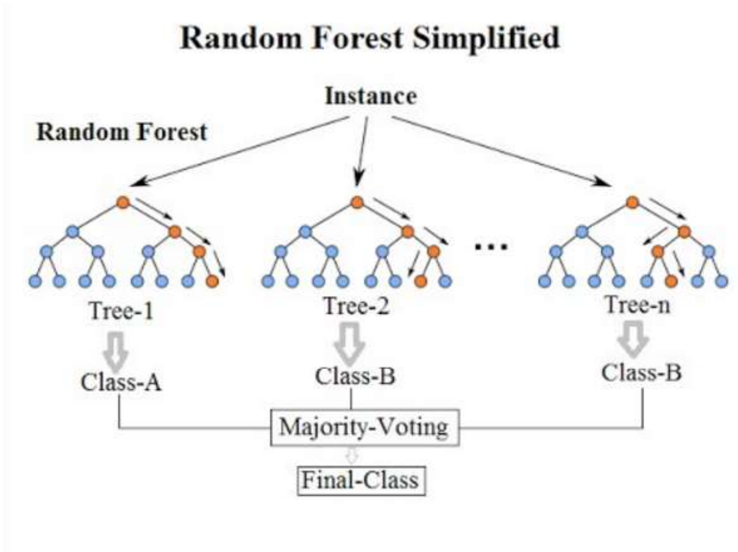

Figure 3.8: Random Forest based Classification [31]

The basic approach in Random Forest is theoretically rather simple. Firstly pick 'n' data points from the training set randomly. Build the decision tree associated with these n data points. Choose the number of Ntree you want to build and repeat the first two steps. For a new data point, make each of the Ntree predict the value of Y for the data point in question and assign the new data point the average across all of the predicted Y values. Finally the accuracy of the Random Forest is estimated from which 'out of the bag' error is used to optimize the number of variables that should be used in the classifier. Figure 3.8 illustrates a simplified random forest.

3.10 ERD/ERS calculation

The term ERD refers to an event related localized amplitude attenuation whereas ERS refers to event-related localized amplitude enhancement within mu and beta frequency bands [52].

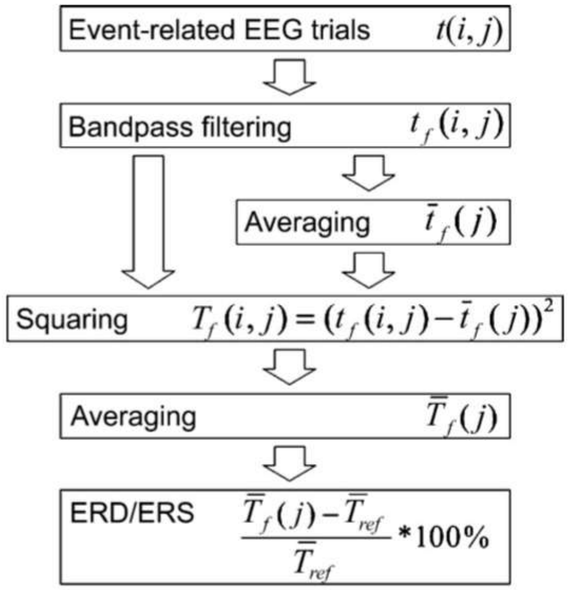

Figure 3.9: Calculation of ERD/ERS using Inter trial Variance method [62]

The common ERD/ERS detection can be processed in four steps, which contains band pass filtering of the EEG signal, squaring of amplitude of the signal and averaging of their power within all experiments in order to smooth the data [52]. Figure 3.9 depicts the several steps taken to calculate the ERD/ERS using the Intertrial Variance method.

As study in [62] shows, short red light flashes of 10 ms duration were presented on patients for visual stimulation at intervals of at least 2s using alpha power in the 7 to 13 Hz band. This stimulation resulted in an ERD followed by resynchronization. Trials were controlled for artifacts, averaged offline, and the amount of ERD/ERS was calculated.

Chapter 4

Proposed Model

In this chapter, we present our proposed model, an overview of the steps carried out in our study. EEG is the non-invasive BCI used for detecting the cognitive load in VIPs. Initially signals have noise and gaps due to connectivity issues. Preprocessing is done to reduce deviations, noises and inconsistent signals. The preprocessed signals are then further refined and features extracted using WPSD. The features are labelled with corresponding cognitive loads based on recordings and post experiment interviews. Finally these features are fed into RBF SVM and classified accordingly. Figure 4.2 represents our proposed model.

