Exploring Cognitive Load and Emotional States for the Visually Impaired

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A thesis submitted to the Department of 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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Abstract

Cognitive load and emotional states may impact for designing an assistive navigation aid for the Visually Impaired Peoples (VIPs). In this study, electroencephalogram (EEG) signals were captured from participants with different degree sight loss peoples (DDSLPs). EEG signals were then used to measure various cognitive loads and emotions to test the usability of an intelligent navigation aids. To support the argument of testing the usability of a navigation aids, the complexity of the tasks in terms of cognitive load and emotions were quantified considering diverse factors by extracting features from various well established entropies when DDSLPs will navigate unfamiliar indoor environments with different obstacles. Experimental results show that classification accuracy for narrow space is 97.61% for cognitive load. Moreover, the experiment achieves that 90.40% and 50.60% classification accuracy for arousal and valence in the open space and stairs, respectively.

Keywords: Cognitive Load; Emotional States; Bands; EEG; Human Brain; Entropy; Machine Learning; SVM

Dedication

This thesis work is dedicated to our parents.

Acknowledgement

First of all, we would like to express our gratitude to Almighty Allah for keeping us safe and sound to initiate the research work and to put our best efforts and successfully complete it. Secondly, we would like to thank and show our immense respect to our honorable supervisor Dr. Mohammad Zavid Parvez, for his enormous contributions, incomparable guidance and tireless support in conducting the research work and preparing this report. His constant involvement and supervision ensured our gradual progress towards the completion of this thesis work. We are really grateful and humbled to have him as our supervisor. We also thank our parents as well as our beloved friends for the patronage, moral support and aids. They helped us a lot with their valuable suggestions and direct or indirect participation which helped us maintaining a better workflow and achieving our goal. Last but not the least, we would like to thank specially our very own BRAC University for providing us the opportunity to conduct this research.

Table of Contents

List of Figures

List of Tables

Nomenclature

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

α	alpha band
α_{F3}	alpha band of channel F3
α_{F4}	alpha band of channel F4
β	beta band
β_{F3}	beta band of channel F3
β_{F4}	beta band of channel F4
γ	cognitive index
μ	Micro
ρ_b	base line interval of band power
ρ_t	test interval of band power
υ	valence
φ	arousal
a_0	intercept
a_1	coefficient for x_1
$ADHD$	Attention Deficit Hyperactivity Disorder
$ApEn$	Approximate Entropy
$AUROC$	Area Under the Receiver Operating Characteristics
C_j	centroid for cluster j
CL	Cognitive Load
CLT	Cognitive Load Theory
$DDSLP$	Different Degree Sight Loss People
E	Entropy

EDA Exploratory Data Analysis

EEG Electroencephalogram

$EPOC$ Excess Post-exercise Oxygen Consumption

ERD Event-Related Desynchronization

ERS Event-Related Synchronization

$ERSD$ Event-Related Synchronization and Desynchronization

FN False Negative

FP False Positive

g Positive Constant

Hz Hertz

j Objective Function

K Number of Neighbors the algorithm will consider while predicting

k Number of Clusters

KNN K-Nearest Neighbor

$lbs.$ Pounds

MDL Minimum Description Length

N Total Frequency

$O\&M$ Orientation and mobility

p_q relative frequencies of the probable patterns of the symbol sequences

r Number of cases

ROC Receiver Operating Characteristics

S Second

s_i coefficients of s within an orthonormal basis

SVM Support Vector Machine

TN True Negative

TP True Positive

$UCLA$ University of California

V Volt

VC Vapnik–Chervonenkis

VIP Visually Impaired People

WHO World Health Organization

z_i case i

Chapter 1

Introduction

As an introduction of our research paper, we would like to start with how cognitive load and emotional states is related to daily movement of the visually impaired peoples (VIPs).

Eye is an essential organ in our body. It is responsible for receiving large amount of information from information available to a person. Almost 85% information reaches brain through eyes [81]. Hence, navigation aids are quite important as well as helpful for the VIPs. It enables them to overcome many obstacles they may face in their daily lives. Therefore, the navigation aids can make their life smooth and easy.

Measuring cognitive load is challenging to develop navigation aids when VIPs are navigating through unfamiliar environments. Cognitive load theory (CLT) [[24], [48]] is the theory to provide a way to explore cognitive process and instructional model. CLT gives ability to process information by concurrently appraising the information structure and the cognitive architecture [24]. CLT apply obtained knowledge and skills to new situations using the model of instructional strategies which effectively utilize people's limited cognitive processing ability. CLT has founded on a cognitive architecture which used to model an effective instructional strategies. Cognitive architecture discusses mainly two things: limited working memory along with moderately independent processing units for visual and auditory information that communicate with a boundless long-term memory [25]. Whereas, cognitive load expresses the effort that has used in working memory to complete total amount of mental activity and CLT has used to explain this effort.

Working memory is also called short-term memory. In short term memory, there is different storage to keep data. Rather than all data going into one single store, there are distinctive frames for various sorts of data [38]. Working memory plays an important role to help people learn, work and process information. Many information is captured by the people from environment and many work needs to be done. Hence, working memory will be overloaded means cognitive load will increase but working memory has limited capacity. Working memory cannot perform unlimited work or information processing. For this reason, Cognitive Load (CL) has needed to manage to reduce the Cognitive load of working memory. Hence, if we measure cognitive load of VIP, we will get a good overview of their daily activity that has needed to design the assistive navigation aid.

Visual impairment has characterized as the constraint of different activities and purpose of the visual system [48]. It refers to remarkable loss of both eyesight [38]. If visual acuity is 20/60 that means to see an object one have to be positioned at 20 feet whereas at 60 feet a person with normal vision can see that object (see Table 1.1) [85]. According to National Eye Institute, visual impairment cannot be cure by spectacles [48].

There are two degrees of visual impairment [38]:
(i) Low Vision: People with low vision is partially sighted.
(ii) Blind: Blind people cannot see anything.

Visual impairment has also categorized as [38]:
(i) Congenital: People who loses sight from birth.
(ii) Adventitious: People who loses sight after birth because of accident or sickness.

Berthold Lowenfeld states that visual impairment has three basic constraints on a person [76]:
(i) Limitations in the range and several of experiences.
(ii) Limitations in the capability to get about.
(iii) Limitations in the rule over surrounding.

Table 1.1: Different degree of visual impairment [32].

	Visual Acuities	Visual Field	Categorized as
1	20/40 to 20/60		Mild vision impairment
2	20/60 to 20/200		Moderate vision impairment
3	20/200 to 20/400	20 or less but more than 10	Severe vision impairment
4	20/400 to 20/1200	10 or less but more than 5	Profound visual impairment
5	More than 20/12000	5 or less	Near total blindness
6	no light perception	0	Total Blindness

1.1 Motivation

According to World Health Organization (WHO), approximately 285 million people in the world is affected by sight loss with different degrees [81]. Rogers et al. have found that sight loss people have 63% greater risk of developing dementia over eight and half years [45]. Visual perception is of tremendous significance in our regular daily existences. It enables us to move around uninhibitedly. Hence, it is very hard to move for VIPs especially when they walk around in different environments, to do work and maintain smooth life. Our core inspiration for doing this research is to measure the cognitive load and emotional states who are visually impaired and help their navigation through assistive navigation aids when they are navigating unfamiliar environments.

1.2 Objective

- Analysis EEG signals for VIPs when they are navigating unfamiliar environments.
- Use EEG signals to extract pattern based on cognitive load and emotions.
- Use machine learning algorithm to measure cognitive load and emotional states.
- This research focuses to measure relevant complexity due to different obstacles by analysing EEG signals captured from VIPs.

1.3 Methodology

In this research, we have used EEG signals captured from VIPs. Then, pre-processing method is applied to remove noise from the signals. After that, we have extracted five bands from noise-free EEG signals. Besides, we have extracted different types of features from specific bands. After that, machine learning algorithms were used to classify the cognitive load and emotions based on extracted features.

1.4 Thesis Orientation

The thesis is organized as follows:

In Chapter 2, a brief discussion is given about the literature review in which includes detailed assessment about cognitive load, emotional state, EEG machine, EEG bands, human brain and machine learning.

In Chapter 3, experimental setup is explained which comprises site and route, participants, and data collection.

In Chapter 4, system implementation is described which includes system work flow and explanation about it.

Results and discussions is added in Chapter 5. Finally, Chapter 6 is about our conclusion.

Chapter 2

Literature Review

In this chapter, the concept and background study required for this research work has stated. The study includes understanding of the cognitive load, types of cognitive load, cognitive load Theory, effect of cognitive load on VIPs brain and emotional state of VIPs.

Cognitive science and educational psychology appear to spring up wherever of late. Cognitive load theory is imperative since it displays a proof based clarification for critical learning components [72]. Cognitive load alludes the proportion of working memory load constrained on the human subjective limit when playing out a particular errand. [24]. To evaluate, cognitive load of VIPs' can be viewed as various, in view of their diverse memory display, their more dynamic phonological circle and exceptional sketchpad as opposed to visuospatial sketchpad [26]. Individuals having issue with any of their organs are arranged in convenient groups. Therefore these group's memory model is extraordinary [46].

Let's take a two-person typing competition scenario: first one can type without seeing the keyboard, and the other has to see the keyboard all the time. To measure, which one uses more cognitive resources let's take another step: between these two individuals, one is visually impaired or daze from birth and the other one can see yet blindfolded. Is there any distinction in cognitive processing of a sighted yet blindfolded individual and visually impaired individual? The roughness of the answers to such questions will help in designing an assistive navigation aid system with upgraded operations, enhanced ease of use, further reduced cognitive load and versatile to the requirements and dimension of a VIP.

