Detection of Stress from Stressful Environments for Visually Impaired People (VIP) using EEG Band Signals

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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

This paper proposes a model to detect stress from stressful environments for Visually Impaired People (VIP) using EEG signals; EEG is now broadly used for emotion based recognitions and in Brain Computer Interface (BCI). The World Health Organization (WHO) notes stress as the next significant issue of this era which constantly causes damage over physical and mental health of people all over the world. According to WHO's estimation, visual impairment is found in 285 million people around the world and 80% of visual impairment can be prevented or cured if proper treatment is served. However, Visually Impaired People around the world have a concerning rate of living with stressful environments every day. Thus, these motivated researchers to seek a stress detection model which may be used further for supporting Visually Impaired People and higher research purposes. This model refers to work with EEG Bands and detect stress by extracting Absolute Band Power, Average Band Power, Relative Band Power, Standard Deviation and Spectral Entropy from five EEG bands. Support Vector Machine (SVM), K Nearest Neighbors (KNN), Random Forest and Linear Discriminant Analysis (LDA) are used for classification considering their reliability for Multi-Class Classification. Moreover, Stratified 10 Fold Cross Validation method is implemented to ensure the balanced distribution between multiple classes during train and test split in this model. With this experimental dataset, we achieved the best result using Random Forest Classifier (99%) for every environment where SVM, KNN and LDA could secure more than 89% Classification Accuracy, Precision, Recall and F1 Score.

Keywords: VIP, EEG, RBF, Stratified 10 Fold Cross Validation, Spectral Entropy, Absolute Power, Average band Power, Standard Deviation, One VS Rest Strategy, SVM, LDA, Random Forest, KNN.

Dedication

We would like to dedicate our work to all the Visually Impaired People who motivated us to work in this field. We also want to dedicate our work to our parents, without whom we could never come so far in life. And a special Thanks to our supervisor who supported us wholeheartedly.

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Nomenclature

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

$ADHD$ Attention-deficit/hyperactivity disorder

ANN Artificial Neural Networks

BCI Brain Computer Interface

BMI Brain-Machine Interface

CNS Central Nervous System

$DARPA$ Defense Advanced Research Projects Agency

DFT Discreet Fourier Transform

DSP Digital Signal Processing

ECG Electrocardiography

$ECOG$ Eastern Cooperative Oncology Group

EEG Electroencephalography

FFT Fast Fourier Transform

FN False Negative

FP False Positive

FPR False-Positive Ratio

GSR Galvanic Skin Response

$IFFT$ Inverse Fast Fourier Transform

KNN K-Nearest Neighbor

LDA Linear Discriminant Analysis

MMI Mind Machine Interface

OVA one-vs-all

OVO one-vs-one

OVR one-vs-rest

PSD Power Spectral Density

RBF Radial Basis Function

RCC Random Correction Code

ROC Receiver Operating Characteristic

RP Relative Power

SD Standard Deviation

ST Skin Temperature

SVM Support Vector Machine

TN True Negative

TP True Positive

TPR True Positive Ratio

VIP Visually Impaired People

WHO World Health Organization

Chapter 1

Introduction

1.1 Thesis Overview

A Brain Computer Interface (BCI) which is sometimes called a neural-control interface(NCI), or brain-machine interface (BMI). Brain Computer Interface(BCI) is a direct communication pathway between a wired brain and an external device. BCI is often focusing on researching to assist or to repair human cognitive or sensorimotor functions [38]. Based on the research work of researcher we have found that non-invasive BCI techniques have helped to establish a safe path for VIPs to perform regular tasks and for mobility [22]. These help us to solve the issue tackling the physical disadvantage of the blind people more clearly.

Stress is kind of a body reaction when change occurs [4]. Many research has been going on in the field of stress detection by both psychologists and engineers. Many Technologies has been developed in the recent past for detecting human stress by using wearable sensors and bio-signal processing [36]. Bio signals like Electrocardiography (ECG), Electroencephalography (EEG), Skin Temperature (ST), Galvanic Skin Response (GSR) etc. has been used to detect stress. Moreover, physiological features of human can be used to measure the level of stress using physiological signals. Difference exists between person to person when he/she responses for stress, for example, how physiological feature changes of a person to a stressful event in response [36].

Moreover, there are some issues in understanding emotion in the definition and assessment of emotion. Even researcher and psychologists have been facing problem to decide what should be considered as emotion and how many types of emotion [19]. Emotions has major impact on motivation, perception, creativity, cognition, decision making, attention and learning [15][31]. However, when it comes to the matter of visually impaired people, then should be taken more seriously. According to WHO, visual impairment affects approximately 285 million people around the world [49]. Mobility in indoor and outdoor can be stressful for visually impaired people, while roaming around in unfamiliar areas. While roaming around a site visually impaired people face some problems which is being categorized in four primary problems: for avoiding barrier (e.g., people passing or standing in the road, stagnancy, branches of tree, doors opening outwards, randomly parked cars); while discover ground level changes (e.g., stairs, ramps, pavement edge); while crossing the street (e.g., traffic lights, sound signal lack of curbs); while to find out exit/entry point (e.g., automated doors, elevators); and to accommodate with light variation (e.g., sudden changes between different environments) [40].

1.2 Major Contribution

In our studies we have used Brainwaves (Alpha, Beta, Delta, Gamma, Theta) for our feature extraction. Our model refers to detect the stress from the features Absolute Band Power, Average Band Power, Relative Band Power, Standard Deviation and Spectral Entropy which have been extracted from Brainwaves (Alpha, Beta, Delta, Gamma, Theta). Later on, machine learning algorithm such as, Support Vector Machine (SVM), Random Forest Classifier, K-Nearest Neighbor (KNN), Linear Discriminant Analysis (LDA) have been to use to for classification.

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 gives 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

An important research topic for both psychologists and engineers is Stress detection. Many innovation has been built up for human stress detection by using various sensors and bio signal processing. Stress can be detected by applying human bio-signals such as Electroencephalography (EEG), Electromyography (EMG), Electrocardiography (ECG), Skin Temperature (ST) and Respiration. Difference exist between person to person when and he/she response to stress. In this research paper [36] researcher proposed a collection based analysis method for measuring stress using physiological signal. By following this system, researchers are able to estimate the stress using the various physiological features. Researcher extracted the feature from 10 subjects and computed the feature extracting with respect to two different segment. The first segment indicates the low stress and second segment indicates the high stress.

In the research paper [21], they used Brainwave signals which were used to calculate EEG and analyze them by applying intelligent signal processing techniques and specific algorithm. The goal of their analyzation is to create the basic brainwave balancing index (BBI) applying EEG signals. They have showed a chart with the four kinds of brainwaves compared to the frequency and amplitude. Their research was conducted among 51 participants. Firstly, they separated the waves based on the four frequency bands (Delta, Theta, Alpha and Beta) by using Butterworth Low pass and Band Pass filters. After that, the waves were again processed to reject artifacts using specific filtration algorithms and to access only the suitable parts to pass through the correlation Analysis. Moreover, the power spectral density was examined by using FFT and lastly, to observe left and right brainwave, the correlation was used. As a result, brainwave balancing index and brainwave dominance were displayed as regards graphic user interface on a computer screen. Simultaneously, for validation purpose, to compare with BBI from EEG, psychoanalysis tests were executed. The result showed that the PSD analysis provided reliable BBI with 80% conventionality. They had claimed that the fundamental findings from this research can be represented as an indicator of one's thinking which will lead to great opportunity for positive human potential development.

In the research paper [37] done by Kyriaki Kalimeri and Charalampos Saitis which is established on stress detection by using multimodal bio-signal to measuring the cognitive and emotional states of sightless and visually impaired people when moving in unknown indoor sphere according to mobile monitoring and unification of electrodermalactivity (EDA) and electroencephalography (EEG) signals. This research were conducted among nine healthy visually impaired adults with categorical degrees of sight loss who were asked to walk individually a complex route in an educational building First of all, they extracted features from EEG and EDA signals and then based on the recorded biosignals from VIP waking, they proposed a model established on a random forest classifier which inferred in an automatic way effectively (weighted AUROC 79.3%) among five predefined categories of environment which express general daily situations of difficulty and struggle. Different levels of stress are likely to occur in those environments. Their research goal is to understand the environmental factors which are responsible for increasing stress and cognitive load to help VIP by designing intelligent mobility technologies that are capable to adapt to stressful environments from present biosensor data.

An investigation was proposed by Sulaiman, Hamid, Murat and Taib which is a new strategy to quantify and indicate the degree of human physical stress and it is done by considering and assessing the example of the brainwaves utilizing Electroencephalogram (EEG) [17]. For the research, they enrolled four solid members (3 males and 1 female). In this paper, at first, they recorded the EEG data and assessed to quantify or determine physical pressure. Here, some of the existing signal processing technique were employed for examining the EEG signals, for example, Short-Time Fourier Transform (STFT) and Power Spectral Density (PSD). Then, they use Butterworth Bandpass Filter which was used to isolate the EEG crude data to its specific frequency bands. Moreover, the artifacts are removed by applying threshold value into the signal analysis program. The outcomes which were obtained from the STFT and PSD were considered to see any pattern for physical stress. Further, to inspect its correlation with physical stress, the data was also investigated in term of histogram.

In this research paper, [23] for performing a comparison between PCA, ICA, LDA) researcher used Support Vector Machine. Researcher calculated the feature with statistical feature parameters. Later on, they extracted the feature using PCA, LDA, ICA for reducing the dimensionality and classification has been done using SVM classification. Among all the classification, the highest classification rate has been recorded with Linear Discriminat Analysis which is (100%) and ICA got second place with (99.5%). In comparison to LDA and ICA the PCA have the measly accurate classification percentage which is (98.75%). Moreover, simulation states SVM's performance quite better when using feature extraction applying PCA, ICA, or LDA than that without feature extraction (98%).

Chapter 3

Background Studies

3.1 Brain

Brian has most importance rather than any organ and central organ for any living being. No matter what, it is humans or animals, it is responsible for all the coordinating and processing the information of the body. The brain also reacts as center of all control which is responsible for our movement of limbs, understanding the speech and other organs of our body. The ability of brain is to perform all these actions as it is the never ending stream of information as electrical pulses from the neurons of all our sense organ, for example eyes, nose, tongue etc. The human brain

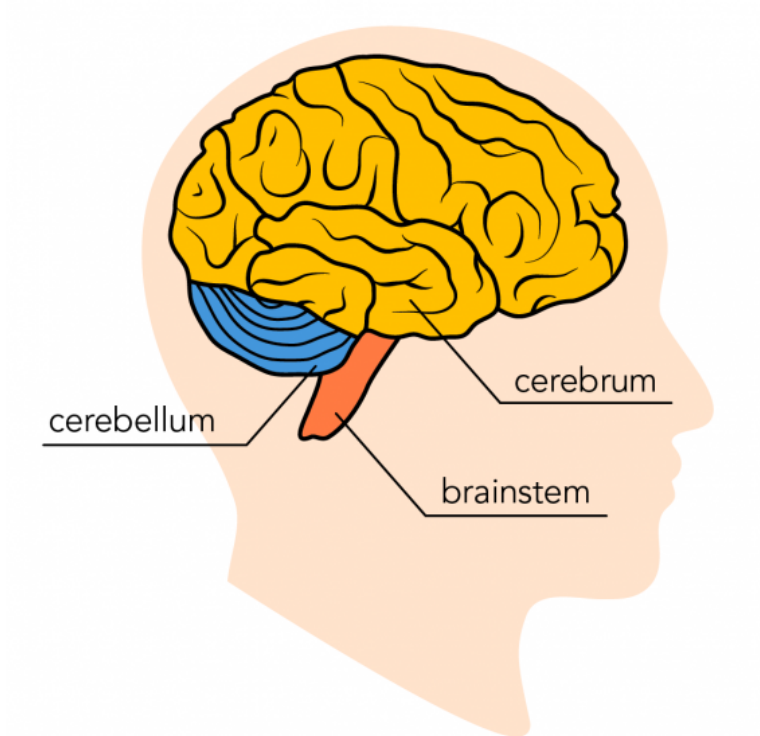

Figure 3.1: Basic Structure of Human Brain. [50]

is also the part of the central nervous system alongside the spinal cord. Brain has three major components and they are – Brain stem, Cerebrum, Cerebellum (Figure

3.1).