4.1 Data Description

The data used in our study has been obtained from an experiment conducted in the indoor environments of the University of Iceland, Reykjavik [48].

The project was funded by the European Union to aid VIP for their navigation. The data set they collected [48] has been used in our study.

The EMOTIV EPOC+ EEG headset is used to collect EEG signals from 9 healthy participants as they navigate through indoor environments [48]. EPOC+ is chosen because it provides a good compromise between performance and usability with respect to other wireless EEG recording devices available. Participants of various levels of visual impairment (VI-2, VI-3, VI-4), have been described in Table 4.1. Indoor environments are divided into 6 types (Door, Narrow Space, Open Space, Elevator, Stairs, Moving Objects). The EEG signals from the subjects at each of these labels are recorded.

Table 4.1: Categories of Visual Impairment.

Category	Description	Participant Gender
VI-2	Vision less than 10% and more than 5%	2(F,M)
VI-3	Vision less than 5%	4 (F, F, M, F)
VI-4	Not being able to count fingers less than one meter away	3 (F, M, F)

Electrodes Placement:

In order to place the electrodes, a standard method , the 10-20 system with probes at AF3, F7, F3, FC5, T7, P3 , P7, O1, O2, P8, P4 , T8, FC6, F4, F8, and FC is used as shown in the figure 4.1.

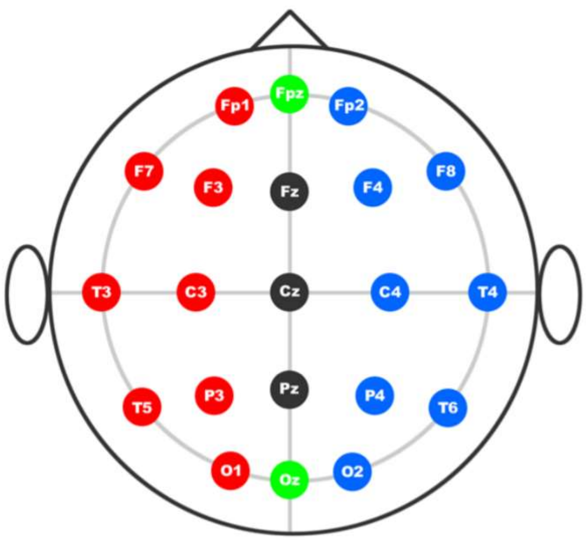

Figure 4.1: 10-20 Electrode Placement System [1]

Different bands such as Delta (up to 4 Hz), Theta (4-8 Hz), Alpha (8 -15 Hz), Beta (15-32 Hz), and Gamma (above 32 Hz) can be extracted from EEG signals. The ones relevant to our study are Alpha (8 -15 Hz), Beta (15-32 Hz) waves, and Gamma (above 32 Hz) waves.

The cognitive tasks, problem solving, planning, self awareness can be observed using beta waves [45]. The results conducted shows a relationship between cognitive load

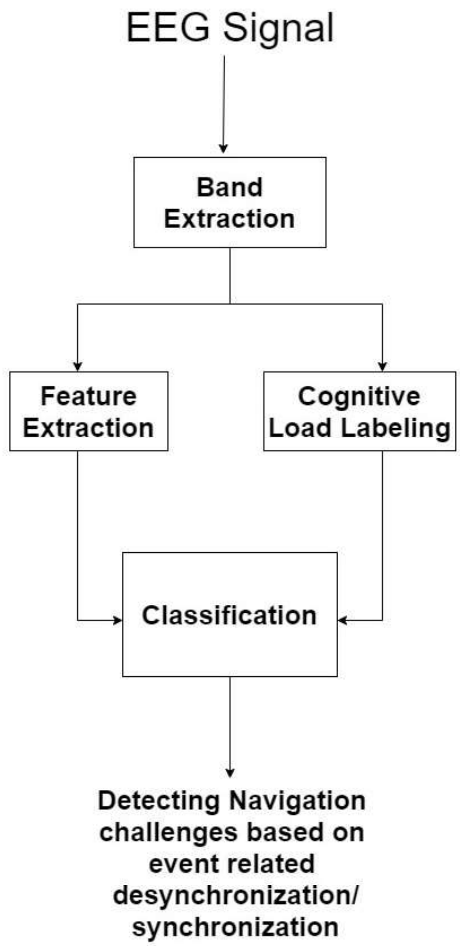

Figure 4.2: Workflow Of the Proposed Model

and beta frequency [36]. This leads to the conclusion that beta waves should be taken into consideration for our research.