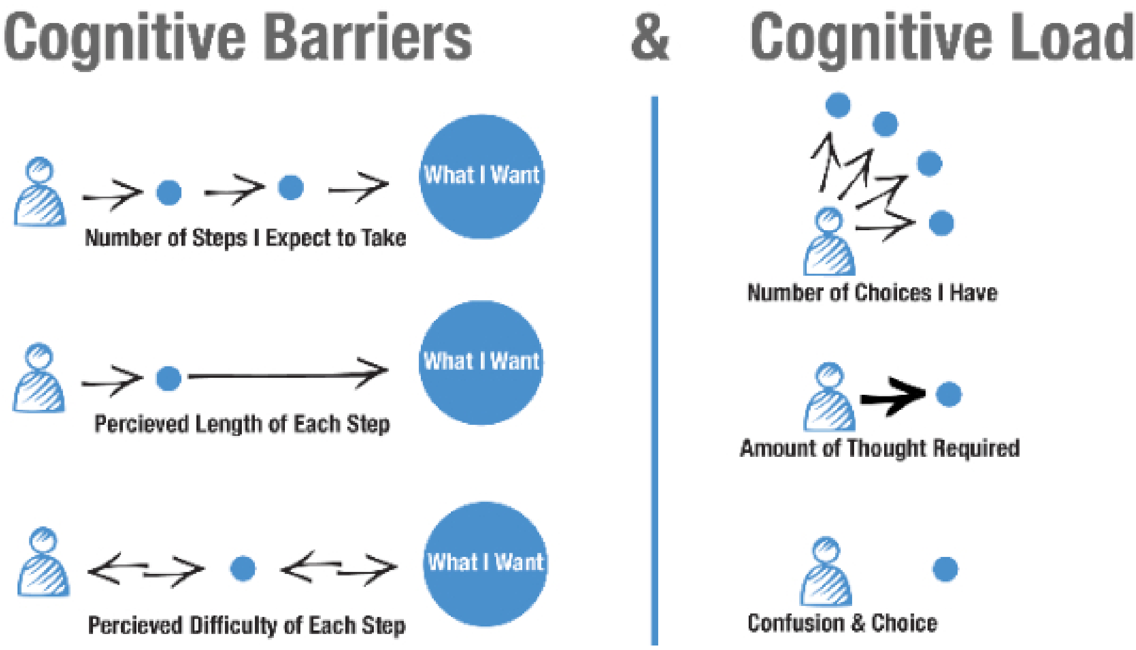

Figure 2.1: Cognitive load theory [9].

2.1 Cognitive Load

Cognitive load generates when managing new information creates load on finite working memory and this load can develop impotence to save new information in long-term memory. There are a few vital ideas that make up cognitive load theory. First is working memory, which is a type of cognizant constrained memory that can procedure finite number of information for a least amount of time. Research proposes that normal working memory can process around four "lumps" of data at any one time. Besides, working memory, there is long term memory which has no restrictions on capacity. The learning it stores is composed into "schemas", which are aggregate. Furthermore, capable ability is made by joining lower level schema into more multiplex higher-level ones [72]. Schema is a memory blueprint which is a conceptualization of a specific thought which discloses what to anticipate when experience it later on [75]. Whole schema can assist as a single lump within the working memory despite their complication [72]. In the 1980s, cognitive load was utilized as a hypothetical develop to clarify exploratory outcomes with next to no endeavor to straightforwardly measure load [6]. Around then, the main endeavor to give an autonomous pointer of load was to utilize computational models with quantitative contrasts between models utilized as intellectual load intermediaries [7]. The initial rating scale proportion of cognitive load was presented in the mid-1990s by Fred Paas [11]. Lessened performance on an optional task shows an expanded working memory load forced by the essential task. Furthermore, endeavors have been made to create psychometric scales that recognize classifications of cognitive load [54].

2.1.1 Types of Cognitive Load

The types of cognitive load which has been introduced: i) intrinsic cognitive load, ii) extraneous cognitive load and iii) germane cognitive load. Intrinsic cognitive load refers the interest made of a people by the intrinsic nature of information being educated. The load applied on a people relies upon the difficulty of task set or idea being exhibited, and an individual's capacity to comprehend the new information [75]. Intrinsic cognitive load is the "natural complexity of the topic," in light of the multifaceted nature of the material itself joined with the person's earlier learning. With additional earlier learning, innately complex material ends up less demanding. Along these lines, intrinsic cognitive load is relative. Framework and presenting material through its essential individual parts first is one approach to confine intrinsic load [72]. Nevertheless, the cognitive load coming from a complicated task can be diminished by separating it into littler, more straightforward strides for an individual to finish independently [75]. Extraneous cognitive load is referred as a negative cognitive load [72]. It is initiated by the dictates forced on individuals. It is increased by inappropriate approach towards someone to make that individual understand or learn something. Another reason of increasing extraneous cognitive load is make a task more complex than it needs to be and mislead with hindrance information. Efficient strategies can help decrease the load forced on an individual. Strategies like teach something by showing an image or graph is easier than showing lot of texts. It is also easier for learner to remember [75]. Germane cognitive load is appraised as positive load. This load originates from the specific procedure of learning [72]. It helps with adapting new aptitudes and other information [75]. This load alludes to the psychological assets gave to gaining and computerizing schemata in long term memory (see in Fig. 2.2). Learning can happen without the load however it can improve learning [53].

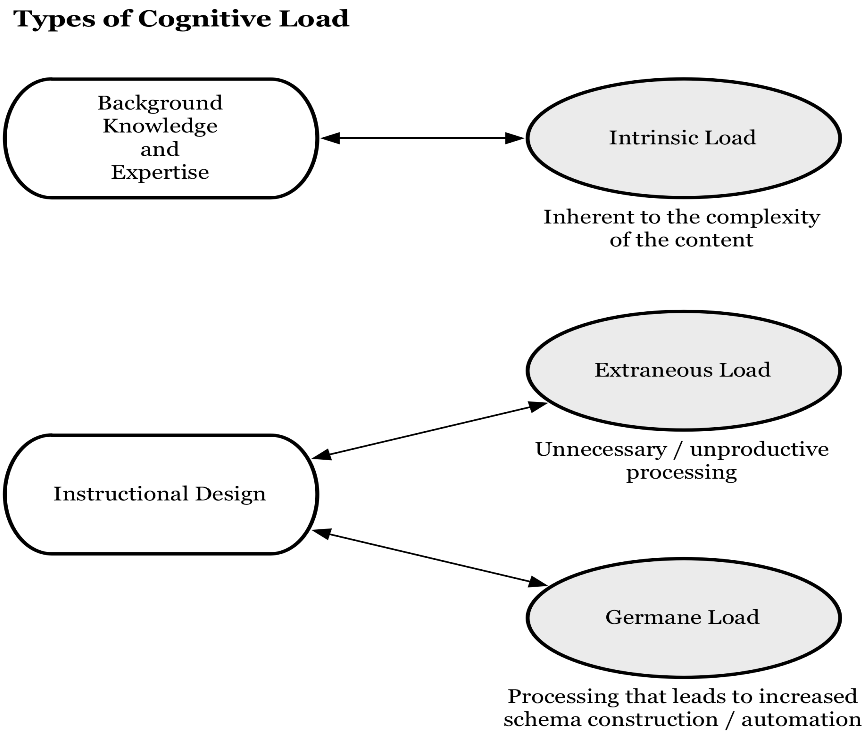

Figure 2.2: Different types of cognitive load [16].

2.1.2 Cognitive Index

Cognitive load theory (CLT) is a theoretical framework based upon human cognitive architecture of long-term and working memory constructs [82]. It relates these two topics: Working memory restraints with the instruction's effectiveness (see in Fig. 2.1). Learning process is executed in the working memory which has limited capacity and duration as it can hold 7 ± 2 chunks of information of a given time [16] and new information can store within about 15 to 30 seconds [3]. Three are the most common types of cognitive load, intrinsic, extraneous and germane, are described by the current CLT [82]. The inherent complexity of the task imposes Intrinsic load while extraneous and germane load are imposed by the way something has to be learned. To estimate participant's Cognitive Load, we are considering to use ERSD. Antonenko et al. illustrated that the alpha band power is increase during event-related synchronization (ERS) and decrease during event-related desynchronization (ERD) of the task interval with baseline interval [43]. Therefore, cognitive index of ERSD is calculated using the following equation:

$$\gamma = (\frac{\rho_b - \rho_t}{\rho_b}) * 100 \tag{2.1}$$

Here γ is a cognitive index, b is a base line interval of band power, and t is a test interval of band power.

2.2 Emotional State

Emotions are the most dependable measurement of complex psychological state considering three parts which includes physiological response, behavioral expressive response, and experience [5]. Emotional feelings can be express with arousal and valence [78]. Arousal is estimated by quieting or energizing information while valence is estimated by the negative and positive significantly of the information [36]. Emotional impact is an immense subject on which from the dimensional point of view, valence and arousal dimensions are supported by Russell [5]. Beta band is exhibited as an alarm perspective while alpha band is more prevailing in a relaxed. Hence, proportion of beta and alpha band of a sign of the condition of arousal of the VIPs' [36].

A few speculations of discrete emotions have been proposed by the theories of Darwin and James [[8], [1], [10]]. Psychology literature proposes that emotions amid exceedingly requesting exercises weaken psychological handling efficiency [58]. Similarly, the feelings experienced by members, named an incidental load, amid reproduction preparing may adversely influence learning exchange. Fraser et al. connected an approved system for announcing emotions and recognized that negative emotions encounters expanded the cognitive load of reproduction exercises and brought about lessened learning results [50]. During a task emotional state of VIP is also effected and possibly overpowers their cognitive load. If a task is not explained legitimately or the situation is not custom fitted to enhance information transfer, there is danger of exposing VIPs' to undue emotional stress and immoderate extraneous load on their working memory [14]. The emotions experienced by VIPs' categorized as an extraneous load, during performance information exchange can be influenced negatively. Fraser et al. has given an approved philosophy for detailing emotions and distinguished that negative emotional feeling can expand cognitive load and brought about decreased learning [50].