3.1.1 The Cerebral Cortex

The outer layer of the Cerebrum is The Cerebral Cortex, dwelling in highest district of the mind. It is subject for our cognizant sensations, complex idea preparing, thinking, arranging, just as other key balanced cycles. It is once in a while alluded to as the dark matter of the cerebrum from its shading, which appears differently in relation to the white issue in the layer underneath [47]. The cortex can be partitioned into four portions called lobes.

3.1.2 The Cerebral Lobes

The cerebral cortex can be partitioned length ways into two cerebral halves of the globe, which stay associated by the corpus callosum. There are four areas in every locale called projections [51]. The four parts are Frontal Lobe, Parietal Lobe, Temporal Lobe and Occipital Lobe, where every one of the projection's usefulness is unmistakable [51].

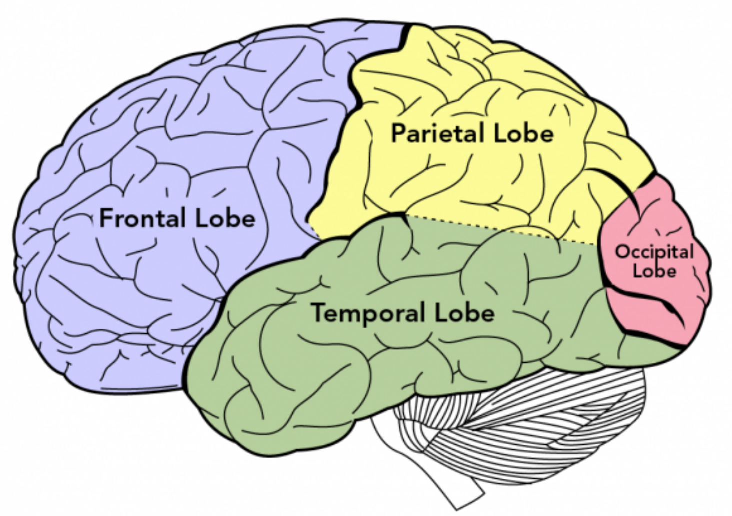

Figure 3.2: Different Lobes of Cerebral Cortex. [50]

Frontal Lobe

The frontal lobe, situated at the front of the cerebral cortex, is isolated from the parietal and worldly lobe by the focal sulcus and worldly sulcus, individually (Figure 3.2). The essential obligation is to accumulate inputs from all different territories to create complex comprehension, for example, considerations, decisions, what's more, long haul plans [47]. Moreover, capacities, for example, arranging, thinking, furthermore, enthusiastic guidelines occur here [51].

Parietal Lobe

Behind the Frontal Lobe and isolated by the focal sulcus lies the Parietal Lobe. Contributions from visual, hear-able and enthusiastic territories show up here to incorporate tangible data, for example, torment, pressure, contact, taste, and so forth (Figure 3.1). To create a comprehension of the current condition [47] [51]. A significant part of the somatosensory cortex dwells in this lobe which is fundamental and significant for handling the faculties of the body.

Temporal Lobe

It is situated in the base part of the mind, being isolated from the frontal lobe by the parallel fissure (Figure 3.1). It contains areas whose design is to perform visual handling - appearances and scenes. Moreover, there are likewise parts where hear-able data handling happens to make feeling of what we hear. Last however not the least, making recollections [51]. The fleeting projection does as such by assembling perceptual data to give a complete comprehension of the event at any second [47].

Occipital Lobe

The Occipital Lobe is situated in the back of The Cerebrum (Figure 3.1). It measures and deciphers all that we see. The major visual handling happens in this lobe, where it gets data from the eyes. It is at that point moved to optional visual handling zones that decipher separation, profundity, area, and so on. This specific lobe is additionally liable for investigating shapes, hues and causing ends to what we to watch [51] [52].

3.1.3 The Cerebellum

The cerebellum is arranged back of the cerebrum (Figure 3.1) [47]. Despite the fact that, it possesses one tenth of the cerebrum's all out volume it contains over half of the complete neurons. This is the reason it is now and then called the 'little mind'. The significant elements of the cerebellum are the control of parity, stance and deliberate developments. Moreover, it assumes a significant part in tuning engine intends to execute exact and precise developments through a progression of experimentation (Figure 3.1) [53].

3.1.4 The Brain Stem

The cerebrum stem is the center aspect of the mind (Figure 3.1). It assumes a significant function to manage the heart and respiratory capacity of the focal sensory system. Moreover, it controls the development of the eyes and mouth, keeping up automatic muscle developments, awareness and managing the rest cycle appropriately. It comprises of three sections the midbrain, pons and the medulla [54] [39].

3.2 Brain Computer Interface (BCI)

BCI – Brain Computer Interface is also known as Neural Control Interface or Mind Machine Interface (MMI) [55]. In BCI there is a link between brain and externally exist device. Brain Computer Interface is different from neuromodulator in that it allows for information flow bidirectional. Research had started on Brain Computer Interface at 1970s from Los Angeles based university called University of California. This project was being appreciated from the National Science Foundation as well as DARPA made a contract. Human brain controls all the function of the body, for instance heart activity, movement, speech, however it also thinks by itself. All these activities can be measured by using the EEG which is fundamentally collects the electrical potential from the brain. How BCI works as a means of communication and independence, for example if a person has been suffering for damage in the Central Nervous System (CNS) causing blindness, in that time BCI can be used to give them artificial vision. In the recent developments of Brain Computer Interface technology may be introduced with the hands free control methods. Brain Computer Interface which is the plaform for communication and controlling the system where human thoughts are being translated in to the real world (Figure 3.3). For instance, to utilize BCI, people who doesn't have no limbs or whose limbs has been damaged or who are suffering with damaged sensors in the skin can use artificial limbs which is directly influenced with the signals from the human brain, so it allows them to carry out their normal activities.

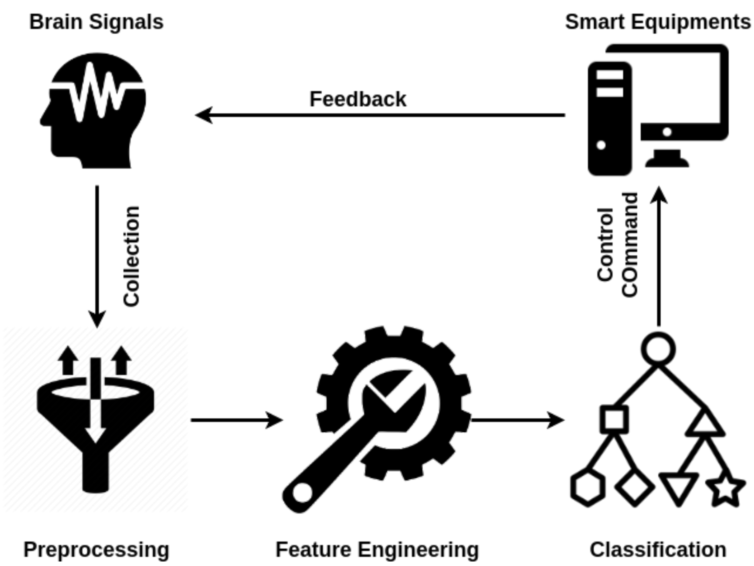

Figure 3.3: Brain Computer Interface Workflow. [56]

Recent advanced development in these sectors shows that the devices which is made based on Brain Computer Interface has a tremendous influence in medicine and also can create an impact in the further studies [28]. In BCIs, there are three parts. Those parts are Partially Invasive BCI, Non-invasive BCI and Invasive BCI. [44].

3.2.1 Invasive BCI

In Invasive BCI it is needed to setup the surgery electrodes below the pericranium for brain signals to communicate. The primary favor of invasive BCI is providing more exact results, but it has also some drawbacks including the side effect along with the surgery. After the surgery is done scar tissues may weaken the brain signals.

3.2.2 Partially Invasive BCI

Partially invasive BCIs are constructed in the skull, but outside of the brain. This thing uses a technology which is called ECoG where all the electrodes are embedded in a thin plastic pad that is situated just above the cortex and under the mater [44]. It produces a better signal but this is weaker than invasive BCI.

3.2.3 Non-invasive BCI

It means all the electrodes are being placed on the surface of skull. Moreover, it records the changes of EEG State. Thus, it is an easy and safe way to record the EEG signal from brain module.

3.3 EEG

An EEG can be used to make an accurate diagnosis and control of a variety of brain disorders. In another word, we can say that it is a procedure that tracks the brain's electrical impulses with metal disks (known as electrodes) connected to the scalp. It is also called a tool often used to diagnose epilepsy and other disorders that affect our brain. The electric signals are used to interact with the brain cells. And if you're sleeping, they're still running. This brain function occurs as wavy lines on an EEG chart. This is a snapshot of the brain's electric operation. (Figure 3.4)

Figure 3.4: EEG Setup [57]

A technician positions the electrode on the scalp with small disks. Instead, you should use a specific limit. The electrodes attach to a system, which amplifies and tracks brain waves on a screen. Though it seems very complicated, it's safe and painless. An EEG tracks brain wave patterns and records them [58]. Natural brain electrical activity makes a pattern visible. Doctors can scan via an EEG for abnormal patterns which show seizures and other problems. And this EEG procedure is generally conducted on a brief visit to the hospital by a specially qualified neurophysiologist. During an EEG, the medical professional typically reviews about 100 pages of actions or computer screens. The simple structure of the wave is paying particular attention, but even fleeting energy blasts and reactions such as blinking lights are seen [59]. The theoretical experiments evoked are similar techniques that can also be carried out. This experiments test the brain's electrical activity to activate the vision, sound or touch.

3.3.1 Why EEG is Needed

Some EEGs are used for neurological conditions to detect and control. EEGs may also recognize conditions such like disturbances in sleep and changes in personality. Often they are effective in measuring brain function for any kind of serious head injuries, transplantation of heart or liver. In individuals with brain lesions, which can be caused by cancers and strokes, EEG waves can be extremely sluggish based on the extent and position of the lesion. These are some fields where EEG are used to confirm or rule out various conditions [60] [61]:

- Encephalopathy; the disease responsible for brain dis-functionality.
- Dementia.
- Memory problems.
- Stroke.
- Sleeping irregularity and related disorders.
- Head injuries.
- Brain tumor.
- Several seizure disorders like epilepsy.
- Encephalitis; inflammation of the brain.

Your healthcare professional may even prescribe an EEG for other purposes.

3.3.2 Risk of EEG

The EEG has been used for many years as a simple technique. The test doesn't have any issues. The electrode activity is recorded. They make absolutely no sense. They make no sense. In comparison, there is no anticipated electric shock. An EEG can rarely lead to seizures in a person with a seizure disorder. This is attributed to the deep or blinkered lights during the test. The healthcare professional takes care of you instantly after a seizure. Depending on your individual medical condition, other threats can be present. Before the operation, please raise your questions with your surgeon. An EEG examination may be impeded by certain causes or circumstances. That comprise:

- Fasting-induced low blood sugar(s)
- Body or eye expression during the experiments (but seldom interferes with the perception of the examination if ever)
- Lights that are exceptionally bright or strong
- Such drugs, including sedatives
- Caffeine-containing beverages like chocolate, coffee and tea (while often the EEG findings can be changed, this almost never substantially interferes with test interpretations)
- Oily hair or water sprinkling

3.3.3 Different Types of EEG

Routine EEG

The EEG routine takes about 20-40 minutes to record. You will have to relax and open your eyes or shut your eyes periodically during the test. You are also advised to take a few minutes to breathe slowly in and out which is known as hyperventilation [62]. A blinker could be put nearby at the conclusion of the operation to see if it changes the brain function.

Sleep EEG or Sleep-deprived EEG

A sleep-deprived EEG is a form of EEG, which allows the patient, before completing the examination, to gain less sleep than normal. During the night, EEG sleep is achieved. Sleep problems may be monitored if a regular EEG does not provide ample information [62]. Under certain cases, it might be prudent to warn you to relax the night before the test. This is referred to as a low EEG nap.

Ambulatory EEG

The ambulatory EEG is used over a time of one or two days during the day and night to monitor brain activity. The electrodes may be connected to a portable EEG compact panel. During processing, much of the normal daily routine can occur, but the equipment must not be moistened [62].