Similarly, gamma band activity participates in various cerebral functions, such as perception, attention, memory, consciousness, and motor control [60]. Therefore, it shows the significance of gamma frequency to detect cognitive load.

Cognition has shown association with alpha frequency when the frequency is detected in the visual cortex of the brain. Repeated observations from experiments show that signals in the alpha band tend to correspond to brain activity associated with cognitive load, for instance, alpha activity is observed to fall in magnitude with higher task difficulty [8].

The comprehensive sources contribute the indispensable information and data to conduct our research for navigation of VIPs.

4.2 Feature Extraction

In the dataset collected from the European Union, EEG signals are recorded using the Emotiv EPOC+, a mobile headset with 16 dry electrodes registering over the 10-20 system locations. A sampling rate of 128 Hz is used. In this experiment there are 9 participants each of whom are stimulated to 6 different indoor environments and EEG signals are recorded from 14 different channels
When extracting features, three frequency bands are taken into consideration, aforementioned in Section 4.1, namely, alpha (8 -15 Hz) waves, beta (15-32 Hz) waves, and gamma (above 32 Hz) waves. The following passage demonstrates how feature extraction is carried out on the relevant bands.

4.2.1 WPSD

Welch's method is an approach for spectral density estimation. It uses FT to compute a smoother signal. Welch had the idea to split the entire signal into segments before carrying out the FT on each individual segment. This reduces computation time and complexity and thus makes the process much more appropriate for devices involving mobility [61]. Since we are trying to build a navigation aid which provides real time classification, this is a useful property for the logic involved in our backend computation. The FT of each separate segment are then averaged to obtain the final WPSD. The segments are intentionally taken in a manner that they overlap with each other. This is done so that any data attenuated as a result of modifying the segments before FT are made up for by adjacent overlapping segments.The method is ideal for portable navigation aids with limited core storage.

4.3 Cognitive Load Measurement

The definition used in our study to measure band power change in EEG is based on the technique first developed by Pfurtscheller and Aranibar[42]. It is defined as follows:

$$ERD/ERS(\%) = \frac{baselineIBP - testIBP}{baselineIBP} \tag{4.1}$$

, where IBP stands for interval band power. The baseline IBP refers to a prestimulus time period without any task demands, which in our case is the resting state, while the testIBP is the band power obtained during the time frames when the different stimuli are presented to each participant.

The ERD/ERS is calculated using beta band. From the estimation of the ERD/ERS the cognitive load is found. The value of the cognitive load represents the level of mental difficulty a participant faces due to the combination of parameters that lead to the cognitive label.

4.4 Cognition Classification

Our data, like most real life data, consists of too much overlapping for clear classification using simple classifiers like linear regression or logistic regression. The machine learning model, SVM has the ability to classify overlapping data with no clear linear classification by visualising the data in a higher dimension and estimating the classifier better than any linear model.

The extracted features were fed into a SVM kernel for classification. The higher dimension in a SVM is chosen based on which one provides a hyperplane for clear classification [10]. RBF in particular maps the data points in the existing dimension into an infinite dimensions subspace. SVM with 5 fold cross validation and grid search is implemented. That is, the data set is divided into five parts. The first section is used to train the algorithm and the remaining 4 sets are used for testing. In its existing dimensions, our data is difficult to differentiate. So visualising it in the infinite dimension subspace makes it easier to classify the data. Grid search is used as an approach for hyper-parameter tuning to build the SVM model for each combination of parameters specified in our data.

Chapter 5

Results and Discussion

EEG signals are captured from 9 VIP as they navigate through the indoor environments in a university. Features are extracted per second with a sampling rate of 128 Hz. ERD/ERS is calculated using beta bands. From the calculation, the measurement for the cognitive load is found and labelled accordingly. These labels are used to train the RBF kernel of SVM using 5 fold cross-validation. In this section, the results and its corresponding ROC (Receiver Operator Characteristics) curve is described and analyzed.

5.1 Analysis Of Results

In medical diagnosis, test sensitivity is the ability of a test to correctly identify those with the disease (true positive rate), whereas test specificity is the ability of the test to correctly identify those without the disease (true negative rate)[54]. A graph of the sensitivity by 1-specificity plotted at different cut off points for classification is called the ROC curve. This curve is useful for analysing the efficiency of a model.
The ROC curve can be used to pick the cut off point that optimises sensitivity and specificity for a given curve. Common criteria for picking the cut off point include the point on ROC curve where the sensitivity and specificity of the test are equal, or the point on the curve with minimum distance from the left-upper corner of the unit square[25]. The area under the ROC curve gives the accuracy. This area under the curve is commonly referred to as the AUC (Area Under Curve). The best test is the one with the ROC curve that clusters up to the left.