2.2.1 Arousal & Valence

Emotions and feelings are the most reliable indicators of complex psychological states. Considering the following three components it has been established: physiological response, behavioral expressive response and experience. Emotional influence is a vast topic on which from the dimensional perspective, valence and arousal dimensions are advocated by Russell [5]. We generally measure Arousal by calming or exciting information whereas, Valence is measured by the negative and positive effectively of the information. In order to regulate consciousness, awareness, and alertness; arousal plays an important role. Arousal is also designated as a response to a difficult challenge for which the subject has moderate skills [15]. Two bands (Alpha and Beta) are used in this measurement. Alpha band represents dominant in a relaxed mind whereas the Beta band represents as an alert or cautious state of mind. Thus, the ratio of these two can be used as an indication of the state of arousal of the participants as follows [36]:

$$\varphi = \frac{\beta}{\alpha} \tag{2.2}$$

Here φ is an arousal state, β is a beta band, and α is an alpha band.
To measure Valence, it is estimated based on both side of frontal inactivation which indicates the withdrawal response and approach response, are often called negative and positive emotion respectively. It can be calculated in the following equation:

$$\upsilon = \frac{\alpha_{F4}}{\beta_{F4}} - \frac{\alpha_{F3}}{\beta_{F3}} \tag{2.3}$$

Here υ is a valence, α_{F4} and α_{F3} are the alpha band of channel F4 and F3, and β_{F4} and β_{F3} are the beta band of channel F4 and F3.

2.2.2 Dimensional Model of Emotion

Russell and Cacioppo et al. have developed a dimensional models of emotion which has four parts [28]. James Russell established the Circumplex model of emotion also called as the circumplex model of affect to significantly represent how emotional states are connected [77].

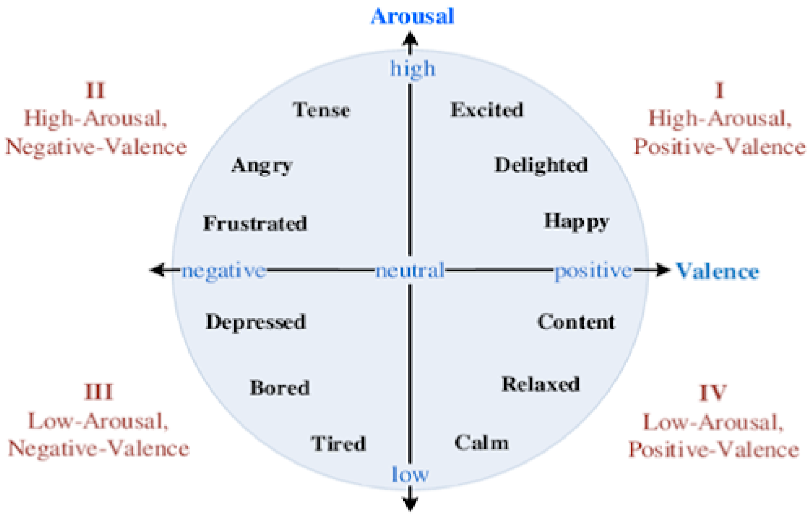

Figure 2.3: Emotional states [67].

There are four types sparking emotions. To spark an emotional response that increments long term memory storehouse, it's best to go for the positive valence. High-arousal, high-valence emotions make the most impactful reaction (see in Fig. 2.3). High-arousing emotions such as nervousness, excitement and stress are normal. High arousal increased heart rate and blood pressure and a condition of sensory alertness, mobility and readiness to respond. However, low arousal decreased heart rate and blood pressure and it does not require much alertness. Motivational speech are a case of positive-valence, high-arousal occasions. They rouse positive activity. Negative-valence, high-arousal is an unsafe strategy. It implies individual pushing antagonistic and tension inciting emotions, not what a great many individual need to do. Low-arousing emotions such as depression, relaxation and tiredness are common. Low-arousal, negative-valence are emotions that are both negative and quiet. Truly, not a procedure that works regularly on the grounds that it doesn't spur activity. Despite the fact that arousal is the thing that gets consideration much of the time, positive-valence is a typical methodology to frame positive environment [78].

2.3 EEG Machine

An electroencephalogram (EEG) machine is a useful tool which creates a clear image of the electrical movement of the brain. It is useful because of its application on both medical diagnosis and neurobiological research. The important elements of an EEG machine include electrodes, amplifiers, a computer control module, and a monitor device (see in Fig. 2.4). Fabrication completes in three steps, first one is including separate production of the different components then assemble task is done and lastly packaging finishes. From the development time of the prior twentieth century, this machine keeps progressing [27]. It is expected that this machine will provide different types of essential discoveries both in basic brain feature and cures for different neurological diseases. The work of an EEG machine relies upon the reality that the nerve cells inside the brain are continuously making minor electrical signals. Information transmits to the whole body electrically with the help of nerve cells or neurons. They make electrical driving forces through diffusion of calcium, sodium, and potassium particles over the cell layers [42]. The function of EEG machine is a one kind of non-invasive procedure. It captures the waves as sinusoidal shapes and measurement is done by from peak to peak, approximate range is from 0.5 to 100 μV in amplitude [57].When an individual engages in thinking, reading, or watching television etc. various types of work, that time various parts of the brain receives stimulation. This creates diverse electrical signals which can be observed by this machine. We all know that there are four mind states (alertness, rest, sleep and dreaming) which lead to distinctive EEG displays. All the states have related brain waves named alpha, beta, theta, and delta. Each of these brain wave designs include distinctive frequencies and amplitudes. EEG machines are being utilized for various purposes. Different types of diseases like seizure disorders, brain tumors and head injuries etc. are analyzed by this machine. Information collected from this machine can be translated by a computer and gives a geometrical image of the brain's action [27]. Doctors can easily find out where the real brain action issue remains.

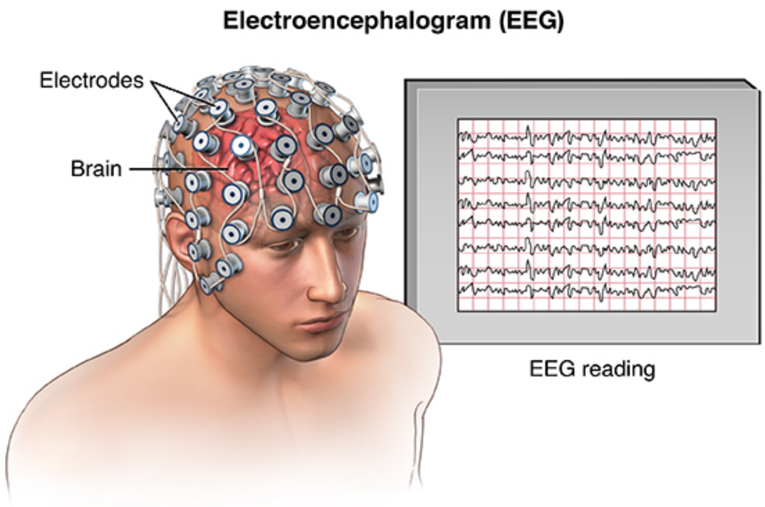

Figure 2.4: EEG Processing [4].

2.4 EEG Band

During Electroencephalogram (EEG) process, small electrodes and wires are used to attached on the surface of head to measure and record brain waves. Brain waves are something when billions of nerve cells create very small electrical signals in a form of patterns [74]. EEG waveforms are usually classified based on their frequency, size, amplitude and recorded portion of the scalp [19]. Each of them is known as EEG bands (see in Fig. 2.5). Classifications are described below-

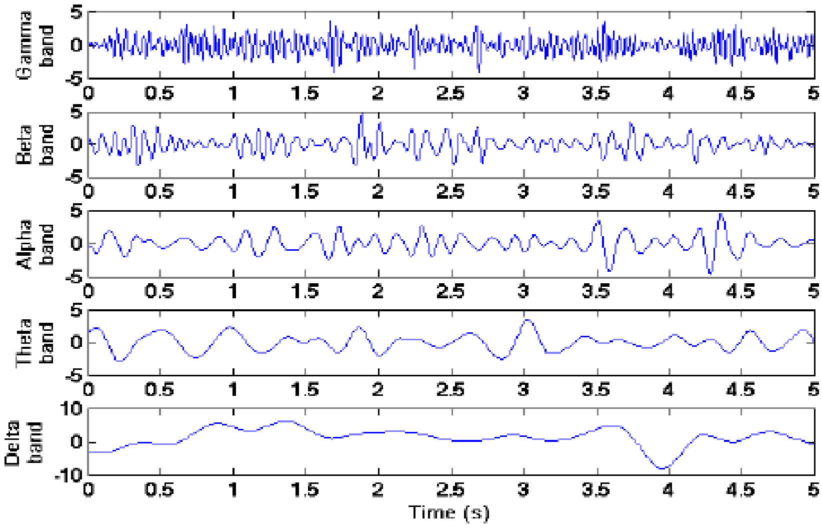

Figure 2.5: Types of EEG bands [7].

2.4.1 Alpha Waves

Frequency range of alpha wave is 7.5 to 12.5 Hz. At this time brain is non-aroused. It rises because of synchronous and coherent electrical movement of thalamic pacemaker cells [74]. Brain enter slightly higher amplitude It occurs at the previous stage of human sleep. Human feel relaxed and very soon start for falling asleep. Too much alpha waves causes daydreaming, not able to focus on work. On the other hand, fewer alpha waves make human stressful, human suffer from anxiety and insomnia. Optimal result of this wave is relaxation [19]. Alpha waves are usually seen among adults [74]. As example, a person after completing a particular task, sits down to take rest. This state is because of alpha waves. Meditation is also done by alpha waves.