Video Telemetry

Video telemetry, also known as the EEG camera, is a special EEG method that catches you while you catch an EEG. This provides a deeper glimpse into the brain's work. The procedure is typically performed within several days in a clear hospital room [62]. EEG signals are sent to a computer wirelessly. The video is constantly recorded by the computer and supervised every day by experts.

3.4 Brain waves

Brain is called the epicenter of the sensory system as well as a central processor of a human body [3] [5]. The cells of the brain which are called neurons, connected through a line of signal pulses creating brainwaves [21]. Brain waves are wavering electrical voltages in the brain estimating only a couple of millionths of a volt [35]. Sensors are used to identify them which are set on the skull. These waves are splitted according to their bandwidths to represent their usefulness, however are supposed best as a constant scale of cognizance. Brainwaves change depends on what humans are doing and feeling. In Figure 3.5, frequency bands along with it's corresponding symptoms are shown; the lower brain waves indicate when tired, slow or lazy is felt whether the higher frequencies determine the feeling of wired, or hyper-alert [63]. Five types of waves are labelled from the brainwaves and they are Delta,Theta, Gamma, Alpha and Beta [35].

Frequency band	Frequency	Brain states
Gamma (γ)	38-42 Hz	Concentration
Beta (β)	12–35 Hz	Anxiety Dominant, Active, External Attention, Relaxed, Stress
Alpha (α)	8–12 Hz	Very Relaxed, Passive Attention
Theta (θ)	4–8 Hz	Deeply Relaxed, Inward Focused
Delta (δ)	0.5–4 Hz	Sleep

Figure 3.5: Characteristics of The Five Brain Waves.

Alpha and beta waves signals are found in most of the brain waves as alpha waves increase during relaxation conditions and beta waves are supreme in the state of wakefulness with open eyes. Moreover, the lower frequency bands power rises when the subject is in sleep [8].

3.4.1 Alpha

Alpha waves (8-13 Hz) are the reflection of brain's inactive state and are seen in most people in the conscious condition with shut eyes [12]. They are prevailing at the time of quiet thoughts and in some meditative states [63]. These brain waves are the prime pointers of cognizant responsiveness and they work as a door between the outer and the inner world [12]. Alpha waves indicate the present and these waves are also called the resting state for the brain (Figure 3.6) because they help in general mental coordination, smoothness, readiness, mind/body joining and learning [63]. Alpha waves also teache to stay relaxed and focused during stress. Therefore, by keeping balance between relaxation and awareness, the high Alpha state can be achieved [12].

3.4.2 Beta

Beta waves (12-38 Hz) characterize a mind's wakefulness during focusing on performing mental tasks and connecting to the outside world. (Figure 3.6) These waves are usually called the muscles of the brain [12]. They are qualities of a strongly involved mind. Beta Waves are generated when the cerebrum is stimulated and actively involved in focused mental activities such as problem-solving, decision making etc. These waves are not only comparatively lower in amplitude, but also the fastest among the various brain waves [79]. It is not an effective process to handle high frequency frequently because an outcome of this, tension, problems in relaxing and stay awake at night, can create problems to relax the brain and fall asleep. Beta waves are conditional to lead in the left sphere of the brain, and so that when they are present excessively on the right can be related to madness [64].

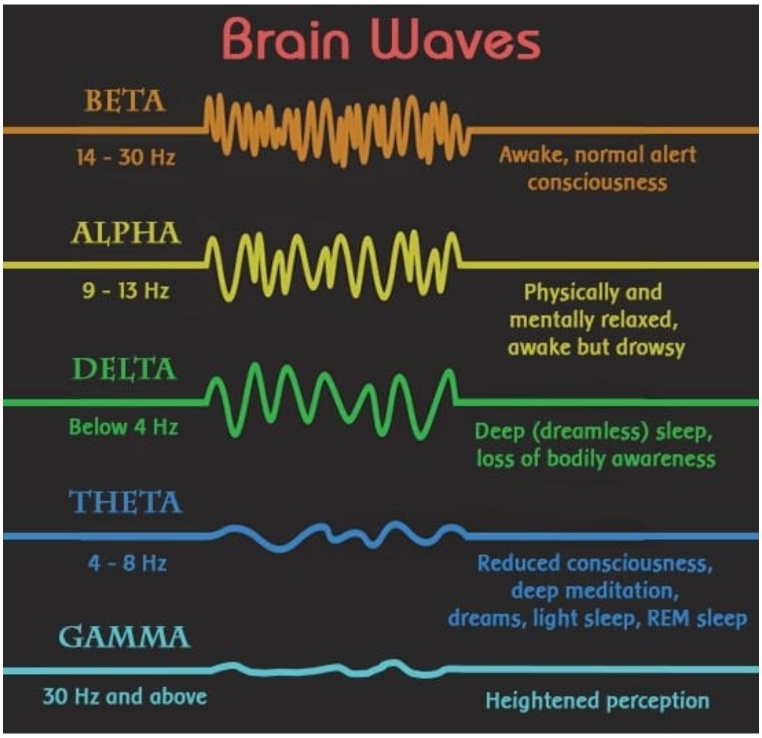

Figure 3.6: Frequency Ranges of EEG Bands. [65]

3.4.3 Theta

Theta waves are basically related to dreams and sleep. (Figure 3.6) These waves are often observed in small kids, however inside grown-ups, it will in general show up during thoughtful, sluggish, or resting states (yet not during the most profound phases of rest). At the point when the brain is conscious, additional theta levels can bring about inclination dispersion which is generally described in ADHD. An excess presence of theta in the left sphere of the brain is considered the lack of organization. In individuals with consideration issues, theta is regularly observed more to the forepart of the cerebrum [64].

3.4.4 Gamma

Gamma brain waves have the highest frequency among the brain waves (Figure 3.6) and are used to synchronize information of different brain parts. They are related with top attentiveness and excessive levels of brain functioning [64]. These brain waves process data quickly and inaudibly. The brain has to stay still to the entry of gamma because these are the most subtlest of the brain wave frequencies. Gamma was terminated as it was supposed as spare brain noise before scientists revealed it was highly operative in states of love, humanity, and higher values [63]. Low frequency of gamma have been associated with difficulties in learning, reduced mental processing and limited memory. On the other hand, high values of gamma waves are connected with a high IQ, empathy, brilliant remembrance and pleasure. At present, this wave has restricted medical value because it is disputed in current EEG technology it cannot be measured effectively, because of muscle contamination [64].

3.4.5 Delta

Delta Waves (1-4 Hz) are slow and low among the brainwaves, which begin to work in stage 3 of the sleep- cycle, and by stage 4 control almost all EEG activity. They indicate the deepest meditation and dreamless sleep. (Figure 3.6) These waves create interruption in external awareness and are the origin of empathy. This state stimulates healing and reactivation, and so that deep restorative sleep is so important for the healing process [63]. It has been found that those who have various types of brain injuries produce delta waves in waking hours which makes it extremely difficult to do cognizant activity. While delta production is high, sleep walking and talking are likely to occur [64].

3.5 Digital Signal Processing (DSP)

Digital signal processing is such a way where signals have previously been digitized and these signals are taken as audio, voice or video. Even some signals are considered as temperature or pressure also. After that the recorded signals are manipulated mathematically. DSP handles various kind of signals and these signals are recorded for different reason, for example, measuring, filtering, producing or compressing analog signals. After transforming the Digital signal data into a binary format where each and every bit of data is showed by two different amplitudes, analog signals are differentiated by taking information. After taking the data, it is converted into electric pulses [86]. There is a two-step procedure for an analog signal in digital signal processing. The first one is known as 'Sampling' and another one is known as 'Layering'. After completing the two steps, the analog signal is converted into a digital signal [26]. In addition, we know that there are two ways to represent signals. One is time domain and another one is frequency domain [82]. There are so many sites where DSP is used. It is used to process oil or for sound reproduction. It is also used in image processing in medical science and even in telecommunications also. Using digital signals are more compelling and efficient as opposed to using analog signals because in DSP framework the filter function is used which is based on software and not only that, one can add multiple filters here. Moreover, only the DSP software is required so that both adjustable and flexible filters with high order responses can be created where analog signal processing requires additional hardware [86].

3.5.1 Time Domain

Time domain representation represents that the function's value or signal is being identified for real valid numbers, in both situations of discrete time and continuous time. In the time domain current or voltage is stated as a function which consist time. An oscilloscope is used to measure signal which is presented in the digital information and in the time domain is regularly transported as a time function by the voltage [47]. Generally, in time domain analysis it shows how with respect to time signal changes. An Energy spectrum represents time limitation of signals and power spectrum states periodical signals [82].

3.5.2 Frequency Domain

With phase of frequency function and a magnitude, signals are being demonstrated in the frequency domain [82]. Analysis of Frequency domain evidences how energy of signal can be dispersing in the frequency range [66]. From the demonstration of Frequency domain, it is shown that how much portion of signal is there within one conferred frequency band over a frequency range. It further adds data on the phase shift which has to be applied to every single frequency component to re back the main time signal of all the individual frequency mechanisms with a combination. One of the most important reasons to use frequency-domain representation is to simplify mathematical analysis [67].

3.6 Fourier Transform

A transform is a pair of mathematical operators that are used to convert a signal. Through Fourier transform a function is broken down into the sum of a number (probably infinite) which are the frequency parts of sine wave [67]. It is broadly used to identify linear systems and categorize the parts of the frequency for making up steady signals. There are several application methods available to convert data from time-domain to frequency domain and vice-versa. Time-frequency analysis is one of the most used one's [68]. The Discrete version of Fourier transformation is called Discrete Fourier Transform. FFT and IFFT algorithms are applied to determine a signal's Discrete Fourier transform (DFT) and the opposite of this respectively [67].

3.6.1 Fast Fourier Transform (FFT)

A mathematical procedure for transforming a signal from time domain to frequency domain is called Fast Fourier Transform (FFT). This technique allows determining in O(nlogn) time of DFT where using divide and conquer method is the primary goal. If the coefficient vector of the polynomial is divided into two vectors, it recursively computes the DFT for each of them. Additionally, it combines the results which computes the DFT of the complete polynomial [69]. It can simply distinguish the magnitude and phase of a signal and combine with other operations to find out convolution and correlation [70].

3.6.2 Inverse Fast Fourier Transform (IFFT)

IFFT (Inverse FFT) does the exact opposite transformation of FFT. It transforms a signal from its frequency domain to time domain where the spectrum of frequency parts is the frequency domain representation of the signal. [67]. To perform inverse (or backward) Fourier transform (IDFT) which undo the process of DFT, it is a fast algorithm to apply. If an IFFT is performed on a complex FFT result computed by derivation, this will in principle convert the FFT result back to its original data set [71].

3.7 Stress Measurement

A classic pointer of unbalanced cerebrum activity in the frontal outer layer that indicates imbalance task between the left sphere and right sphere of the brain is called Frontal asymmetry [29]. Among the sub-bands of EEG, alpha wave (8–12 Hz) is related to the idleness of human brain and it shows the best connection with mental stress [2].Wheeler et al. (1990, 1993) found the opposite relation between alpha band power and its correlative operation in the brain [2]. Because of this relationship between (8-12 Hz) alpha power and brain activity (means that the fewer alpha activity there is, the more brain activity it indicates), decreased alpha power reflects increased engagement, which helps to measure stress [9]. Wheeler et al., Niemiec, and Lithgow [2] [14] studied mental imbalance and measure of emotion depending on alpha-band power proportion between left-right frontal lobes. The rise of alpha band power in the left frontal lobe shows negative emotions such as mental stress, sorrow, disgust while in the right frontal lobe refers to positive emotions such as joy, surprise etc. Therefore, when mental stress level rises, the alpha activity in the brain also increases which ultimately results in the decrement of alpha-band power. The rise of alpha power indicates relaxation and conscious situations. However, the reduction of alpha power and rise of beta band specify the brain is in under intense activity [14]. In frontal and occipital lobes of the brain, Alpha waves are more operative. Beta band power is high at the time of stress due to tension, excitement, and anxiety [17]. These waves also show varying behavior in different areas of the cerebrum (Figure 3.5) [11]. Frontal asymmetry indices are calculated by subtracting the natural log of the power of the left hemisphere electrode from that of the homologous right hemisphere electrode (ln [right (F4)]- [left (F3)]) (Allen, 2004). It is stated that the opposite relationship between alpha power and brain activity (Oakes et al., 2004), positive alpha imbalance scores are explained as left-frontal activity relative to right, while negative scores are as right-frontal activity [20].