In our experiment, ROC curves are plotted with pairs of sensitivity and specificity obtained at each hyper plane. The hyper planes are exponential functions discovered by the RBF kernel of the SVM. As more iterations are carried out, the kernel learns better and the hyper plane obtained provides a new value of sensitivity and specificity, that is, the ratio of true positive and the ratio of true negative change with respect to total predictions made. So each classifier gives a unique set of sensitivity and specificity values.

The sensitivity, specificity, and accuracy are calculated from confusion matrix defined as:

$$Sensitivity = \frac{TP}{TP + FN} \tag{5.1}$$

$$Specificity = \frac{TN}{TN + FP} \tag{5.2}$$

$$Accuracy = \frac{TP + TN}{TP + FN + TN + FP} \tag{5.3}$$

where TP is the number of true positive, TN is the number of true negative, FP is the number of false positive,FN is the number of false negative.

In this paper, the cognitive load, labelled as stress, has been classified based on features extracted from the EEG signals of nine healthy participants of various levels of visual impairments in different indoor environments. Features were extracted from three frequency bands alpha, beta and gamma for all 14 channels using the WPSD. The environments can be divided into 6 different types, each subjecting the VIP to a unique set of challenges. Environment A is the annotation for any door that the subject faces in their route and the corresponding challenges they may face, for instance a rotating door can be a potential obstacle for a physically disadvantaged individual. The Table 5.1 shows corresponding challenges for each environment for the VIPs.

Table 5.1: Descriptions and corresponding challenges for each environment

ID	Environment	Challenges
A	Door	Rotating door, Bumping into closed doors
B	Narrow space	People, Chairs, Table, Furniture, Walls, Shelves
C	Open Space	People, Crowd, Losing direction
D	Elevator	Finding button, Selecting floor, People, Elevator door close
E	Stairs	Steps starting, Steps ending, Finding railing, Slippery
F	Moving Object	Avoiding people, Trolleys

5.2 Discussion

5 fold cross validation was carried out for each environment based on the features extracted from alpha, beta and gamma bands and ROC curves were plotted to analyze the classification for each environment, shown in Figure- 5.1. The ROC curve for environment A has an AUC of 0.91, B of 0.89, C of 0.96, D of 0.86, E of 0.88 and F of 0.90. Table 5.2 shows this in details. From the AUC values, we can see that the classification in environment C is done the most efficiently as it has the highest AUC. On the other hand, environment D has the least effective classification. However, the classification of stress for all environments using the RBF from SVM is very valid because the AUC for all shows a significant improvement compared to paper [27]. This proves that the algorithm picked is appropriate for this experiment.

Table 5.2: Sensitivity, Specificity and Accuracy table

Environment	Sensitivity%	Specificity%	Accuracy%
A	96.17	82.14	90.77
B	94.04	72.37	89.26
C	95.74	76.92	96.41
D	90.57	83.33	86.42
E	97.55	92.31	88.46
F	93.05	83.67	90.17