2.4.2 Beta Waves

For beta wave, frequency range is greater than 13Hz [23]. At this time brain is aroused. Human can actively connect with mental activities. Usually they are called high frequency low amplitude waves. They are engaged in cognizant thought, consistent considering, and tend to have a invigorating influence. Too much beta waves cause stress, anxiety and also can't feel relax. On the other -side, less amount of beta waves causes ADHD. Depression and destitute cognition [19]. Coffee, various types of energy drinks increase the rate of beta waves. That time human can give their full focus on work, able to solve many issues with logical thinking [64].

2.4.3 Theta Waves

Theta is very slow rate waves where frequency range is between 4 to 8Hz [23]. Human experiences deep and raw emotions. They are known as light meditation and sleeping waves. Optimal result is making passionate, intuition. Theta waves when increase it causes hyperactivity even one can't give proper attention. Also, this wave responsible for stressful tasks and might occur depression. They are differently connected with task difficulty. Increase level of theta waves can cause higher task difficulties [[60], [64]].

2.4.4 Delta Waves

Delta is the slowest waves among four of the other waves because of having frequency range between 0.5 to 4Hz [23]. Here brain activity slows down so brain can go for deep sleep. Having proper amount of delta waves make human brain totally restored after waking up from a proper 6 to 7hr sleep. More sleep increases more delta waves. They provide abnormality among awake adult [74].

2.4.5 Gamma Waves

Here, frequency range from 30 to 200Hz. That means this type of waves create comparatively fast waves then others with very small amplitude. On the basis of frequency range gamma waves can be divided into 2 portions, one is low gamma-waves oscillations (30–60 Hz) and other one is high gamma-waves oscillations (60–200 Hz) [69]. They are able to link information from all parts of the human brain. Basically, gamma waves can influence the entire brain easily. They also put great impact upon complex cognitive functions [60].

2.5 Human Brain

Human brain is a one kind of wondrous organ among all human body parts. Primary basic work of this brain is spreading messages to those all other parts by the help of nerves. The brain weighs approximately 3.3 lbs. (1.5 kilograms) and contains a whitish-pink appearance. Main components are nerve cells (neurons) nerve fibers (axons and dendrites). These neurons are engaged through synapses. Here, a few nerves are directly connected to the brain. Others got to reach the brain through a sort of control line down the back, called the spinal line. This spinal line along with brain is responsible for making the central nervous system. Human brain not only can control one's organ, but also able to think and remember. This portion of the brain is known as mind. Also, to protect the brain there are twenty-eight bones which make-up the skull. Among them eight bones are for interlocking plates which create the cranium. Cranium has minimum weight that provide maximum protection to the brain. Rest of the bones engage in making up the face, jaw and other parts of that skull [80]. According to computer science point of view, brain acts just like the processor of an individual body, which receives information from various sensory systems (organs) like visual system (eyes), auditory system (ears), somatosensory system (skin) etc., processes it, interprets it, analyze it, then makes selection. These are then transmitted back to the various organs [71].

For the visually impaired people, case is quite different. Visually impaired people (VIP) are those whose eye function is hindered due to congenital, heredity or acquired conditions such as age-related changes, trauma, infection or disease [13].

Their brain can't receive information properly from visual system (eyes). The neural system that supports our vision begins with the retinas. These are actually outgrowths of the brain, holding typical brain cells as well as specially designed light-sensitive detectors which are rods and cones. The cones function in daylight conditions and provide color vision. The rods function under low illumination and provide vision only of shades of gray. In a visually impaired person these rods and cones do not function properly and hence they fail to provide light signals to the brain that they receive from their environment [55].

Brain plays a very crucial role in causing visual impairment. According to Steven Feldon, many diseases that affect the brain may heavily affect our vision as one-third of our brain deals with the processing of vision in one way or another. Once an individual suffers visual impairment, there comes a period of time that the individual takes to adjust to the shock of experiencing complete darkness. However, with time the brain adjusts itself and receives signals through its other sensory organs. Scientists from the UCLA Department of Neurology have approved that blindness affects the human brain to go through certain structural changes, which indicated that the brain has the capability of restructuring itself to adapt to a loss in sensory input. It was discovered that visual regions of the human brain were lesser in volume in blind persons compared to those of the sighted persons [79]. Nonetheless, for non-visual areas, they were bigger in the blind. It indicates, the brains of blind persons are compensating for the lessened volume in areas ordinarily devoted to vision with enlarged volume of brain areas of other parts of the brain.

In a carefully conducted research over a closed group of blind people consisting of two blind age groups; one who got blind before the age of 5 years and the other who lost their eyesight after the age of 14. It was found that, the early-blind people differed from the later blind people in the brains corpus callosum that aids in the transmission of visual messages among the two hemispheres of the brain. The researchers assume it may be due to the reduced quantity of myelination in the absence of visual input. Myelin, is a fatty sheaf which surrounds nerves and allows for quick communication, grows speedily in the very young. When the onset of blindness happens in adolescence or later, the growth of myelin is already relatively complete that is why structure of the corpus callosum might not be strongly dominated by the loss of visual input [79].

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2.6 Machine Learning

Machine learning is used to extract knowledge from data. The research area in machine learning is vast and various. Mostly machine learning is all about predictive analysis [63]. From Google's automatic recommendation to recognizing people in photos and many devices and renowned services have machine learning at their core.In recent years, the use of machine learning methods have spread all over in everyday life.

We require machine learning in the accompanying cases:
(i) Human ability is missing. Such as Exploring on Mars.
(ii) People can't clarify their mastery. For example, Speech Recognition.
(iii) Arrangement changes with time. For example, temperature control [65].

Machine Learning can be three types depending on the input data and desired output: Supervised learning is where input and output is known and the system is trained using both the inputs and outputs. Unsupervised learning is where only input data is known and no corresponding output data is available. There is another learning if you have a large amount of data and only few of the data are labeled called semi-supervised algorithm [39].

2.6.1 Supervised Learning

Supervised Learning has a set of predictors and a target variable which is learned to be predicted from that set. These set of variables generate a function that maps inputs to desired outputs. The training process continues until the accuracy level is desirable on the given training data [34]. Classification and regression are the two major types of supervised machine learning algorithms.In classification, main target is to predict a class label from a set of predefined lists of possibilities. For regression tasks, the goal is to predict continuous number. There are some supervised algorithms which are commonly used such as K-Nearest Neighbor, Linear Regression, Naïve Bayes, Decision Tree, Random Forest, Support Vector Machine, Neural Network and Gradient Boosted Regression Trees.

K-Nearest Neighbor

The k-Nearest Neighbor algorithm finds the closest data points in the training dataset to predict. KNN algorithm is based on feature similarity. KNN can be used for both classification and regression predictive issues. Here "K" defines the number of neighbors the algorithm will consider while predicting [41]. It is one of the simple learning algorithms which depends upon the prediction that "things that look alike must be alike". The main theme is memorizing the training set and after that need to predict the label of any new instance. It depends upon the labels of its closest neighbors in the training set [83].

Linear Regression

Linear regression is famous for modeling relationship among real valued outcome and explanatory variables. It is known as statistical tool. It can not able to compute the sample complexity by the help of VC dimension as this is not a binary prediction task. For this purpose, computation depends upon the "discretization trick" [83].

Linear models are models that make a forecast of using a linear function of the input features.

$$y = a_0 + a_1x_1 + a_2x_2 + ... + a_nx_n \tag{2.4}$$

Here, we can see the linear relationship where y is the response, a values are called the model coefficients, a_0 is the intercept, a_1 is the coefficient for x_1. At the time of training a linear regression model, actual target is finding out a coefficient for the linear function that best describe the input factors [61].

Naïve Bayes

Naïve Bayes uses the Bayes Theorem. Rev. Thomas Bayes introduced this theorem. Basic ideology of Naïve Bayes is conditional probability. Conditional probability is a one kind of probability where something will happen, given that something else has already occurred. For a document d and a class c, and using Bayes' rule,

$$p(c|d) = \frac{p(c) * P(c)}{P(d)} \tag{2.5}$$

Here, classes are the categories the documents belong. P(c) is the total probability of a class [51].

Decision Tree

Decision Tree uses a tree-like model of decisions which can used to predict class or value of target variables from training data. Each internal node of the tree represents an attribute, and each leaf node represents a class label. Decision Tree is rely on the procedure of partition and conquer [17]. It is known as intuitive predictor. Predictors that are created by human programmer look like decision tree. It is seen that VC dimension of decision trees along with k leaves is k. Also, MDL paradigm is suggested to learn decision trees. The main challenge behind decision tree is, it is computationally difficult to learn [83].

Random Forests

Random forest consists of multiple decision trees which are merged to get more accurate and stable prediction. Every tree itself doing a prediction, however, there is always a higher chance of overfitting. If we build many trees, the average result of the trees will have lower chance of overfitting. While growing trees, random forest includes additional randomness. Random forests split a node in the basis of the best feature among a random subset of features rather that searching for the most valuable feature [22].

Support Vector Machine

Support Vector Machine Unlike other classifiers are mainly pivoted on the points that are very tough to tell apart. The idea behind this approach is that if a classifier is good at the most challenging comparisons then the classifier will even express the easy comparisons better. SVM is a supervised learning method and it is based on statistical learning theory. It is one of the best approaches for data modeling. It solves both classification and regression challenges [83]. The principal goal of the support vector machine is to design a hyperplane (see in Fig. 2.6). All training vectors will be categorized in two classes by this hyperplane. The most excellent choice will be the hyperplane that spares the maximum margin from both classes [30].