3.8 Machine Learning

The subdivision of Artificial Intelligence is Machine Learning where a machine or program studies from some trained data or experience and make forecasts or results dependent on the test information or experience. The reason behind this is, machines today approach an extraordinary measure of information, more significant computational power of machines and better machine learning algorithms. It predominantly gives effort on creating decisions which are data driven choices as opposed to being expressly modified for performing certain task [27]. These algorithms execute in such a way where they learn from their error and develop over time gradually when they are being tried to new data and progressively coming to good accuracy. Also, informations are split-ted into preparing set and test set where algorithms are prepared via training data and estimated data are contrasted with test information for checking accuracy [30] [32]. It has numerous applications, for example, its utilization in search engines to make suggestions as indicated by what the clients search over some undefined time frame, spam filters in email, identification of potential fake bank exchanges, voice acknowledgment in telephones, and so on. It has a huge effect in the field of clinical science today. Machine learning algorithms are prepared and tried constantly until an acceptable precision results are acquired. Machine Learning calculations can be classified in four different types [32].

3.8.1 Supervised Learning

Supervised machine learning algorithms can be applied on those data which has been learned in the past training to new test data using labeled instances to calculate the desired outcome. The algorithm uses the training labeled data to create a function via which it can make predictions outputs. The algorithm can make output predictions for the corresponding input that is provided, after a certain quantity of training. To adapt the model for getting more accurate results, the system can relate its output with the given correct, preferred output and then find mistakes and slowly reduces the error on each step. Supervised learning has an exceptionally high computational complexity and usually produces very precise outcomes. Some of the supervised machine learning algorithms are Decision Trees, Naive Bayes, Logistic Regression, Support Vector Machines, K-nearest Neighbors (KNN), and Artificial Neural Networks (ANN). After randomly split the data for testing and training, the model is estimated using various accuracy assessments.

3.8.2 Unsupervised Learning

When the information or data used to train is neither classified nor labeled, unsupervised machine learning algorithms are useful. The main goal of unsupervised learning algorithms is to find out a function that shows the invisible patterns or structure from the given unlabeled data. The foremost focus of this algorithm is not to predict output for a corresponding input rather it aims at finding a hidden pattern to explore the data and draw implications from the data sets to describe unknown structures from unlabeled data. Even though Unsupervised Learning has low computational complexity, it produces moderately accurate outcomes. It can further be classified into clustering and association. Clustering denotes to finding clusters such as underlying grouping within the data. On the other hand, Association refers to a set of certain rules that describe a large amount of the data.

3.8.3 Semi-supervised Learning

In both labeled and unlabeled data for training, semi supervised machine learning algorithms are beneficial. That's why this type falls somewhere between supervised and unsupervised machine learning. Generally, it takes a small portion of labeled data and an enormous quantity of unlabeled data to train the data set. So as to increase accuracy of predictions, this method is suitable. When the acquired labeled data requires skilled and appropriate resources in order to train it or learn from it, at that time semi-supervised learning method is used. However, obtaining unlabeled data usually does not require further resources to learn.

3.8.4 Reinforcement Learning

Reinforcement learning is an area of machine learning algorithms that are interconnected with its environment by generating actions and hence determines errors or rewards. In a random, potentially complex situation, the agent studies to reach a goal by this learning. Simple reward feedback enables the agent to evaluate which action is best and which is not and this is acknowledged as the reinforcement signal. This method permits machines and systems to automatically learn the ideal performance within a specific context. Therefore, it can produce maximum accuracy.

3.9 Machine Learning Algorithms

3.9.1 Support Vector Machine (SVM)

In the field of Supervised Machine Learning, Support Vector Machine is one of the mostly used learning system for solving classification problems; binary or binomial [23]. Support Vector Machine had been developed for computational learning theory. SVM got more attention in biomedical application as for their accuracy and for dealing with the predictors and number is vast for predictors [23]. Many of previous classifiers separated the classes by using the hyper planes where it split the classes and used a flat plane within the predictor space (Figure 3.7) [23]. Whereas, Super Vector Machine broads the concepts of hyper plane separation to data which is not separated linearly, SVM mapping the predictors into a new higher dimensional space in which the data can be separated linearly (Figure 3.7) [23]. Its name derived from the super vectors which are the lists of the values of predictors which are taken from cases and that stays near to the decision boundary and separates the classes [23]. Practically it is assumed that all these cases have the largest impact on the location of the decision boundary [23]. Most importantly, if they have been removed or replaced they could have much more effects on its location. One of the most intelligent part of this system is that it remains a hyper plane in the place of predictor (Figure 3.7) which is evaluated in terms of the dot products and input vectors in the space of feature [23]. In the higher dimensional space dot product is being to use to identify the distance between the vectors [23]. Without the representation of the space explicitly a Support Vector Machine locates the hyper plane which divides the super vectors [23]. By a complex curve the two classes can be separated in the original space of vector(Figure 3.7) [23]. However, in another cases if the main predictor values can be programmed into a feature space which is flexible, it is

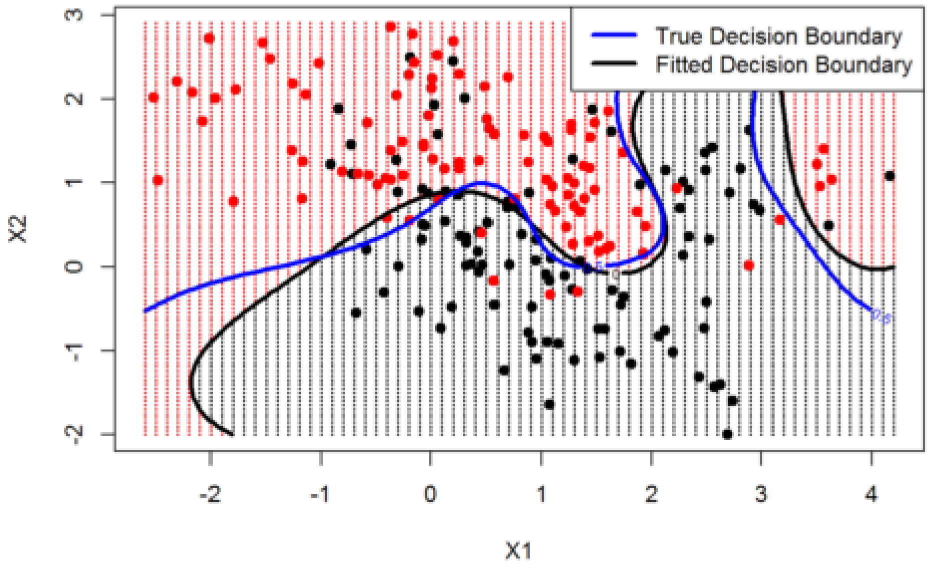

Figure 3.7: Implementation of RBF Kernel in Support Vector Machine. [72]

feasible to differentiate them completely with the boundary of linear decision [23]. The basic SVM is almost similar to the perception. Both of them are known as linear classifiers in terms of differentiated data but for Multiclass problems, SVM's RBF Kernel is mostly appreciated. There are several strategies applied for that; one vs one, one vs rest.

3.9.2 K Nearest Neighbor (KNN)

K Nearest Neighbors algorithms which solves both regression predictive problem and classification problem [25]. Within this industry, this algorithm is highly used. Many

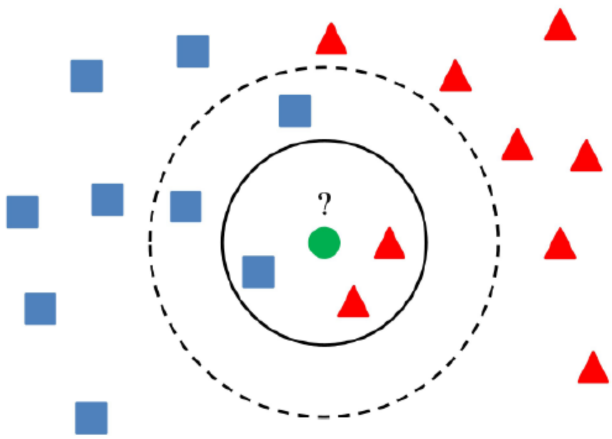

Figure 3.8: Classification Method using K-Nearest Neighbor [49]

researcher uses KNN classifiers as KNN is facile and intuitive method of classifier

[25]. In this KNN classification, new decision has been made by comparing the new data (unseen and testing data) along with the base line data (training data). (Figure 3.8) By and large, for a given unlabeled time arrangement X, the KNN rule finds the K 'nearest' (neighborhood) marked time arrangement in the preparation informational index and doles out X to the class that shows up most regularly in the area of k time arrangement [25]. There are two fundamental plans or choice standards in KNN calculation which is comparability casting a ballot conspire and larger part casting a ballot plot [25].

3.9.3 Random Forest Classifier

Random decision forest was created by Tin Kam Ho, he used random subspace method which is known by Ho's formulation [73]. This is the way to implement the 'stochastic discrimination' approach to classification which was proposed by Eugene Kleinberg. Random Forest is an ensemble learning method for classification which operates by creating multitude of decision trees the time of training and outputs the class that is class's mode (Figure 3.9). For creating number of decision trees, data and variables are selected in a randomized way from the set of data and variables which is available [41]. A finite set of threshold is being used for building a tree during training time in where this threshold is selected for each node [41]. In the time of constructing a tree for separated classes is being done and data point probability will be different for each node [41]. The data point which is newly arrived go down straight in tree and it ends at leaf and the highest probability class for the node present the actual class of data point in that tree (Figure 3.9). It is not suggested to use single random tree as a classifier rather then it is suggested to use number combined random trees as it is a very good classifier [41]. All the input has some features. For creating more randomness among these data points some data points are selected and from these inputs some features have been selected randomly to create decision tree.

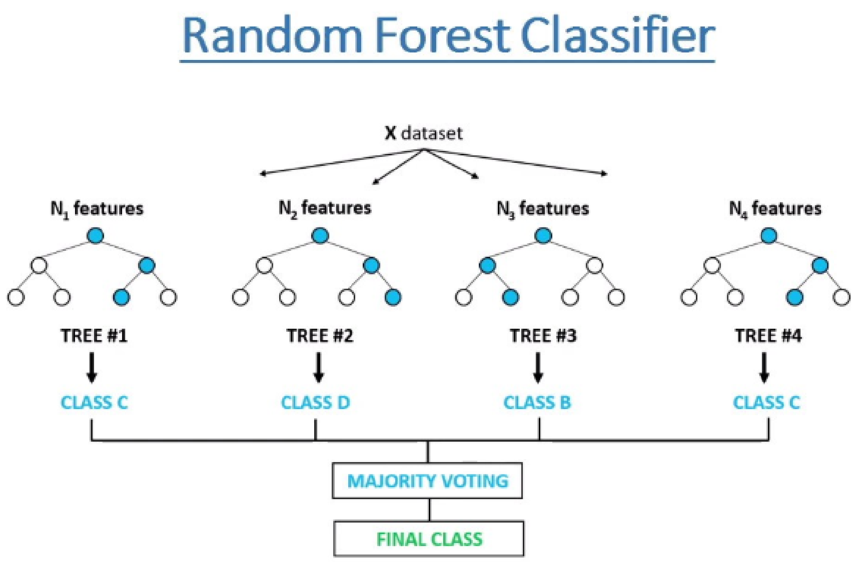

Figure 3.9: Classification Method using Random Forest Classifier [74]

If there are one or more than one feature which are very strong predictors for the targeted output, this features will be nominated in the many decision tree [41].

3.9.4 Linear Discriminant Analysis (LDA)

Linear Discriminant Analysis a method which is being used Pattern Recognition, in the field of Statistics as well as machine learning to determine a linear combination of features that characterizes multiple classes of objects. LDA works in time of measurements made on the variables which are independent for each observations (Figure 3.10)[75]. Similar like support vector machine, LDA classifier also going through testing and training phases [34]. In the phase of training the features which is extracted training set are being put as an input in to the linear discriminant analysis classifier and existing data points which have similar frequencies are accrued into various groups which is resolved in to separate classes [34].
In the phase of testing, the test matrix which is being put in to the linear discriminant analysis and the distance of the Euclidean distance of the test data points with the Eigen vectors represent various classes has been weighed. The nearest point to the Eigen Vector belongs to that category [34]. After that, accuracy has been measured by doing comparison the results with the informed targeted matrix [34].