Aforementioned, the ROC curve can also be used to pick the hyper plane that

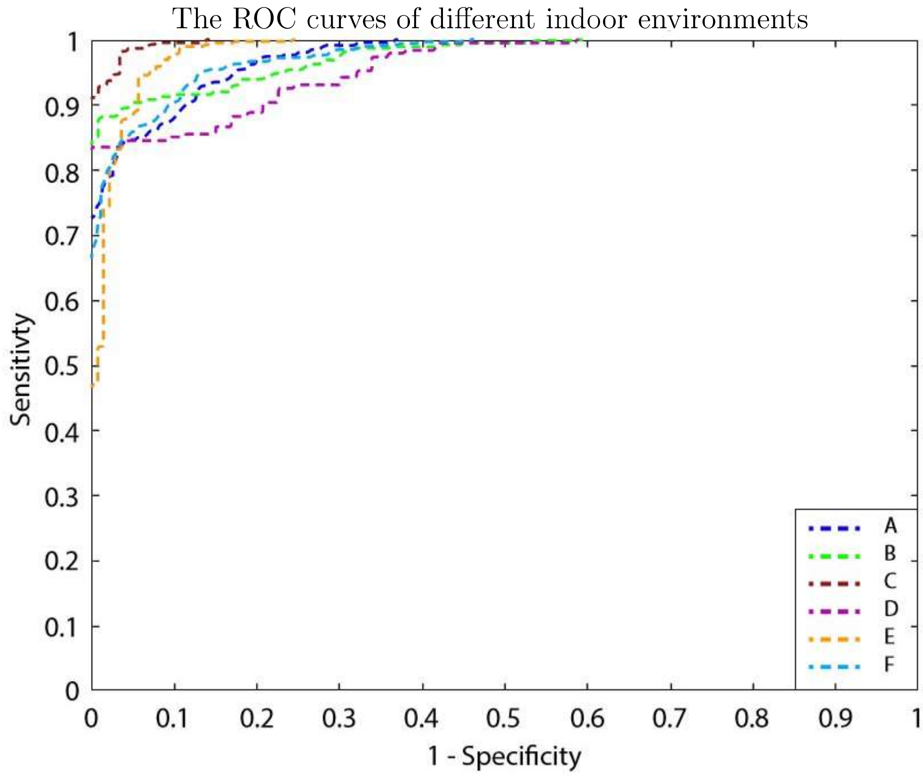

Figure 5.1: The ROC Curves

optimises sensitivity and specificity.

The ROC curves can be observed to find the point where the specificity and sensitivity match. This is also the point at minimum distance from the left upper corner of the unit square. Mapping this pair of sensitivity and specificity to the obtained hyper plane at the iteration which provides us with this pair of specificity and sensitivity values gives us the best classifier for that environment. The function of the hyper plane divides the new test subjects into two categories- high cognitive load or stressed, or low cognitive load or not stressed.

Chapter 6

Conclusion

This paper highlights how real time cognitive load assessment is done as the VIPs navigate their way through indoor environments. The main objective is to reflect the viability of the challenging tasks and find their corresponding cognition level by extracting features from the frequency bands. Our study describes the design of the user study performed, the extraction of cognitive load measured from EEG signals, and how those measures can be used to quantitatively evaluate the effectiveness of navigation aids with the use of features extracted from certain frequency bands. What we have achieved in this research is an effective way to label the cognitive load using WPSD and RBF SVM with an AUROC of above or around 0.9 for each environment.

Since our work agrees with papers[27][48] to say that EEG signals are a stable visualisation technique for cognitive load, further work can include using EEG signals to compare the effectiveness of different visual aids as opposed to individual assessment of people. So research can be done to decide which mobility aids are the most comfortable for impaired users. The work done in this paper opens opportunities for research in a variety of fields. The usability of EEG to detect stress can be applied on non impaired participants during tasks with probable high cognitive loads. Anyone facing cognitive load beyond normal levels can have extra factors like stress, anxiety or illness into play.

Bibliography

[1] *10/20 System Positioning MANUAL*. URL: https://www.scientificamerican.com/article/traveling-brain-waves-may-be-critical-for-cognition/. (accessed: 28.03.2020).

[2] *5 Important Brain Parts and Its Functions - ControlMind*. URL: https://controlmind.info/brain-parts-and-functions. (accessed: 28.03.2020).

[3] P. Abhang, B. Gawali, and S. Mehrotra. *Introduction to EEG- and Speech-Based Emotion Recognition*. 1st ed. Academic Press, 2016. ISBN: 978-0-12-804490-2.

[4] M. Abo-Zahhad, S. Ahmed, and S. Abbas. "A New EEG Acquisition Protocol for Biometric Identification Using Eye Blinking Signals". In: *International Journal of Intelligent Systems and Applications* 7.6 (2015), pp. 48–54.

[5] U. Acharya et al. "Automatic Identification Of Epileptic Eeg Signals Using Nonlinear Parameters". In: *Journal of Mechanics in Medicine and Biology* 9.4 (2009), pp. 539–533. DOI: 10.1142/s0219519409003152.

[6] A. Al-Fahoum and A. Al-Fraihat. "Methods of EEG Signal Features Extraction Using Linear Analysis in Frequency and Time-Frequency Domains". In: *ISRN Neuroscience* 2014 (2014). DOI: 10.1155/2014/730218.

[7] R. Andrzejak et al. "Indications of nonlinear deterministic and finite-dimensional structures in time series of brain electrical activity: Dependence on recording region and brain state". In: *Physical Review E* 64.6 (2001). DOI: 10.1103/physreve.64.061907.

[8] P. Antonenko et al. "Using Electroencephalography to Measure Cognitive Load". In: *Educational Psychology Review* 22.4 (2010), pp. 425–438. DOI: 10.1007/s10648-010-9130-y.