Support vector machine (SVM) acts as a very effective tool because one can learn linear predictors at high dimensional feature spaces. This machine learning method mainly deals with sample complexity challenge by doing searches for "large margin" separators. It is helpful for learning half-spaces with a certain pattern of advance knowledge, especially for large margin. Hard-SVM search for the half- space, which separates the data with perfection along with largest margin. On the other hand, soft-SVM does not try to predict separability of the data and to some extent, it permits all the arises constraints to be violated. Soft-SVM is considered as a relaxation of hard-SVM rule. This is applicable in spite of not having the training set linearly separable [83].

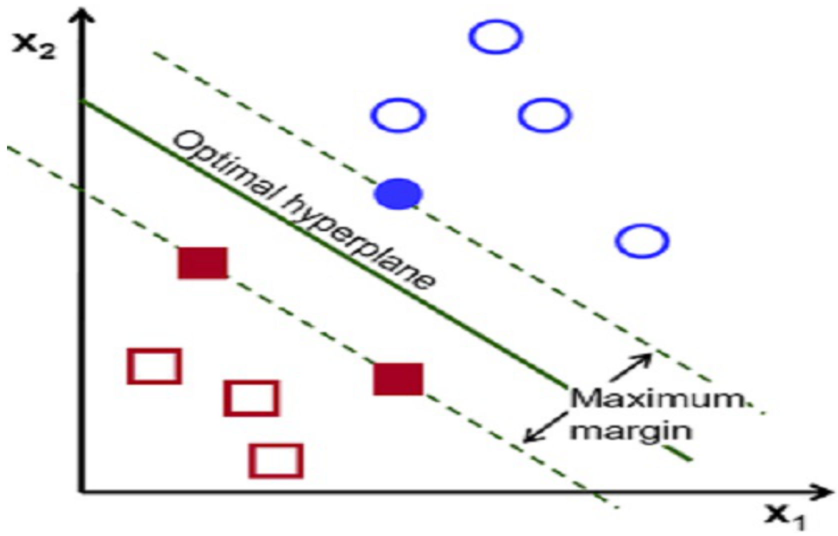

Figure 2.6: Basic SVM Diagram [12].

One of the qualities of SVM are the training is relatively simple and easier. It scales comparatively better to high dimensional data and also the trade-off among classifier complexity and errors will be controlled expressly. The major disadvantage is it requires for a well kernel function. Main application of SVM algorithm is it has been utilized for solving pattern classification problems [33]. Besides, in face detection, text in hypertext categorization, classification of images and bioinformatics, handwriting recognition task are some the commonly used applications [83].

For having satisfactory result, SVM is being used for data classification. Training and testing data are included in a classification task. They are composed of few data instances. One target value and several attributes are included at each instance in the training set. Main aim behind SVM is to create a model that will be used for predict target value of data instances in the training set that are provided only the attributes [33].

Neural Network

An artificial neural network is a one kind of model whose computation influenced by the formation of neural networks in the human brain. The main theme is there are many neurons which can be connected with one another by the help of communication links so that it can carry out complex computations. Through a graph it can be described where nodes indicate those neurons and each of the edges show the output of some neuron to the input of another neuron [83].

Neural Network is more complex, the basic idea is to have three layers of nodes. The nodes have values of 0.0 to 1.0, where 0 represents off and 1 present on. There are many values in between. The three layers are an input layer, an output layer and a hidden layer in the middle. There are weighted connections between the layers. The learning process takes the inputs and outputs and update the hidden layer such that calculated output get as close as possible from the desired output [59].

S(n) indicates size of graphs and it helps to illustrate hypothesis classes of every predictors which has run time of O(s(n)). Also, here sample complexity depends polynomially upon s(n). For this reason, hypothesis classes considered as an excellent choice [83].

Gradient Boosted Regression Trees

Gradient boosted regression trees is like random forests, combines multiple decision trees. Gradient boosting builds trees in a serial manner. In the serial each tree tries to correct the mistakes of the preceding tree. Gradient boosted regression trees don't randomize. Instead, it uses pre-pruning. Gradient boosting usually combines many simple models like shallow trees. Each tree can able to provide good predictions on part of the data, and so more and more trees are added to iteratively improved performance [37].

2.6.2 Unsupervised Learning

Unsupervised algorithm is used where there is no known output, no teacher to instruct the learning algorithm. Unsupervised learning procedures are utilized when no ground truth is accessible. They will likely distinguish structures in the info space that could be utilized to disintegrate the issue and encourage nearby model building [40]. There are two kinds of unsupervised learning e.g. association and clustering. Clustering is a grouping of data and association is where you want to discover rules that describes large portions of the data. Most common method is cluster analysis. Common clustering algorithms included: hierarchical clustering, k-Means clustering, MiniBatch k-Means, Gaussian mixture models and self-organizing maps.

Hierarchical clustering

Hierarchical clustering creates a cluster tree and groups data. The tree is a multilevel hierarchy. In this hierarchy clusters at one level are joined as clusters at the next level. This joining is determined in a greedy way. In bottom up approach each observation starts as a separate cluster. Then, it continues executing two steps until all the cluster merges together: (i) identify the two clusters that are closest together, and (ii) merge the two most similar clusters [18].

k-Means clustering

K-Means clustering algorithm finds groups in the data. The algorithm determines which data points belongs to which of the K groups based on the features that are provided. Based on the feature similarity data points are clustered. Resulting groups are defined by each centroid of a cluster which is a collection of feature values.

$$j = \sum_{j=1}^{k} \sum_{i=1}^{r} \mid\mid z_i^{(j)} - C_j \mid\mid^2 \tag{2.6}$$

Here, k=number of clusters, j=objective function, r=number of cases, C_j=centroid for cluster j, z_i = case i [4].

MiniBatch k-Means

MiniBatchK-Means is an amended form of k-means clustering. Time complexity of k-means clustering is much higher.On the other hand, MiniBatchK-Means algorithm takes little clusters which are haphazardly chosen from the dataset for each iteration. It at that point relegates a cluster to each data point within the batch. The data points are given depending on the previous locations of the cluster centroids. Afterwards, based on the new points from the batch, it starts upgrading. This update is a gradient descent update, which is noticeable speedier than a normal Batch K-Means [70].

Gaussian Mixture Models

To find out the origin of all the data points which are participated from a mixture of a finite number of Gaussian distributor's with unknown parameters, we use a probabilistic model called Gaussian mixture model. When query data points are assigned to the multivariate normal components we can cluster Gaussian mixture models. By this process we can maximize the component posterior probability the data. We do not need to clarify about the subpopulations of specific data's rather the mixture model automatically learn about the subpopulations [12].

Self-Organizing Maps

A self-organizing map is better alteration of artificial neural network which builds a two-dimensional map of an issue space utilizing unsupervised learning. The contrast between a self-organizing map to other approaches is that a self-organizing map utilizes ruthless learning. The goal is to behave like the way visual cortex of a human brain observes objects. The idea is that every diverse input will have variety of responses from the nodes in the network. A self-organizing map makes utilize of competitive learning where the nodes specialize in the long run [9].

As per the requirement of our dataset, we have used Support Vector Machine (SVM). Since our EEG signal is non-stationary and SVM is best approach to deal with this type of dataset. Moreover, among all the algorithm of machine learning it is less complex, beneficial and easy to use.

Chapter 3

Experimental Setup

In this chapter, a brief overview of site and route is presented in the section 3.1, participants in the section 3.2, and data collection in the section 3.3. In the section of site and route, explanation about indoor environment for participants is described. In the participants section, there is a brief discussion about their health condition of VIPs either mentally and physically. Finally, in the data collection section, detail discussion are given about the dataset.

3.1 Site and Route

We have worked on a benchmark dataset which was acquired in the University of Iceland [[82], [60], [86]]. The experiment was arranged within the premises of university which included two restaurants, a bookstore, classrooms, reading rooms and different service units [[82], [60], [86]]. For the help of our study, this dataset gave adequate complex indoor environments. They took the VIP through conditions where various dimensions of stress were oftentimes happen (i.e. of variation of complexity and difculty). VIP caretakers and O&M instructors also took part in this experiment.

In their dataset, the route connected the entrance at the back of the building (START) to the main entrance at its front (END) and encompassed ve distinct environments representable of a variety of indoor mobility challenges. Specially, participants needed to enter through automated entryways, utilize a lift, move over a bustling open space, and stroll down a substantial winding staircase. The route was generally around 200 meters long and took overall 5 minutes to walk (range = 4-8 minutes) [[82], [60], [86]].

3.2 Participants

Their dataset contain 9 healthy visually impaired adults with different degrees of sight loss [[82], [60], [86]]. Each of them completed the route on their own in an educational building (6 female, average age = 41 years, range = 22–53 years). They were recommended to walk using their navigation aids if they wanted so and were attended by their own O&M instructor with the goal that they feel comfortable and safe. Participants were advised to abstain from smoking typical or e-cigarettes and consuming caffeine or sugar (e.g., coffee, coke, chocolate) about 60 minutes before the test. Enrollment depended on volunteering and all VIP were fit for providing free and educated assent. The study was approved by the National Bioethics Committee of Iceland. All information was anonymized to validate the research and to avoid bias before analysis.

They also mentioned, all participants effectively experience indoor situations other than where they live every day: three works all day, three works part-time, and three go to educational/vocational establishments. There were two contributors, who regularly use white cane while walking, they felt safe enough with no guide to walk the indoor course. While reviewing their experiences about the stress of mobility over the previous year, four reported to be unchanged, another three of them believed to become easier, while rest of two admitted to be harder [[82], [60], [86]].