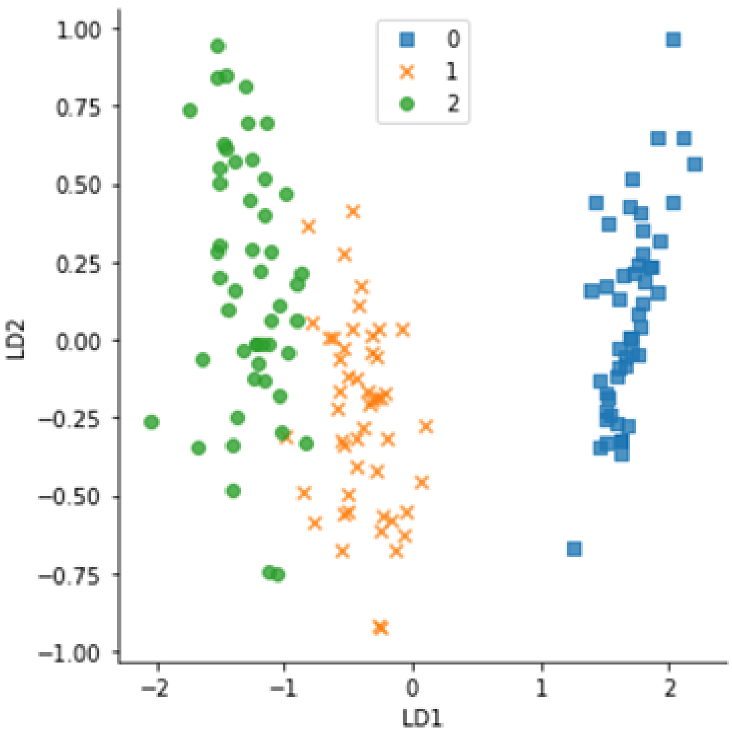

Figure 3.10: Classification Method using Linear Discriminant Analysis (LDA) [76]

Chapter 4

Proposed Methodology

For our research purpose, we have extracted 5 bands from the EEG Signals from several environments by setting frequencies and decided to extract 5 features for each of the bands; which are Relative Power, Absolute Power, Standard Deviation, Average Band Power and Spectral Entropy. In this research we have considered EEG signals captured for seven indoor environments; such as before doors, using stairs, navigating for elevators, response for moving objects, reacting for sudden sounds and walking in narrow and open space. These extracted features are merged for the detection of Stress by Machine Learning Classification Algorithms.

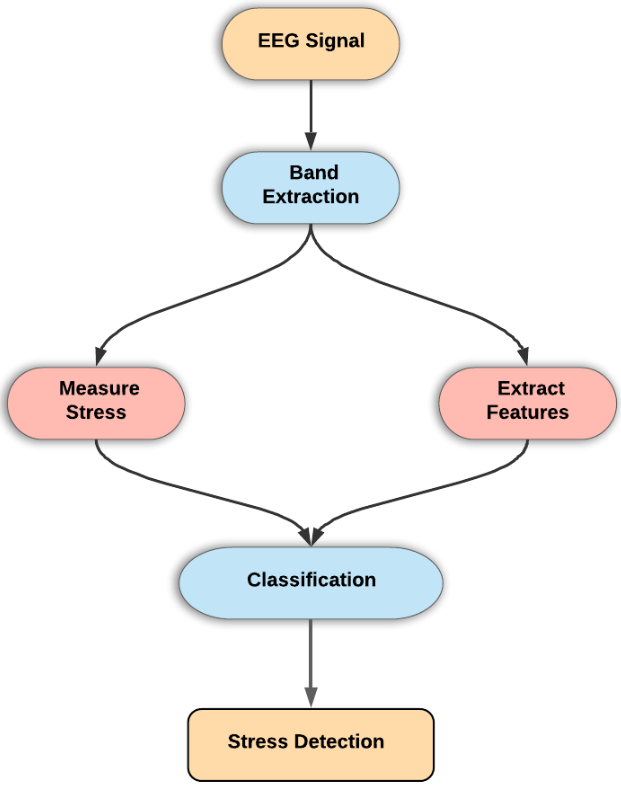

Figure 4.1: Work Flow Diagram for Detecting Stress using EEG Signals.

Here in our proposed methodology (Figure 4.1), the values of Stress were categorized in equal portion and labeled as Low, Medium and High Stress. We used Linear Discriminant Analysis (LDA), Support Vector Machine (SVM), Random Forest Classifier and K-Nearest Neighbors (KNN) Algorithm for classifications.

We worked with EEG Signals from seven different indoor places like elevator, stairs, doors, narrow-spaces and even for sounds and our goal was to detect stress for every situation; we had detected and the accuracy of our model we are promoting is very satisfying.

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 [45]. The project was funded by the European Union to aid VIP for their navigation. The dataset they collected 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 [45]. EPOC+ provides a good compromise between the performances and usability in terms of other wireless EEG recording devices available. Participants of various levels of visual impairment (VI-2, VI-3, VI-4), have been described in the Table 4.1. Indoor environments are divided into 7 types (Door, Stairs, Open Space, Sounds, Elevator, Narrow Space and Moving Objects). The EEG signals from the subjects at each of these labels are recorded.

Table 4.1: Classification of Visually Impaired Participants. [46]

Category	**Description**	**Participant Gender**
VI-2	Vision less than 10% and more than 5%	2 (Female, Male)
VI-3	Vision less than 5%	4 (Female, Female, Male, Female)
VI-4	Unable to count fingers from less than one meter away	3 (Female, Male, Female)

4.2 Feature Extraction

The process of identifying the important features or attributes is called feature extraction. The general framework of the process diminishes dimensionality by disposing the data which are excess. Of course, it will make an increase in the speed of training stage and inference stage. Feature extraction is the name of a technique that selects and/or combines variables into functions and reduces the amount of data which is to be handled, while still accurately and thoroughly representing the original data set.

After extracting some features from input data, as Feature Selection and Extraction increase the accuracy of learned models and is inevitable in signal processing due to its improved efficiency, here we have selected some features (Figure 4.2) that include

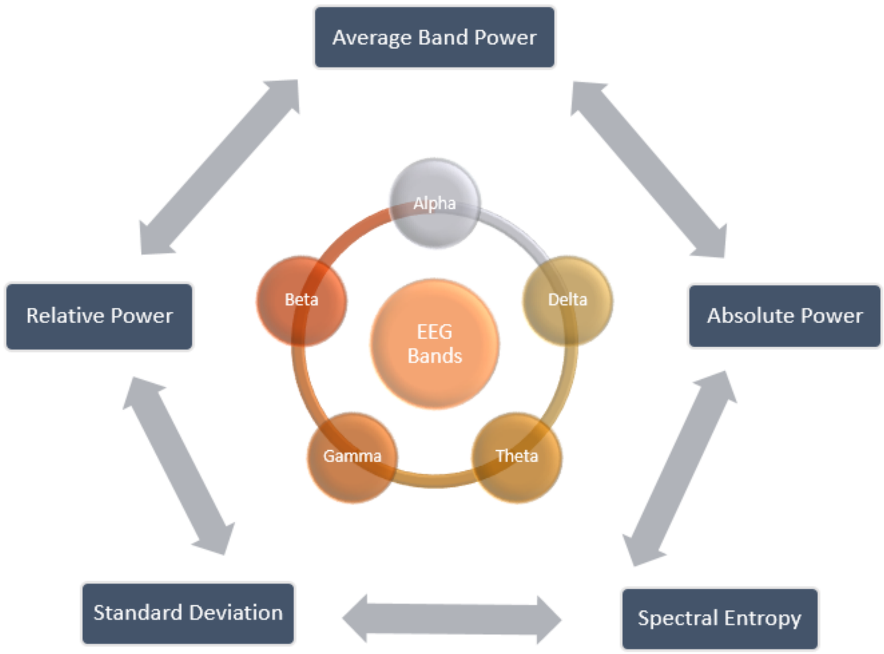

Figure 4.2: Feature Extraction from Different Bands.

absolute power, average band power, relative power, spectral entropy, standard deviation within each sub-band.

4.2.1 Average Band Power

Considering the data points, It is the average of the sum of absolute value which is divided by N where N determines the number of data points. As an example, we can consider 20 data points that are -10 and 10 points that are 10 do not result in an average of 0. The average power of a signal can be determined in a particular frequency range by using either Welch method or the multitier spectral estimation methods. This period gram spectrum object and the window hamming method are used to calculate the average spectrum power [84]. Here is the formula which is followed for window hamming method:

$$W(n) = 0.54 - 0.46\cos(2\pi n/N - 1), 0 \leq n \leq N - 1 \tag{4.1}$$

After completing the phase of windowing, the values will be changed over to a logarithmic incentive by utilizing the accompanying formula is used:

$$AvP = 10xlog(W(n)/2) \tag{4.2}$$

4.2.2 Absolute Power

Absolute power is the power of the whole signal. Therefore, it does not make a distinction between the various frequencies. This can be determined by summing up the power of each frequency (i.e. the signal integral) [18]. In addition, you have the total amount of power inside the signal. Absolute power can be used to normalize the PSD by dividing the PSD by absolute power. Absolute power and asymmetry EEG variables both were transformed as log variable (log (x)) [64].

Absolute power can be calculated as:

$$\int_{-\infty}^{\infty} |x(t)|^2 dt \tag{4.3}$$

All in all, during the emotional incitement, the appropriation of absolute power in theta, alpha, and beta were maximum at foremost sites and maximum delta at posterior destinations. [24].

4.2.3 Relative Power

In reality, one would need to depict the power in the frequency band as a percentage of complete signal power instead of announcing the absolute band power. This is called the relative band power [33].

$$RP = \frac{Power\ in\ band}{Total\ power} \times 100\% \tag{4.4}$$

The relative power (RP) files for each band which is gotten by communicating the absolute power. Here, the absolute power in each frequency band is as the percentage of the totaled over the four frequency bands. [43]. Relative Power is to be considered in correlation with all other bands where relative power is characterized as the power in a recurrence band or the total power distributed at each position [84]. Compared to the other equivalent measures by other people in the sample, it is conceivable to choose whether a single frequency overwhelms other essential cerebrum frequencies and it also decide whether the force is low [1].

4.2.4 Standard Deviation

The standard deviation is a statistic measurement and it figures out the dispersion of the dataset corresponding to its mean. Here, it is characterized as the square root of the variance where the variance is determined for every data point which is relative toward the mean.

$$SD = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \bar{x})^2}{n-1}} \tag{4.5}$$

x(i) = Value of the i(th) point in the dataset
x(bar) = The mean value of the dataset
n = no. of data points in the dataset

If the data points are far from the mean, there is a larger variance within the dataset. Thus, the further the data stretches, the larger the standard deviation. There are two key methods of measuring the standard deviation; population standard deviation and the sample standard deviation [77].

At the point when you accumulate or set data from all individuals from the populace, you include the sample standard deviation and when we take data that reflects a survey of a wider population, then use population standard deviation method. The computations are actually the equivalent for both two special cases. The first one is that the variance is divided by the quantity of data points (N) to compute the population standard deviation where on the other hand, it's divided by (the number of data points after subtracting one from it) for computing the sample standard deviation [77].

4.2.5 Spectral Entropy

Spectral entropy was made by applying the Shannon entropy rule to the Fourier transformed electroencephalograph (EEG) power dissemination. For example, it measures the consistency of power spectral density underlying EEG before and after training. It was also used in support of the linear kernel vector classifier. [10].

In order to measure PSD Psd (f), the retention time was derived using the Welch method for each test. The distribution of power as a function of frequency was defined as the PSD of a time series. The standardized PSD was characterized as the Psd (f) partitioned by the total power where it will get the capacity of probability density,

$$\widehat{Psd}(f) = \frac{Psd(f)}{\sum_{f=0.5}^{f=45} Psd(f)} \tag{4.6}$$

We also tested PSD-based spectral entropy for 0.5–45 Hz. In the following equation the entropy of Psd (f) was generated:

$$SEn = -k \sum_{f=0.5}^{f=45} \widehat{Psd}(f) log(\widehat{Psd}(f)) \tag{4.7}$$

Where k = 1. The consistency of the power spectrum dispersion was basically expressed in the form of spectral entropy. The higher spectral entropy, the more balanced was the distribution of power spectrum [43].