[9] C. Berka et al. “EEG correlates of task engagement and mental workload in vigilance, learning, and memory tasks”. In: *Viation, space, and environmental medicine* 78.5 (2007). PMID: 17547324.

[10] H. Bhavsar and M. Panchal. “A Review on Support Vector Machine for Data Classification”. In: *International Journal of Advanced Research in Computer Engineering Technology (IJARCET)* 1 (2012).

[11] A. Bhowmick and H. Shyamanta. “An Insight into Assistive Technology for the Visually Impaired and Blind People: State-of-the-Art and Future Trends”. In: *Multimodal User Interfaces* 11.2 (2017), 149–172. DOI: 10.1007/s12193-016-0235-6.

[12] N. Birbaumer et al. “Slow potentials of the cerebral cortex and behavior”. In: *Educational Psychology Review* 70.1 (1990), pp. 1–41. DOI: 10.1152/physrev.1990.70.1.1.

[13] *Blindness and vision impairment*. URL: https://www.who.int/news-room/fact-sheets/detail/blindness-and-visual-impairment. (accessed: 31.03.2020).

[14] D. Bos. “Eeg-based emotion recognition”. In: *The Influence of Visual and Auditory Stimuli* 56.3 (2006), 1–17.

[15] V. Calhoun, K. Kiehl, and G. Pearlson. “Modulation of Temporally Coherent Brain Networks Estimated Using ICA at Rest and during Cognitive Tasks”. In: *Human Brain Mapping* 29.7 (2008), pp. 828–838. DOI: 10.1002/hbm.20581.

[16] J. Callicott. “Physiological Characteristics of Capacity Constraints in Working Memory as Revealed by Functional MRI”. In: *Cerebral Cortex* 9.1 (1999), pp. 20–26. DOI: 10.1093/cercor/9.1.20.

[17] M. Chandani. “Statistical Wavelet Features, PCA, MLPNN, SVM and K-NN Based Approach for the Classification of EEG Physiological Signal”. In: *International Journal of Industrial and Manufacturing Systems Engineering* 2.5 (2017), p. 57. DOI: 10.11648/j.ijimse.20170205.12.

[18] P. Comon. “Independent Component Analysis, A New Concept?” In: *Signal Processing* 36.3 (1994), pp. 287–314. DOI: 10.1016/0165-1684(94)90029-9.

[19] J. Dauwels, F. Vialatte, and A. Cichocki. "Diagnosis of Alzheimers Disease from EEG Signals: Where Are We Standing?" In: *Current Alzheimer Research* 7.6 (2010), pp. 487–505. DOI: 10.2174/156720510792231720.

[20] J. Degutis. "Tonic and Phasic Alertness Training: a Novel Behavioral Therapy to Improve Spatial and Non-Spatial Attention in Patients with Hemispatial Neglect". In: *Frontiers in Human Neuroscience* 4 (2010). DOI: 10.3389/fnhum.2010.00060..

[21] Anderson E. et al. "A User Study of Visualization Effectiveness Using EEG and Cognitive Load". In: *Computer Graphics Forum* 30.3 (2011), 791–800. DOI: 10.1111/j.1467-8659.2011.01928.x.

[22] *EEG Measures of Cognition: H.V.M.N. Biohacker Guide*. URL: blog.hvmn.com/biohacker-guide/cognition/eeg-measures-of-cognition. (28.03.2020).

[23] J. Fell, N. Axmacher, and S. Haupt. "From alpha to gamma: Electrophysiological correlates of meditation-related states of consciousness". In: *Medical Hypotheses* 75.2 (2010), pp. 218–224. DOI: 10.1016/j.mehy.2010.02.025.

[24] L. Guo et al. "Classification of Mental Task From EEG Signals Using Immune Feature Weighted Support Vector Machines". In: *IEEE Transactions on Magnetics* 47.5 (2011), pp. 866–869.

[25] P. Yadollahie M. Habibzadeh F. Habibzadeh. "On determining the most appropriate test cut-off value: the case of tests with continuous results". In: *Biochemia Medica* 34.7 (2016, doi = 10.11613/BM.2016.034, note =, URL = , eprint =), 838–848.

[26] K. Ho. "Random Decision Forests". In: *Proceedings of 3rd International Conference on Document Analysis and Recognition* (1995). DOI: 10.1109/icdar.1995.598994..