3.3 Data Collection

The researchers captured EEG using the Emotiv EPOC+, a mobile headset with 16 dry electrodes registering over the 10-20 system locations AF3, F7, F3, FC5, T7, P3 (CMS), P7, O1, O2, P8, P4 (DRL), T8, FC6, F4, F8, and FC4 (sampling rate fs = 128 Hz) [[82], [60], [86]]. Given that, the practical restraints included in a mobility study, EPOC+ was chosen as it gives a decent trade off between performance (i.e., amount of channels and quality of the recorded EEG signals) and usability (i.e., flexibility, rehearsal time and user well-being) as for other profitable remote EEG frameworks.

Participants walked the planned route 3 times (i.e. trail 1, trial 2, and trial 3) for training purposes. To enable the VIP to acclimate with the course they were given directions only during the first walk. They were advised to overlook superfluous head movements just as conversing with their O&M instructor except if there was an emergency. Video and sound were captured by means from a cell phone camera to categorize data annotation accurately (observing behaviors across the various indoor environments) and synchronization (start/end of walk, environments and obstacles). Toward the finish of the third walk, members were approached to clarify distressing minutes along the route [[82], [60], [86]].

Chapter 4

System Implementation

In this chapter, system work-flow is described in the section 4.1 and explanation of system work-flow is presented in section 4.2. The whole concept of our research is to explore knowledge about cognitive load and emotions of VIPs by analysing EEG signals during navigation so that they can face less difficulty in their life.

4.1 System Work-flow

The work flow of our thesis is described in the Fig. 4.1. Firstly, the EEG signals are captured through surface electrodes placed on the skull using Emotiv headset placement scheme. Then, a pre-processing is applied to eliminate unwanted signals from EEG signals. After removing the disturbance signals, band and feature extraction techniques are applied for feature extraction of EEG signals and then theses features are sent to a classifier to detect cognitive load and emotions.

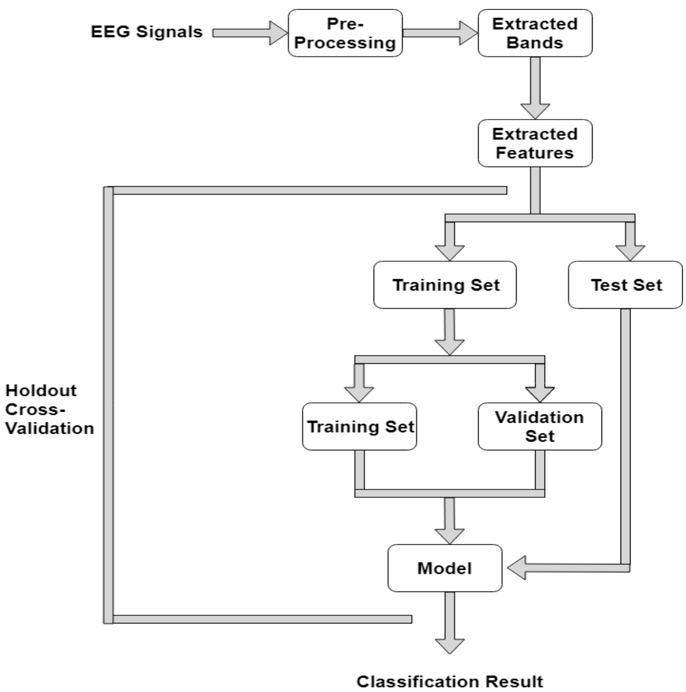

Figure 4.1: System Work-flow.

4.2 Explanation of System Work-flow

EEG is a widely acceptable and reliable technique for detection of cognitive load and emotions [60]. Therefore, we have captured EEG signals from the VIPs to measure cognitive load and emotions.

4.2.1 Pre-processing

It is an important steps in EEG signal processing as EEG signals are representing temporal resolution with affected by different types of noises. Mean of the resting state (i.e., consider it during capture EEG signals) is applied to remove unwanted signals from actual EEG signals [44].

4.2.2 Bands Extraction

Different bands have extracted after pre-processing. We have used "db8" wavelet function to extract different bands (e.g. alpha,beta, so on) from signals [66]. The reason we used "db8" wavelet function is, it is better for non-stationary EEG signals [68]. Decomposition flow of "db8" wavelet function is given in Fig. 4.2.

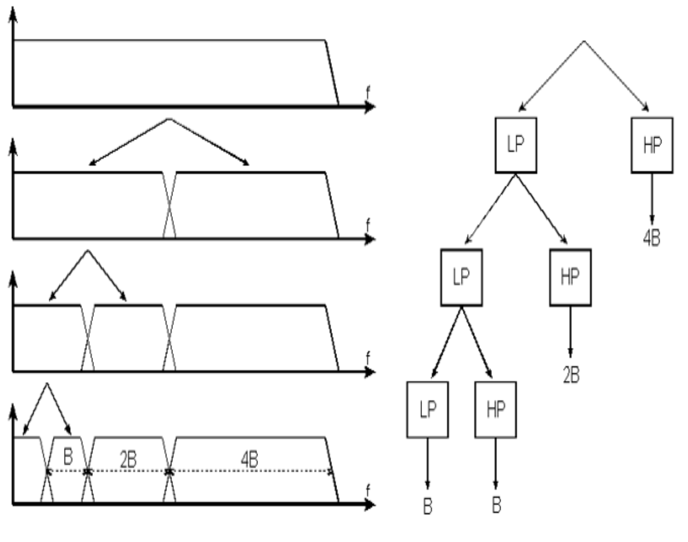

Figure 4.2: Wavelet Decomposition [66].

In our research, five bands are extracted from EEG signals namely, gamma(30-60 Hz), beta(13-30 Hz), alpha (7.5-12.5 Hz), Delta (0.5-4 Hz), theta (4-8 Hz) (see in section 2.4). Alpha, beta,and gamma bands are play significant role for cognitive load and emotions detection [[60], [82]].

4.2.3 Features Extraction

EEG signal is complex, non-stationary and random in behaviour. EEG signals are viewed as stationary just within the short interim of time, however, the signals are non-stationary over longer time frames. As aftermath, many linear feature extraction processes often apply brief windowing method to EEG signals to fulfill this demand. Yet, this belief is for normal brain condition but for mental and physical action this is not acceptable [35]. Therefore, we have considered short term (i.e., one second) window for feature extraction. We have extracted different entropies as features considering specific bands. Before feature extraction, we have split these bands into short time window (i.e., one second). Necessity of entropies and their details description are listed below:

Entropy

The theory of entropy, initially got from thermodynamics, has been effectively applied to EEG study [31]. Shannon brought this theory of entropy into the field of information theory and characterized what is usually known as statistical entropy.

$$E = -\sum p(w)log(p(w)) \tag{4.1}$$

The idea of entropy to time series like electroencephalography (EEG) is an approach to estimate the amount of unpredictable or arbitrary pattern in the signal which is similar to the amount of information kept in the signal. Entropy determines in the time domain basically divide the signal into segments that are then set side by side to find the sameness either from main signal or transformed signal. This regularly relies upon a couple of major parameters: (i) the length of segment chosen, (ii) the transformation of the signal and (iii) the distance metric or the way the segments are compared. Other kinds of entropy initially change the EEG signal into the frequency domain utilizing distinctive strategies such as Fourier Transform or more difficult strategies such as wavelets [84].
There are different types of entropy. Some of them which we have decided to use are discussed below-

Approximate Entropy

Approximate entropy (ApEn) is a recently developed statistic, quantifying regularity and complexity. Approximate entropy quantifies the unpredictable characteristics of fluctuations in a time series. The development of ApEn was made to collect data where the measurement is challenged due to the length of data signals, e.g., in heart rate, EEG, and endocrine hormone secretion data sets. ApEn indicates that there won't be a consecutive series of 'similar' observations. Rather a complex set of data will be followed each time a measure is taken. A time series that contains repetitive patterns has a relatively small ApEn. On the other hand, a less predictable (i.e., more complex) process has a higher ApEn indicating higher levels of delicacy [20]. Researchers able to measure the complexity within relatively small data sets based on significant experimental comparisons to regulate groups by the help of this entropy. ApEn might extricate among noisy and chaotic time series with a comparatively short variety of data points [52]. The rule for computing approximate entropy has been revealed everywhere. It is a one kind of mathematical algorithm which is extremely sensitive to its input parameters. This algorithm bring about a delayed reconstruction Y1:N where N means data points along with parameter m and lag r. After that at point i which is within range points, we get:

$$N_i = \sum_{i=1, i\neq k}^{N} 1(\parallel Y_i - Y_k \parallel_\infty < R) \tag{4.2}$$

Here, 1 stands for indicator function and R indicates radius of similarity. Last step is approxEnt $=\phi_m$-ϕ_m+1 where [87]:

$$\phi_m = (N-m+1)^{-1} \sum_{i=1}^{N-m+1} \log(N_i) \tag{4.3}$$

Shannon Entropy

Shannon entropy can be used to quantify the level of noise in a signal [35]. It is a non-linear measure determining the degree of complexity in a time series [47]. Shannon entropy is one in all the foremost necessary metrics in information theory. Since this entropy is the measure of randomness, it can be used as an effective way of pertaining data regarding the level of disorder where higher entropy will indicate higher level of complexity [88]. Claude E. Shannon was first described this concept [2]. Entropy contains helpful data and options which are distinctive to people, thus entropy is often used for person identification. The use of probabilities to explain a situation causes some uncertainty. That means this entropy overall works as the measurement of order and uncertainty. In brain-computer interface systems, the level of chaos of the system can be measured by this entropy [62]. Let us suppose a finite discrete random variables F=f_1, f_2, ..., f_m, f_i $\in$R^d. Hence, the equation will be [62]:

$$H(F) = -g \sum_{i=0}^{m} p(f_i) \ln\left(p(f_i)\right) \tag{4.4}$$

Here g is the positive constant that plays the role of a measuring unit and $p(f_i)$ indicates the probability of f_i which belongs to F set. For $p(f_i)$, equation is [62]:

$$\sum_{i=0}^{m} p(f_i) = 1 \tag{4.5}$$

Log Energy Entropy

$$E_{Lenergy}(s) = \sum_i \log(s_i)^2 \tag{4.6}$$

Within convention log(0)= 0.
Here, s is the given signal and (s_i)i is the coefficients of s within an orthonormal basis. Moreover, Entropy (E) estimated by this $E_{Lenergy(s)} = \sum_i$E$_{Lenergy(si)}$ formula [90].