4.3 Classification

For Machine Learning Classification, he has chosen Linear Discriminant Analysis (LDA), K-Nearest Neighbors (KNN), Random Forest Classifier and Support Vector Machine (SVM); where we have performed Stratified 10 Fold Cross Validation technique.

First of all, we divided the whole data according to their subjects such like position before doors, navigating the elevator, walking in narrow space or open space and reacting to sudden sounds; when we found separated data for each subject, we used them for detection of Stress. Then, we divided the whole data into training and testing set maintaining the test size keeping 20 percent and rest for the training. Here 80 percent data of the dataset were left for all the algorithms to learn the data in there; after that based on that the testing part was performed for 20 percent of the rest.

For training the records we have applied Stratified 10 Fold Cross Validation process; Stratified 10 Fold Cross Validation ensures the train test split being balanced by mixing the record samples from every class like shown in the Figure 4.3 [6]. As ours is a multi-class classification problem with huge number of records, Stratified 10 Fold Cross Validation is a great and advanced feature as there is always a high possibility of existing imbalance in each training folds. Basically it ensures a proper participation of every class in every fold and avoids the risks of folds being crowded with same class.

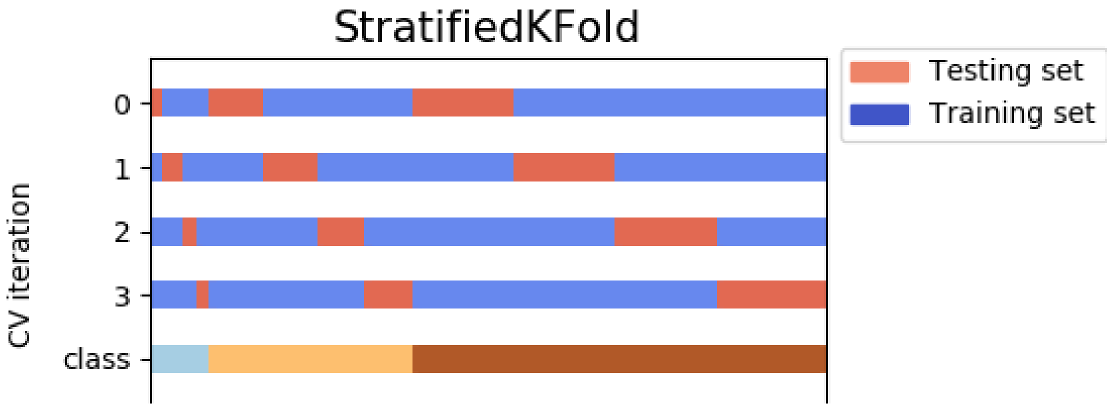

Figure 4.3: Working Procedure of Stratified 10 Fold Cross Validation. [83]

Support Vector Machine (SVM)

For our model's classification part, the first classifier we chose is Support Vector Machine (SVM). It performs well for high dimensional spaces and it's a supervised learning technic. It may be well known for its binary classification methods but SVM classifications might be more exact than the generally utilized choices accessible. For example, we can consider how decision tree or neural network-based approaches [7] [13]. SVM fits an optimal hyper plane for separation between classes by focusing on the training samples that lie at the edge of the class distributions, the support vectors and its method is more accurate for both single class and multiclass classification problems [16].

We aimed to get our results using Radial basis function kernel; as SVM is basically designed for binary classification, we used one vs rest strategy to use SVM as a Multi Class Classifier and got satisfactory results. We used stratified 10 fold cross validation, so that we could assume worst and best possible outcome of the model.

K Nearest Neighbors(KNN)

For the model classification our second choice was K Nearest Neighbors (KNN) algorithm; Neighbor's based classification is a lazy learning and classification is computed from a simple majority vote of nearest neighbors of each point [25].

We aimed to get our results using k=5; here decisions were made comparing with nearest 5 outcomes. For large records, K Nearest Neighbors (KNN) has better accuracy assumption rate. For making sure data getting shuffled well, we implemented stratified 10 fold cross validation method; which basically gave us the mean accuracy after classifying using 10 folds.

Random Forest

For multi class classification, one of the most used algorithms is Decision Tree algorithm. But Random Forest classifier is a meta-estimator; fits a number of decision trees on various sub-samples of a dataset and uses average to improve the predictive accuracy of the model and controls over-fitting [81]. So it has better accuracy generation than normal Decision Trees.

Here we kept our estimator number=40 and implemented stratified 10 fold cross validation method to keep the accuracy most granted. The main reason behind going for Random Forest is, we had a large number of records, so there was high possibility of over-fitting the data. Random Forest has the least chances of over-fitting and we could bring out a satisfactory outcome.

Linear Discriminant Analysis (LDA)

For classification of two classes, one of the most used and widely implemented algorithm is Logistic Regression; which has limitations for multi class classification problems. But in this case Linear Discriminant Analysis (LDA) is better in both binary and multi class classification problem. LDA makes predictions by estimating the probability that a new set of inputs belongs to each class. The class that gets the highest probability is considered as the output class and a prediction is made through it [80] [75].

We estimated the outcome using stratified 10 fold cross validation, so that even after using Bayes Theorem, LDA can generate us the mostly granted accuracy and we were satisfied by the performance.

Here we have worked on data from seven different subjects like doors, open space, sound, stairs so that it can be used for figuring out where visually impaired people suffers the most and initiatives can be taken upon that by the social workers, Government or the specialists. Following our detection process, this model can be used even in devices for alerting visually impaired people early and for higher research.

Chapter 5

Result and Analysis

5.1 Result

In this paper our goal was to work with EEG Bands and using band features detecting stressful environments (Figure 4.1) so that in further researches it gets quite easy in building any kind of navigation aids based on the level of stress imposed on Visually Impaired People (VIP). The goal was to build a bridge between different environments and the stress computed. And lastly, implementing appropriate and most reliable Machine Learning Algorithms to come up with a reliable Prediction Accuracy. We believe, we have been successfully in many extend.

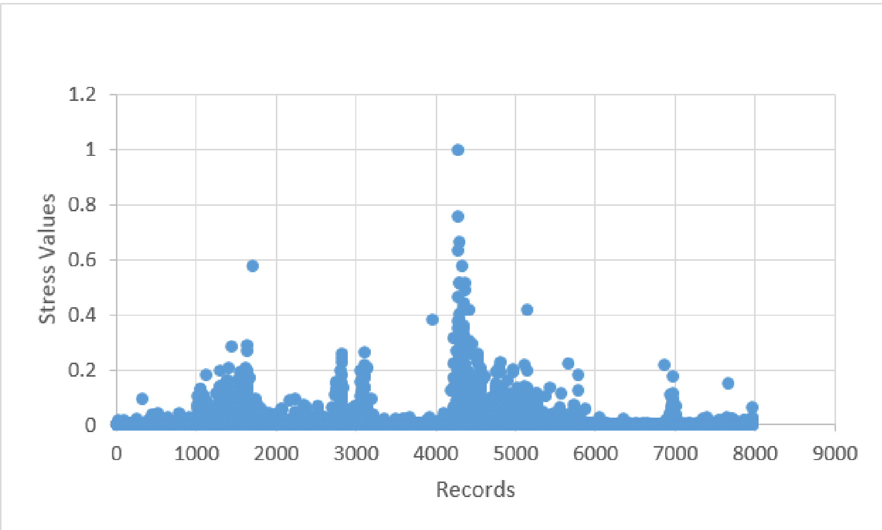

Figure 5.1: Scatter Plot for Record Vs Stress Values.

In the figure above, we have visualized the computed values of the stress according to data records; we had divided the values in equal intervals to categorize and labelled them as low, mid and high stress level. Here we can see all the results together for seven indoor environments; such as before doors, using stairs, navigating for elevators, response for moving objects, reacting for sudden sounds and walking in narrow and open space. Altogether there is 7,978 numbers of records (Figure 5.1) where; We had to separate them considering the environments; altogether there 903 records are for Doors, 1587 records are for Elevator, 602 records are for Moving, 1045 records are for Narrow Space, 2385 records are for Open Space, 2234 records are for Stairs and 302 records are for Sounds. The extracted records for the environments are as shown in the Figure 5.2.

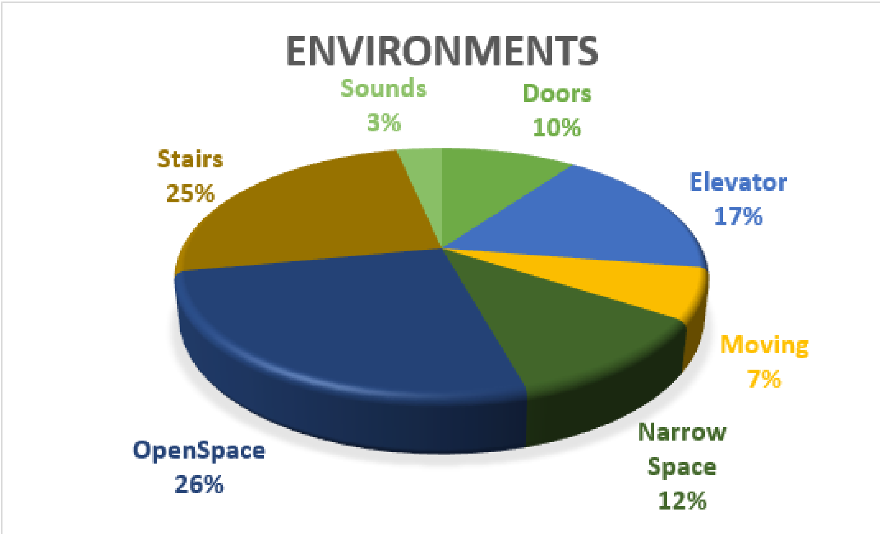

Figure 5.2: Pie Chart of the used Data Records and Stressful Environments.

We have then implemented Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Random Forest and Linear Discriminant Analysis (LDA); these Machine Learning Algorithms for all the Seven different environments separately. To make the prediction accuracy mostly granted we maintained a train and test split with the test size of 0.2; where again Stratified 10 Fold Cross Validation was performed.

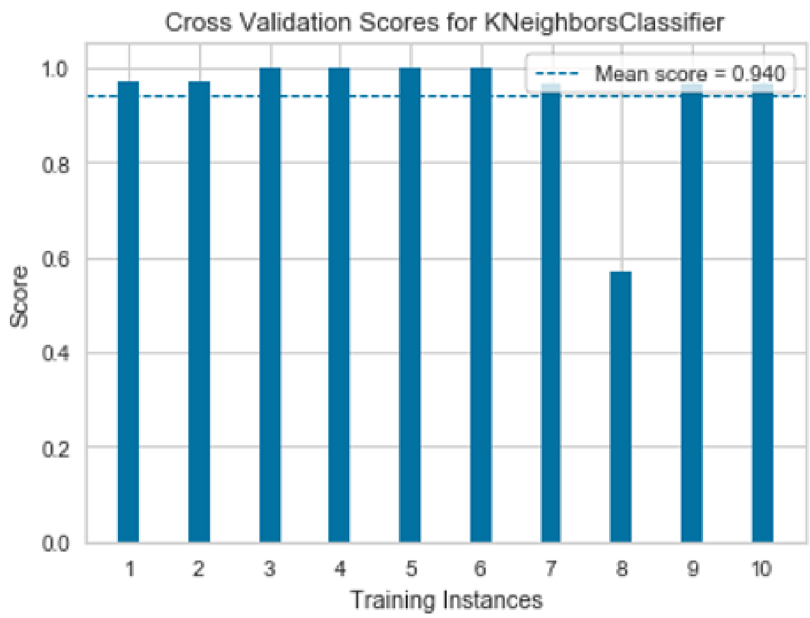

Figure 5.3: Stratified 10 Fold CV (KNN) for Environment 'Sounds'.