[27] K. Kalimeri and C. Saitis. "Exploring Multimodal Biosignal Features for Stress Detection during Indoor Mobility". In: *Proceedings of the 18th ACM International Conference on Multimodal Interaction- ICMI* (2016). DOI: 10.1145/2993148.2993159.

[28] S. Karim and B. Karim. “Wavelet Transform and Fast Fourier Transform for Signal Compression:A Comparative Study”. In: *2011 International Conference on Electronic Devices, Systems and Applications (ICEDSA)* (2013).

[29] A. Keil et al. “Human Gamma Band Activity and Perception of a Gestalt”. In: *International Journal of Intelligent Systems and Applications* 19.16 (1999), pp. 7152–7161. DOI: 10.1523/jneurosci.19-16-07152.1999.

[30] W. Klimesch. “EEG alpha and theta oscillations reflect cognitive and memory performance: a review and analysis”. In: *Brain Research Reviews* 29.2-3 (1999), pp. 169–195.

[31] W. Koehrsen. *Random Forest Simple Explanation.* URL: https://www.medium.com/@williamkoehrsen/random-forest-simple-explanation-377895a60d2d. (accessed: 28.03.2020).

[32] Z. Koudelková and M. Strmiska. “Introduction to the identification of brain waves based on their frequency”. In: *MATEC Web Of Conferences* 210.2 (2018), p. 05012. DOI: 10.1051/matecconf/201821005012.

[33] M. Kołodziej, A. Majkowski, and R. Rak. “Linear discriminant analysis as EEG features reduction technique for brain-computer interfaces”. In: *Przeglad Elektrotechniczny* (Jan. 2012).

[34] Rahimpour S. Krucoff M. et al. “Enhancing Nervous System Recovery through Neurobiologics, Neural Interface Training, and Neurorehabilitation”. In: *Frontiers In Neuroscience* 10 (2016). DOI: 10.3389/fnins.2016.00584.

[35] J. Kumar and P. Bhuvaneswari. “Analysis of Electroencephalography (EEG) Signals and Its Categorization–A Study”. In: *Procedia Engineering* 38 (2012), pp. 2525–2536. DOI: 10.1016/j.proeng.2012.06.298.

[36] H. Lee. “Measuring Cognitive Load with Electroencephalography and Self-Report: Focus on the Effect of English-Medium Learning for Korean Students”. In: *Educational Psychology* 34.7 (2013), 838–848. DOI: 10.1080/01443410.2013.860217.

[37] Y. Lin et al. “Support vector machine for EEG signal classification during listening to emotional music”. In: *2008 IEEE 10th Workshop on Multimedia Signal Processing* (2008). DOI: 10.1109/mmsp.2008.4665061..

[38] S. Macgregor. "Hypermedia Navigation Profiles: Cognitive Characteristics and Information Processing Strategies". In: *Journal Of Educational Computing Research* (1999), pp. 189–206. DOI: 10.2190/1mec-c0w6-111h-yq6a.

[39] S. Makin. *"Traveling" Brain Waves May Be Critical for Cognition.* URL: https://www.scientificamerican.com/article/traveling-brain-waves-may-be-critical-for-cognition/. (accessed: 28.03.2020).

[40] S. Oh et al. "A Deep Learning Approach for Parkinson's Disease Diagnosis from EEG Signals". In: *Neural Computing and Applications* 5 (2018), pp. 866–869. DOI: 10.1007/s00521-018-3689-5.

[41] W. Penrod, M. Corbett, and B. Blasch. "Practice Report: A Master Trainer Class for Professionals in Teaching the UltraCane Electronic Travel Device". In: *Journal of Visual Impairment Blindness* 99.11 (2005), pp. 711–715. DOI: 10.1177/0145482x0509901110.

[42] G. Pfurtscheller and A. Aranibar. "Event-related cortical desynchronization detected by power measurements of scalp EEG". In: *Electroencephalography and Clinical Neurophysiology* 42.6 (1977), pp. 817–826.

[43] H. Pham, T. Le, and N. Vuillerme. "Real-Time Obstacle Detection System in Indoor Environment for the Visually Impaired Using Microsoft Kinect Sensor". In: *Journal of Sensors* 2014 (2016), pp. 1–13. DOI: 10.1155/2016/3754918..

[44] Michael I Posner and Mary K Rothbart. *Educating the human brain.* American Psychological Association, 2007.

[45] W. Ray and H. Cole. "EEG Alpha Activity Reflects Attentional Demands, and Beta Activity Reflects Emotional and Cognitive Processes". In: *Science* 228.4700 (1985), 750–752. DOI: 10.1126/science.3992243.