Threshold Entropy

$$E_{threshold}(s_i) = 1 \tag{4.7}$$

if —(s_i)—¿p and 0 elsewhere so $E_{threshold}(s) = \#\{i \;\; such \;\; that \;\; |s_i| \leq p\}$ is the number of time instants when the signal is greater than a threshold p.
Here, s is the given signal and (s_i)i is the coefficients of s within an orthonormal basis. Moreover, Entropy (E) estimated by this $E_{(s)} = \sum_i \mathrm{E}_{(si)}$ formula [90].

Sure Entropy

$$E_{sure}(s) = n - \#\{i \;\; such \;\; that \;\; |s_i| \leq p\} + \sum_i min(s_i^2, p^2) \tag{4.8}$$

Here, s is the given signal and (s_i)i is the coefficients of s within an orthonormal basis. Moreover, Entropy (E) estimated by this $E_{(s)} = \sum_i \mathrm{E}_{(si)}$ formula [90].

Norm Entropy

$$E_{norm}(s) = \sum_i |s_i|^p = \parallel s \parallel_p^p \tag{4.9}$$

Here, s is the given signal and (s_i)i is the coefficients of s within an orthonormal basis. Moreover, Entropy (E) estimated by this $E_{(s)} = \sum_i \mathrm{E}_{(si)}$ formula [90].

Spectral Entropy

Spectral entropy of a particular signal acts as the measurement of its spectral power distribution. That means it quantify the amount of disorders in a given system. This idea came from Shannon entropy or information entropy. This entropy basically differentiates the distribution of energy. It considers its signal's as a probability distribution from normalized power distribution within the frequency domain and after that estimates the Shannon entropy of it [89]. This entropy works in both ways. It can detect silence and also voice as it has voice activity detection. For this unique characteristic, this is also used in speech detection. It can capture the formants of a distribution. It plays a significant role when it comes at speech tracking. Speech can be recognized through this peak capturing ability [29]. This entropy is used to detect fault and diagnosis through feature extraction. As feature this is also used in biomedical signal processing.

For a particular signal x(n), the power spectrum is S(m) = $|X(m)|^2$, here X(m) indicates discrete Fourier transform of x(n). The probability distribution P(m) will be:

$$P(m) = \frac{S(m)}{\sum_i S(i)} \tag{4.10}$$

After that spectral entropy (H) will be:

$$H_{spectral} = -\sum_{m=1}^{N} P(m) \log_2 P(m) \tag{4.11}$$

By normalizing:

$$H_{normalized} = \frac{\sum_{m=1}^{N} P(m) \log_2 P(m)}{\log_2 N} \tag{4.12}$$

Here, N= total frequency points. $\log_2$N indicates maximum spectral entropy. Now the probability distribution will be:

$$P(m) = \frac{\sum_t S(t,m)}{\sum_f \sum_t S(t,f)} \tag{4.13}$$

Where S(t,f) indicates time frequency of power spectrogram. Then,

$$H_{spectral} = -\sum_{m=1}^{N} P(m) \log_2 P(m) \tag{4.14}$$

Probability distribution at time t is:

$$P(t,m) = \frac{\sum_t S(t,m)}{\sum_f S(t,f)} \tag{4.15}$$

Final equation of spectral entropy at time t will be [89]:

$$H(t) = -\sum_{m=1}^{N} P(t,m) \log_2 P(t,m) \tag{4.16}$$

Entropy having low value causes small variations. That means presence of a constant similarity of energy. On the other hand, higher value of this entropy point out disorders, variations and irregularity. Estimation of entropy within EEG signals is applied to determine the change rate of EEG signals with respect to time both in frequency and in phase domain [73].

Permutation Entropy

Permutation entropy is a measure for arbitrary time series based on analysis of permutation patterns. It takes temporal order of the values into account then estimate complexity of time series. Moreover, it is a simple and effective process to define embedding parameters or choose couplings between previously mentioned time series. It also can be employed as a solution to the most important problem of brain studies: measuring dynamic change of the brain state. In addition, accurate detection of this transition between active and inactive state can be a pioneer in future of brain study. So, as permutation entropy is already an effective method of measuring complexity of chaotic and random behavior of a given time series U = u_i1 ... N from temporal order of the values in the successive xi. Bandt et al. proposed the permutation entropy, which reflects the rank order of successive x_i in sequences of length n, is calculated using following equation [21]:

$$H_{permutation} = -\sum_{q}^{n!} p_q \log_2(p_q) \tag{4.17}$$

Here, p_q is the relative frequencies of the probable patterns of the symbol sequences.

4.2.4 Classification

The targets of the classifier is to classify cognitive load, arousal,and valence using machine learning approach. All entropies are considered as feature vector. However, class labels of cognitive load (see equation 2.1), arousal (see equation 2.2) and valence (see equation 2.3) are determined from EEG signals considering one second window based on state-of-the-art methods [[43], [36]].

We have used Support Vector Machine (SVM) classifier to classify cognitive load, arousal,and valence signals as it is best classifier to handle non-stationary signals such as, EEG signals (see in section 2.6). SVM constructs a hyperplane or set of hyperplanes in a high or infinite-dimensional space, which can be used for classification. The parameters selection is automated by optimizing a cross-validation based model selection. Conduction of cross-validation is for tuning the parameters as well as they have used for testing. It is a big challange to find mapping between training set and unseen test set. From the training set features, SVM classifier learn nonlinear mapping. In our thesis, the whole trial is divided into two subsets where 80% subsets are used for training and the remaining 20% is reserved for testing. After that, N fold cross validation is performed on 80% subsets while training to generate an optimal model of the SVM classifier where N-1 is used for the training set and the remaining is used for validation set which required to fit the model, here N=5. Once the model is will-fitted then the model is considered as trained and then the reserved subset is evaluated by testing.

Chapter 5

Results and Discussions

This chapter focuses on experimental results and discussions. The comparison of our results with state-of-the-art method is provided here. Our ultimate goal is to classify cognitive load, arousal and valence based on extracted features and SVM classifier.

Table 5.1 states the sensitivity, specificity and accuracy for six different obstacles which includes Door, Narrow space, Open space, Elevator, Stairs and Moving people for cognitive load. Our method is proposed based on the new extracted features such as Approximate entropy, Shannon entropy, Log energy entropy, Threshold entropy, Sure entropy, Norm entropy, Spectral entropy and Permutation entropy. We have calculated sensitivity, specificity and accuracy using following state-of-the-art methods [[56], [49]]:

$$Sensitivity = (\frac{TP}{TP + FN})100 \tag{5.1}$$

$$Specificity = (\frac{TN}{TN + FP})100 \tag{5.2}$$

$$Accuracy = (\frac{TP + TN}{TP + TN + FP + FN})100 \tag{5.3}$$

Where TP and TN represent the total number of detected true positive events and true negative events respectively. The FP and FN represent the total number of detected false positive events and false negative events respectively. Here, sensitivity is true positive and specificity is true negative. Moreover, high sensitivity means high cognitive load, high arousal and high valence whereas high specificity low cognitive load, low arousal and low valence.
TP are cases in which we predicted high CL, arousal and valence, and they do match the dataset. TN are cases in which we predicted low CL, arousal and valence, and they do match the dataset. FP are cases in which we predicted high CL, arousal and valence, and they do not match the dataset. (Also known as a "Type I error"). FN are cases in which we predicted low CL, arousal and valence, and they do not

match the dataset. (Also known as a "Type II error") [56].

For cognitive load, Table 5.1 demonstrates that the best result for sensitivity is 96.67% which is observed against moving people. Furthermore, the worst result is observed against door which is 69.05%. The rest of four obstacles provides almost similar results. These statements can be graphically viewed at Fig. 5.1. For specificity and accuracy, the best results are observed against narrow space which are 97.76% and 97.61% respectively and the worst results are observed against door which are 92.49% and 90.94% respectively. However, even the worst result is above 90% which clearly emphasizes the stability and wise selection of features for this specific research.

Table 5.1: Sensitivity, specificity and accuracy of different obstacles for cognitive load.