Here two Graph plots of K Nearest Neighbor Algorithm for our Environment Sounds (Figure 5.3) and Moving (Figure 5.4) is shared. It simply shows our prediction accuracies were the mean value of 10 folds. For sounds our mean accuracy after cross validation was 94.02%; where the maximum accuracy we could achieve was 100% and minimum of 58%.

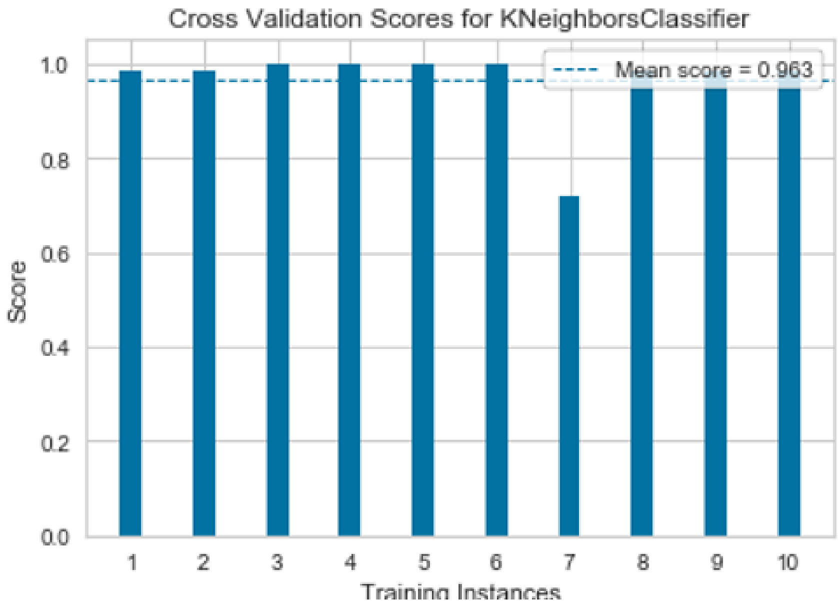

Figure 5.4: Stratified 10 Fold CV for Environment 'Moving'.

For all the Stratified 10 Fold Cross Validation graphs please see the Appendix we have provided. We performed this cross validation process for every classification algorithms and for every environment to ensure we do not get any irrelevant score for the model. The final classification accuracies are recorded in Table 5.1 and a visual comparison between classifiers and environments are shared in Figure 5.5. Keeping test size of 0.2 during train test split and by the help of the Stratified 10 Fold Cross Validation we could come up with really satisfactory results; results are shared below.

Table 5.1: Classification Accuracy for All the Environments Across Various Classifiers.

Classifiers	**Environment**						
	Stairs	Open Space	Narrow Space	Moving	Elevator	Doors	Sounds
KNN	89.71	88.85	90.68	96.34	99.81	95	94.02
SVM	98.71	98.97	98.85	99.17	99.81	99.45	98.02
Random Forest	99.96	99.96	99.91	99.83	99.87	99.45	99.01
LDA	97.53	97.53	98.66	97.84	99.56	99.45	97.68

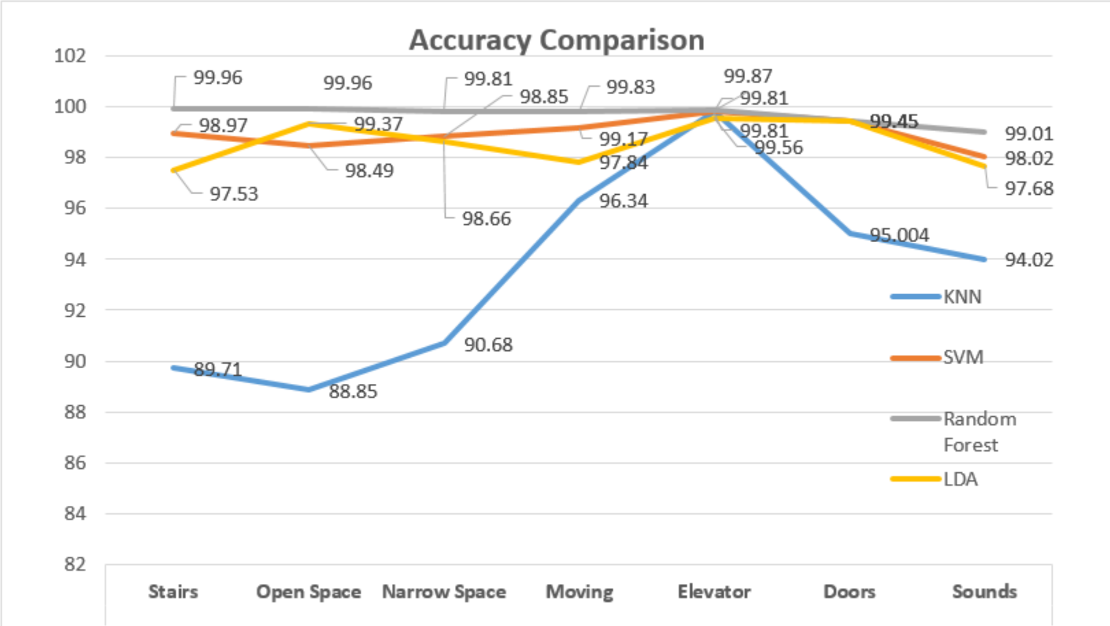

Figure 5.5: Graphical Representation for Accuracy Comparisons.

5.2 Analysis

5.2.1 Evaluation Matrix

For analyzing the outcomes of the classifiers, it is imperative to know about the evaluation metrics that will give the judgment of whether the applied model is good enough or not. There is a misconception that only classification accuracy can indicate which model works better and faster. This is a vague concept because there are other evaluation metrics other than accuracy which also plays vital role in deciding which classifier gives better output. Before analyzing the outputs of each classifier, we will first describe briefly each of the evaluation metrics that is taken into account while determining the best classifier.

Confusion Matrix

One of the best and easiest way to determine the efficiency of a classification model is by observing the confusion matrix. The confusion matrix can give the output of two or more classes of a dataset. It demonstrates the outcomes in the form of a table consisting of rows and columns. In our case the matrix is 3x3 matrix which contains the True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN). We will also need to use these to find TPR and FPR when we will be evaluating through ROC curve and Precision-Recall curve.

Actual Value: This value indicates the exact data which is stored in the dataset. This values will go through different machine learning algorithms during the training phase. It is also divided into two parts which are positive and negative.

Predicted Value: This value shows the amount of data that has been predicted correctly by the classifiers when the testing phase is done. It is also divided into two portions which are positive and negative.

True Positive (TP): When the machine learning models predicts an outcome in a positive manner and it matches with the actual dataset then it falls under true positive category. For instance, if the model predicts that a certain transaction is fraud and it matches with the actual dataset then that is considered as true positive.

True Negative (TN): When the machine learning models predicts an outcome in a negative manner and it matches with the actual dataset then it falls under true negative category. For instance, if the model predicts that a certain transaction is not fraud and it matches with the actual dataset then that is considered as true negative.

False Positive (FP): When the machine learning models predicts an outcome in a positive manner but the actual dataset shows that the outcome is negative then it falls under false positive category. For instance, if the model predicts that a certain transaction is fraud but in the actual dataset, it shows that the transaction is fraud proof then that is considered as false positive.

Classification Accuracy

Classification accuracy shows the performance done by the machine learning algorithms in predicting the outcome. The value accuracy is done between 0 and 1. The model which gives accuracy rate close to one is considered a good model but has issues with over fitting the dataset and the model which gives accuracy rate close to zero is considered a weak model and also has issues with under fitting the dataset. The classification accuracy also depends on whether a dataset is balanced or unbalanced. A balanced dataset can come up with a better accuracy results when it is trained and tested using a model. Classification accuracy can be calculated from the values that are attained via the confusion matrix. The formula is shown below.

$$Classification\ Accuracy = (TP + TN)/\left(TP + FP + TN + FN\right) \tag{5.1}$$

Precision

Precision is a type of evaluation metric which shows that how correctly the machine learning models guessed the outcome. In our case the precision rate will depend based on the model's performance on correctly identifying the fraud transactions. The high precision rate will say that the model has classified the outcome correctly compared to the wrong outcomes. In other words, the ratio of the true positive and the combination of both the true positive and false positive is considered as precision. The formula is shown below.

$$Precision = TP/\left(TP + FP\right) \tag{5.2}$$

Recall

It is another kind of evaluation metric which determines how the machine learning models can detect the positive outcomes after training and testing phase. The higher recall rate indicates that the models are giving higher rate of positive outcomes. In other words, the ratio of the true positive and the combination of the false negative and true positive is called recall. There is always a settlement among recall and precision. Sensitivity of a model is often measured on recall value. The formula to calculate recall is shown below.

$$Recall = TP/\left(TP + FN\right) \tag{5.3}$$

F1 Score

The weighted mean between recall and precision is called F1 score. This value ranges from 0 to 1. F1 score also expresses the stability between the precision and recall. This stability relation is directly proportional to the execution of a classifier. The better the balance, the better performance and durable the model will be.

$$F1Score = 2 \times \left(Recall \times Precision\right)/\left(Recall + Precision\right) \tag{5.4}$$

ROC Curve

Receiver Operating Characteristic curve or ROC curve is an essential evaluation metrics in a classification problem. It is a graphical demonstration of a model's performance where for multi class problem the x-axis and y-axis contains the false positive ratio (FPR) and true positive ratio (TPR) respectively. By screening ROC curve, it can be determined that how a model can easily differentiate different classes of a dataset.

We will be evaluating our model by the Classification Accuracy, Error Rate, Precision, Recall and F1 Score.

5.2.2 Model Performance

Environment A

We had 2234 records for our Environment A; we managed to compute the accuracy using Stratified 10 Fold Cross Validation and used Scikit Learn's in built Classification Report method to compute Average Precision, Recall and F1 Score for these data (Table 5.2).

Table 5.2: Evaluation Table for Environment 'Stairs'.

	Stairs				
	Accuracy	**Precision**	**Recall**	**F1 Score**	**Loss Rate**
KNN	89.71	0.97	0.98	0.98	10.29
SVM	98.97	0.98	0.99	0.99	1.03
Random Forest	99.96	1	1	1	0.04
LDA	97.53	1	1	1	2.47

Basically Precision and Recall value greater than 0.7 is considered as a good and greater than .9 as an excellent Model; thus we have precision value more than .95 in every case. So the Model can be labelled as an effective Model indeed. To balance between Precision and Recall we have also compute the F1 Score which was also very satisfactory. Comparing between our selected classifiers, despite being the difference very low, Random Forest is able to perform better with the lesser error rate of 0.04% (Table 5.2). Again despite being the lowest accuracy, KNN's 89.71% is not ignorable at all.

Environment B

We had 2385 records for our Environment B; we managed to compute the accuracy using Stratified 10 Fold Cross Validation and used Scikit Learn's in built Classification Report method to compute Average Precision, Recall and F1 Score for these data (Table 5.3).

Table 5.3: Evaluation Table for Environment 'Open Space'.

	Open Space				
	Accuracy	**Precision**	**Recall**	**F1 Score**	**Loss Rate**
KNN	88.85	0.99	0.99	0.99	11.15
SVM	98.49	0.98	0.99	0.98	1.51
Random Forest	99.96	1	1	1	0.04
LDA	99.37	1	1	1	0.63

Basically Precision and Recall value greater than 0.7 is considered as a good and greater than .9 as an excellent Model; thus we have precision value more than .95 in every case. So the Model can be labelled as an effective Model indeed. To balance between Precision and Recall we have also compute the F1 Score which was also very satisfactory. Comparing between our preferred classifiers, Random Forest is giving the best outcome, where SVM has fallen short for a very short margin (Table 5.3). Even the last classifier considering predicted accuracy, KNN has a very satisfactory accuracy of 88.85%.

Environment C

We had 1045 records for our Environment C; we managed to compute the accuracy using Stratified 10 Fold Cross Validation and used Scikit Learn's in built Classification Report method to compute Average Precision, Recall and F1 Score for these data (Table 5.4).

Table 5.4: Evaluation Table for Environment 'Narrow Space'.