[46] R. Roy et al. "Mental Fatigue and Working Memory Load Estimation: Interaction and Implications for EEG-Based Passive BCI". In: *2013 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)* (2013). DOI: 10.1109/embc.2013.6611070..

[47] C. Saitis and K. Kalimeri. "Multimodal Classification of Stressful Environments in Visually Impaired Mobility Using EEG and Peripheral Biosignals". In: *IEEE Transactions on Affective Computing* (2019), pp. 1–1.

[48] C. Saitis, M. Parvez, and K. Kalimeri. "Cognitive Load Assessment from EEG and Peripheral Biosignals for the Design of Visually Impaired Mobility Aids". In: *Wireless Communications and Mobile Computing,* (2018). PMID: 27442303, pp. 1–9. DOI: 10.1155/2018/8971206.

[49] S. Sarwar et al. "Noninvasive imaging system for visually impaired people". In: *2010 3Rd International Conference On Computer Science And Information Technology* (2010). DOI: 10.1109/iccsit.2010.5564650.

[50] G. Schalk et al. "BCI2000: a general-purpose brain-computer interface (BCI) system". In: *IEEE Transactions on Biomedical Engineering* 51.6 (2004), pp. 1034–1043. DOI: 10.1109/tbme.2004.827072.

[51] C. Setz et al. "Discriminating Stress From Cognitive Load Using a Wearable EDA Device". In: *IEEE Transactions on Information Technology in Biomedicine* 14.2 (2010), pp. 410–417. DOI: 10.1109/TITB.2009.2036164.

[52] F. Shahlaei et al. "Classification of Motor Imagery Tasks Using Inter Trial Variance In The Brain Computer Interface". In: *2018 IEEE International Symposium on Medical Measurements and Applications (MeMeA)* (2018), pp. 1–6.

[53] J. Shih, D. Krusienski, and J. Wolpaw. "Brain-Computer Interfaces in Medicine". In: *Mayo Clinic Proceedings* 87.3 (2012), pp. 268–279. DOI: 10.1016/j.mayocp.2011.12.008.

[54] A. Subasi and M. Gursoy. "EEG Signal Classification Using PCA, ICA, LDA and Support Vector Machines". In: *Expert Systems with Applications* 37.12 (2010), 8659–8666. DOI: 10.1016/j.eswa.2010.06.065.

[55] S. Sun and C. Zhang. "Adaptive Feature Extraction for EEG Signal Classification". In: *Medical & Biological Engineering & Computing* 44.10 (2006), pp. 931–935. DOI: 10.1007/s11517-006-0107-4.

[56] J. Sweller. "Cognitive Load During Problem Solving: Effects on Learning". In: *Cognitive Science* 12.2 (1998), pp. 257–285. DOI: 10.1207/s15516709cog1202_4.

[57] J. Sweller. "Cognitive Load Theory". In: *Psychology of Learning and Motivation* (2011), 37–76. DOI: 10.1016/b978-0-12-387691-1.00002-8.

[58] J. Sweller. "Element Interactivity and Intrinsic, Extraneous and Germane Cognitive Load". In: *Educational Psychology Review* 22.2 (2010), pp. 123–138. DOI: 10.1007/s10648-010-9128-5.

[59] J. Sweller, P. Ayres, and S. Kalyuga. *Cognitive Load Theory*. 1st ed. Springer New York, 2011. ISBN: 978-1-4419-8125-7.

[60] P. Uhlhaas et al. "The Role of Oscillations and Synchrony in Cortical Networks and Their Putative Relevance for the Pathophysiology of Schizophrenia". In: *Schizophrenia Bulletin* 34.5 (2008), pp. 927–943.

[61] P. Welch. "The use of fast Fourier transform for the estimation of power spectra: A method based on time averaging over short, modified periodograms". In: *IEEE Transactions on Audio and Electroacoustics* (1967), pp. 70–73.

[62] M. Woertz, G. Pfurtscheller, and W. Klimesch. "Alpha power dependent light stimulation: dynamics of event-related (de)synchronization in human electroencephalogram". In: *Cognitive Brain Research* 20(2) (2004), pp. 256–260. DOI: 10.1016/j.cogbrainres.2004.03.014.

[63] M. Yadava et al. "Analysis of EEG Signals and Its Application to Neuromarketing". In: *Multi76media Tools and Applications* 76.18 (2017), pp. 19087–19111. DOI: 10.1007/s11042-017-4580-6.