Cognitive Load			
Obstacles	Sensitivity (%)	Specificity (%)	Accuracy (%)
Door	69.05	92.49	90.94
Narrow space	91.00	97.76	97.61
Open space	83.38	96.86	96.52
Elevator	86.19	94.83	93.90
Stairs	84.67	96.86	96.69
Moving people	96.67	95.84	95.87

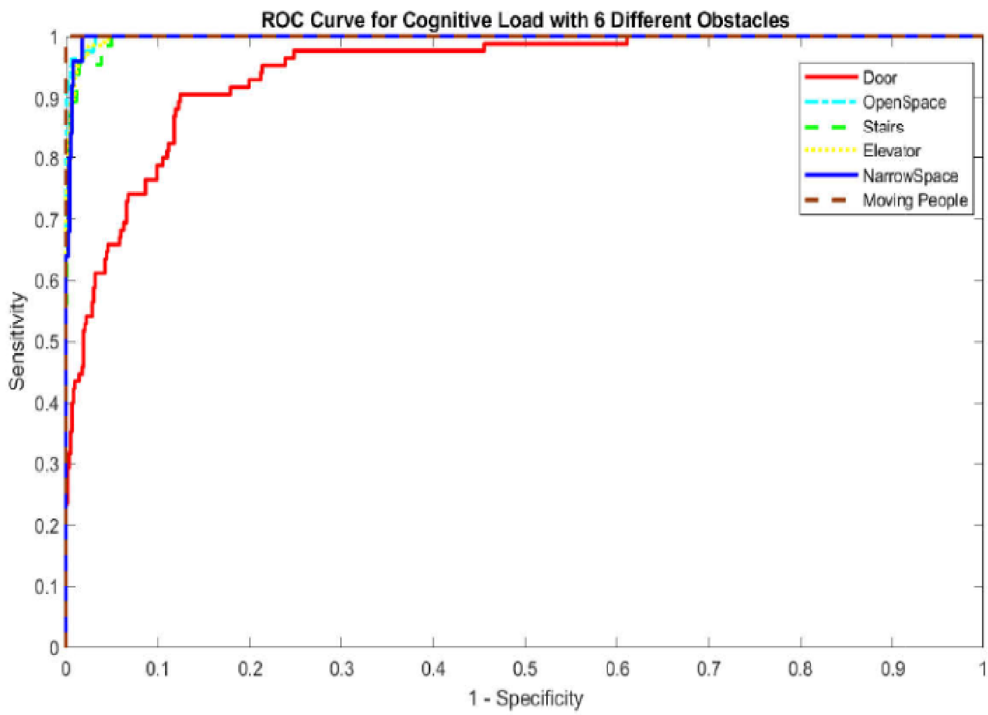

Figure 5.1: ROC curve for cognitive load

For arousal, Table 5.2 also demonstrates that the best result for sensitivity is observed against moving people which is 90.57%. Furthermore, the worst result is

80.75% which observed against door. The rest of four obstacles provides almost similar results. These statements can be graphically viewed at Fig. 5.2. For specificity and accuracy, the best results are observed against open space which are 90.94% and 90.40% respectively but the worst result is different for these two. For specificity, the worst result is 83.42% which observed against moving people. However, for accuracy, the worst result is against door which is 83.20%.

Table 5.2: Sensitivity, specificity and accuracy of different obstacles for arousal.

Arousal			
Obstacles	Sensitivity (%)	Specificity (%)	Accuracy (%)
Door	80.75	83.76	83.20
Narrow space	80.46	86.94	85.36
Open space	88.52	90.94	90.40
Elevator	88.21	87.53	87.74
Stairs	88.30	85.51	86.40
Moving people	90.57	83.42	85.29

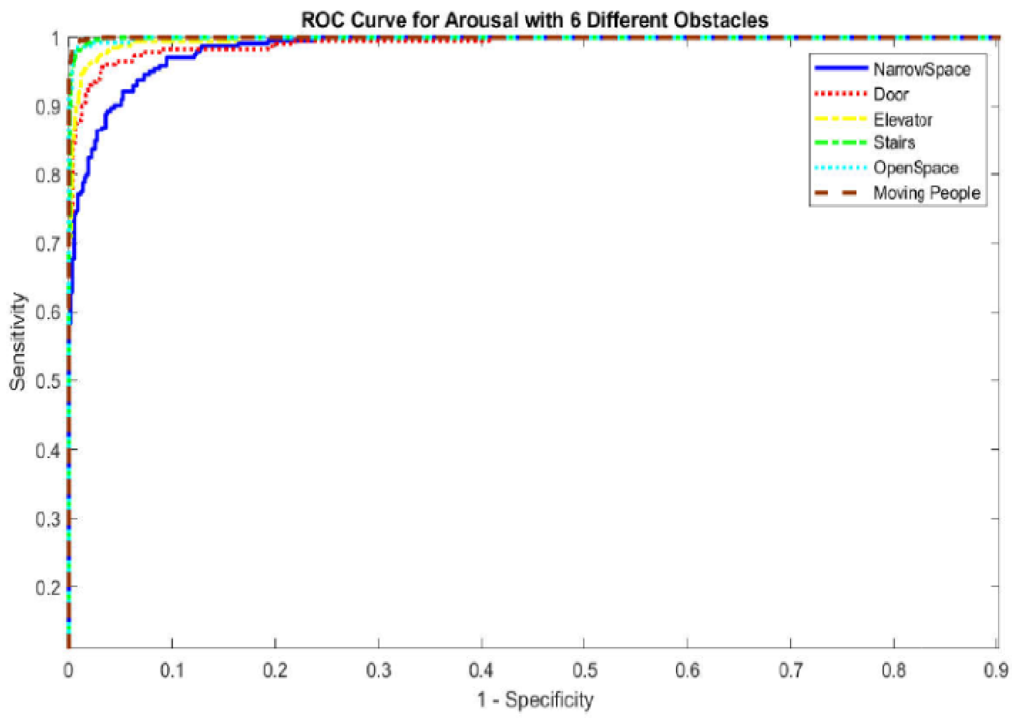

Figure 5.2: ROC curve for arousal

For valence, Table 5.3 states that that the best result for sensitivity is observed against narrow space which is 52.92%. Furthermore, the worst result is 49.43% which observed against door. The rest of four obstacles provides almost similar results. These statements can be graphically viewed at figure 5.3. For accuracy, 52.92% is the best result against narrow space. However, the worst result is 49.01%, against open space.

Table 5.3: Sensitivity, specificity and accuracy of different obstacles for valence.

Valence			
Obstacles	Sensitivity (%)	Specificity (%)	Accuracy (%)
Door	51.14	46.33	48.40
Narrow space	52.59	66.67	52.73
Open space	49.74	51.65	49.98
Elevator	52.098	41.07	51.70
Stairs	53.33	44.80	51.54
Moving people	52.83	47.13	50.74

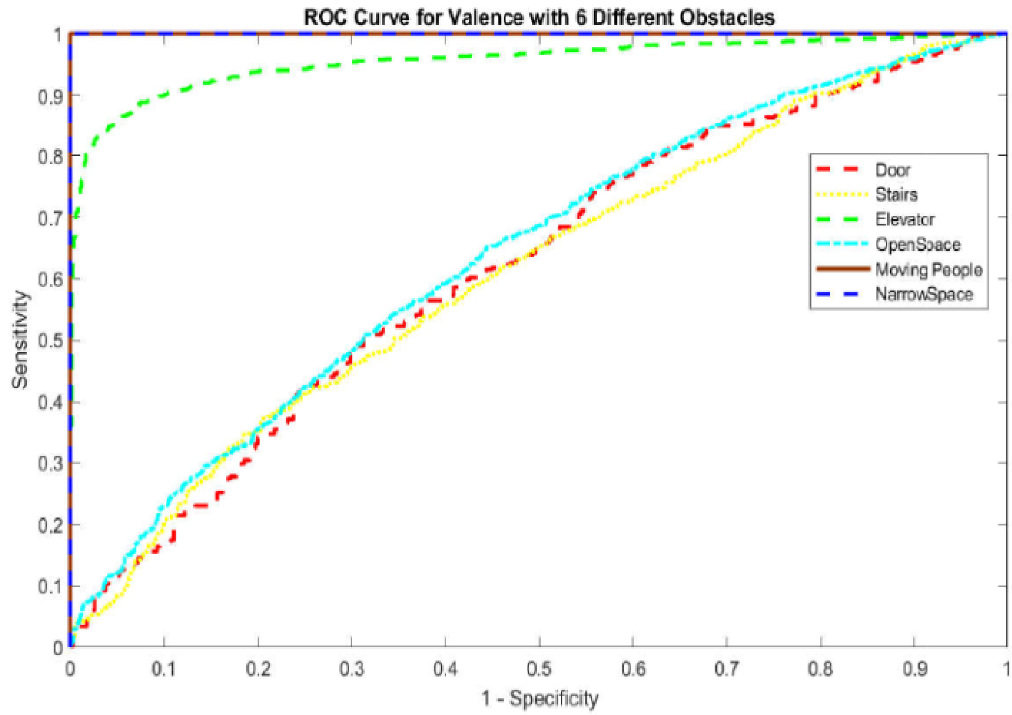

Figure 5.3: ROC curve for valence

Table 5.4: Classification accuracy for stress detection for different obstacles [60].

Single-class classification	
Environment	Accuracy (%)
Door	76.7
Elevator	82.4
Corridor (Narrow space)	70.7
Open space	74.9
Stairs	77.7

Another researcher used the same EEG dataset to detect different stress levels [60] (see Table 5.4) while we detected cognitive load arousal, and valence with better results for cognitive load and arousal.

Chapter 6

Conclusions

Cognitive load and emotional states both plays a very important role to design a navigation aid by regulating awareness and alertness. Mobility system for visually impaired peoples (VIPs) would be benefited by detection of emotional states and cognitive load because we can test how much user friendly it will be for them. In this study, Electroencephalogram (EEG) signals are recorded from participants with nine dierent degrees of sight loss. Afterwards, utilizing EEG signals, we have measured various cognitive load and emotional states that can help to design navigation aid for VIPs. The difficulties of the tasks in terms of cognitive load and emotional states are quantied considering diverse factors by extracting features to support this reasoning. Here, feature extracted from different well-established metrics during navigation in unfamiliar indoor environments of VIPs. Results showed that classification accuracy for narrow space is 97.61% for cognitive load. Moreover, the experiment achieves that 90.40% and 50.60% classification accuracy for arousal and valence in the open space and stairs, respectively.

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Appendix A

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