	Narrow Space				
	Accuracy	**Precision**	**Recall**	**F1 Score**	**Loss Rate**
KNN	90.68	0.96	0.98	0.97	9.32
SVM	98.85	0.96	0.98	0.97	1.15
Random Forest	99.81	1	1	1	0.19
LDA	98.66	0.98	0.99	0.98	1.34

Basically Precision and Recall value greater than 0.7 is considered as a good and greater than .9 as an excellent Model; thus we have precision value more than .95 in every case. So the Model can be labelled as an effective Model indeed. To balance between Precision and Recall we have also compute the F1 Score which was also very satisfactory. Comparing between our 4 classifiers, Random Forest comes up with the best accuracy rate and lesser error rate; whereas SVM and LDA is not ignorable as they both have prediction accuracy more than 98% (Table 5.4). Again KNN performs better it did than previous environments; it has error rate of just 9.32%.

Environment D

We had 602 records for our Environment D; we managed to compute the accuracy using Stratified 10 Fold Cross Validation and used Scikit Learn's in built Classification Report method to compute Average Precision, Recall and F1 Score for these data (Table 5.5).

Table 5.5: Evaluation Table for Environment 'Moving'.

	Moving				
	Accuracy	**Precision**	**Recall**	**F1 Score**	**Loss Rate**
KNN	96.34	0.97	0.98	0.98	3.66
SVM	99.17	1	1	1	0.83
Random Forest	99.83	1	1	1	0.17
LDA	97.84	1	1	1	2.16

Basically Precision and Recall value greater than 0.7 is considered as a good and greater than .9 as an excellent Model; thus we have precision value more than .95 in every case. So the Model can be labelled as an effective Model indeed. To balance between Precision and Recall we have also compute the F1 Score which was also very satisfactory (Table 5.5). Between our Machine Learning Algorithms for this environment also random Forest is giving us the least error rate; other hand SVM, KNN and LDA are also giving much better accuracy comparing to other papers who have worked with multi class classification [42].

Environment E

We had 1587 records for our Environment E; we managed to compute the accuracy using Stratified 10 Fold Cross Validation and used Scikit Learn's in built Classification Report method to compute Average Precision, Recall and F1 Score for these data (Table 5.6).

Table 5.6: Evaluation Table for Environment 'Elevator'.

	Elevator				
	Accuracy	**Precision**	**Recall**	**F1 Score**	**Loss Rate**
KNN	99.81	1	1	1	0.19
SVM	99.81	0.99	1	1	0.19
Random Forest	99.87	1	1	1	0.13
LDA	99.56	1	0.99	1	0.44

Basically Precision and Recall value greater than 0.7 is considered as a good and greater than .9 as an excellent Model; thus we have precision value more than .95 in every case. So the Model can be labelled as an effective Model indeed. To balance between Precision and Recall we have also compute the F1 Score which was also very satisfactory. Here SVM, KNN and Random Forest both have computed very close classification accuracy. Moreover, every classifier is giving more than 99% accuracy for this environment (Table 5.6). So, our model can be considered perfect for this environment.

Environment F

We had 903 records for our Environment F; we managed to compute the accuracy using Stratified 10 Fold Cross Validation and used Scikit Learn's in built Classification Report method to compute Average Precision, Recall and F1 Score for these data (Table 5.7).

Table 5.7: Evaluation Table for Environment 'Doors'.

	Doors				
	Accuracy	**Precision**	**Recall**	**F1 Score**	**Loss Rate**
KNN	95.004	1	1	1	4.996
SVM	99.45	0.99	0.99	0.99	0.55
Random Forest	99.45	0.99	0.99	0.99	0.55
LDA	99.45	1	1	1	0.55

Basically Precision and Recall value greater than 0.7 is considered as a good and greater than .9 as an excellent Model; thus we have precision value more than .95 in every case. So the Model can be labelled as an effective Model indeed. To balance between Precision and Recall we have also compute the F1 Score which was also very satisfactory. For this environment other than KNN, every classifier gives us the same accuracy of 99.45; where KNN has accuracy of 95% (Table 5.7) which is very satisfactory also.

Environment G

We had 302 records for our Environment G; we managed to compute the accuracy using Stratified 10 Fold Cross Validation and used Scikit Learn's inbuilt Classification Report method to compute Average Precision, Recall and F1 Score for these data (Table 5.8).

Table 5.8: Evaluation Table for Environment 'Sounds'.

	Sounds				
	Accuracy	**Precision**	**Recall**	**F1 Score**	**Loss Rate**
KNN	94.02	0.94	0.97	0.95	5.98
SVM	98.02	0.94	0.97	0.95	1.98
Random Forest	99.01	0.98	0.98	0.98	0.99
LDA	97.68	1	1	1	2.32

Basically Precision and Recall value greater than 0.7 is considered as a good and greater than .9 as an excellent Model; thus we have precision value more than .95 in every case. So the Model can be labelled as an effective Model indeed. To balance between Precision and Recall we have also compute the F1 Score which was also very satisfactory. Random forest has the least error rate of less than 1% (Table 5.8) for this environment where other classifiers have also managed to come with very less error rate.

We are successful to come up with better classification accuracy with our model (Figure 4.1) than some papers who worked with same type of Machine Learning Algorithms (SVM, LDA and KNN) and stress detection techniques [85], even by using Deep Neural Networking [48]. We followed papers which have used Relative Power and Absolute Power of the bands and they could manage to get 83.4% when they worked with multi classes; whereas we had better accuracy when we have worked with multi classes for almost all the environments [45].

Chapter 6

Conclusion

A state of mental or psychological pressure or tension which is a result of unpleasant or demanding situations from psychological or social events is called Stress. To record the electrical activity over the scalp, Electroencephalogram (EEG) is used as a tool which is widely applied in medical and research fields. According to statistics of WHO, Visual impairment affects approximately 285 million people of the world [78]. Mobility aids or assistive navigation aids are extremely necessary for improving the quality of life of the visually impaired people (VIP) and also to decrease their dependence. Thus, there stays no reason why detecting stressful environments is so important for aiding them. That's why we have closely monitored these EEG signals we got from those 9 people and it is divided into five bands and 5 features were extracted from these bands. Stratified 10 Fold Cross Validation method is implemented for categorization. So, now it can be easily estimated from the CV graph provided in the appendix that which is the worst performance and best performance. Moreover, Stressful environments have more response over Alpha and Beta bands; therefore, by examining the changes in these bands particularly we can track down the discomfort for a Visually Impaired man in different environments. We have applied four Machine Learning Algorithms; where every classifier individually performed really satisfactory. We cared to generate accuracy more than 90% every time. The results of our model shows (Figure 4.1) that using our five features; Average Band Power, Absolute Band Power, Relative Band Power, Standard Deviation and Spectral Entropy, stressful environments can be detected better than previous models and this model can be used further for biofeedback applications and conducting navigation experiments for the Visually Impaired People.

This research was conducted to improve the accuracy of detecting stress from the previous models by proposing a stress recognition framework based on EEG and we consider our research has been successful to many extents.

Bibliography

[1] H. Chotas, J. Bourne, and P. Teschan, "Heuristic techniques in the quantification of the electroencephalogram in renal failure", *Computers and Biomedical Research*, vol. 12, no. 4, pp. 299–312, 1979.

[2] R. E. Wheeler, R. J. Davidson, and A. J. Tomarken, "Frontal brain asymmetry and emotional reactivity: A biological substrate of affective style", *Psychophysiology*, vol. 30, no. 1, pp. 82–89, 1993.

[3] M. Hutchison, *Mega Brain Power: Transform Your Life With Mind Machines and Brain Nutrients*. Hyperion, 1994.

[4] S. Reisman, "Measurement of physiological stress", in *Proceedings of the IEEE 23rd Northeast Bioengineering Conference*, IEEE, 1997, pp. 21–23.

[5] R. C. O'reilly and Y. Munakata, *Computational explorations in cognitive neuroscience: Understanding the mind by simulating the brain*. MIT press, 2000.

[6] X. Zeng and T. R. Martinez, "Distribution-balanced stratified cross-validation for accuracy estimation", *Journal of Experimental & Theoretical Artificial Intelligence*, vol. 12, no. 1, pp. 1–12, 2000.

[7] C. Huang, L. Davis, and J. Townshend, "An assessment of support vector machines for land cover classification", *International Journal of remote sensing*, vol. 23, no. 4, pp. 725–749, 2002.

[8] M. Teplan, *Fundamental of eeg measurement measurement science review*, 2002.

[9] J. J. Allen, J. A. Coan, and M. Nazarian, "Issues and assumptions on the road from raw signals to metrics of frontal eeg asymmetry in emotion", *Biological psychology*, vol. 67, no. 1-2, pp. 183–218, 2004.

[10] R. K. Ellerkmann, V.-M. Liermann, T. M. Alves, I. Wenningmann, S. Kreuer, W. Wilhelm, H. Roepcke, A. Hoeft, and J. Bruhn, "Spectral entropy and bispectral index as measures of the electroencephalographic effects of sevoflurane", *Anesthesiology: The Journal of the American Society of Anesthesiologists*, vol. 101, no. 6, pp. 1275–1282, 2004.

[11] K. Dedovic, R. Renwick, N. K. Mahani, V. Engert, S. J. Lupien, and J. C. Pruessner, "The montreal imaging stress task: Using functional imaging to investigate the effects of perceiving and processing psychosocial stress in the human brain", *Journal of Psychiatry and Neuroscience*, vol. 30, no. 5, p. 319, 2005.

[12] E. Hoffmann, *Brain training against stress*, 2005.

[13] Y. Bazi and F. Melgani, "Toward an optimal svm classification system for hyperspectral remote sensing images", *IEEE Transactions on geoscience and remote sensing*, vol. 44, no. 11, pp. 3374–3385, 2006.

[14] A. J. Niemiec and B. J. Lithgow, "Alpha-band characteristics in eeg spectrum indicate reliability of frontal brain asymmetry measures in diagnosis of depression.", in *2005 IEEE Engineering in Medicine and Biology 27th Annual Conference*, IEEE, 2006, pp. 7517–7520.

[15] A. Savran, K. Ciftci, G. Chanel, J. Mota, L. Hong Viet, B. Sankur, L. Akarun, A. Caplier, and M. Rombaut, "Emotion detection in the loop from brain signals and facial images", in *Proceedings of the eNTERFACE 2006 Workshop*, 2006.

[16] A. Mathur and G. M. Foody, "Multiclass and binary svm classification: Implications for training and classification users", *IEEE Geoscience and remote sensing letters*, vol. 5, no. 2, pp. 241–245, 2008.

[17] N. Sulaiman, N. H. A. Hamid, Z. H. Murat, and M. N. Taib, "Initial investigation of human physical stress level using brainwaves", in *2009 IEEE Student Conference on Research and Development (SCOReD)*, IEEE, 2009, pp. 230–233.

[18] J. S. Brumberg, A. Nieto-Castanon, P. R. Kennedy, and F. H. Guenther, "Brain–computer interfaces for speech communication", *Speech communication*, vol. 52, no. 4, pp. 367–379, 2010.

[19] S. A. Hosseini and M. A. Khalilzadeh, "Emotional stress recognition system using eeg and psychophysiological signals: Using new labelling process of eeg signals in emotional stress state", in *2010 international conference on biomedical engineering and computer science*, IEEE, 2010, pp. 1–6.

[20] A. Kemp, K. Griffiths, K. Felmingham, S. A. Shankman, W. Drinkenburg, M. Arns, C. R. Clark, and R. Bryant, "Disorder specificity despite comorbidity: Resting eeg alpha asymmetry in major depressive disorder and post-traumatic stress disorder", *Biological psychology*, vol. 85, no. 2, pp. 350–354, 2010.

[21] Z. H. Murat, M. N. Taib, S. Lias, R. S. S. A. Kadir, N. Sulaiman, and M. Mustafa, "Eeg analysis for brainwave balancing index (bbi)", in *2010 2nd International Conference on Computational Intelligence, Communication Systems and Networks*, IEEE, 2010, pp. 389–393.

[22] S. Z. Sarwar, M. S. Aslam, I. Manarvi, A. Ishaque, and M. Azeem, "Noninvasive imaging system for visually impaired people", in *2010 3rd International Conference on Computer Science and Information Technology*, IEEE, vol. 9, 2010, pp. 1–6.

[23] A. Subasi and M. I. Gursoy, "Eeg signal classification using pca, ica, lda and support vector machines", *Expert systems with applications*, vol. 37, no. 12, pp. 8659–8666, 2010.

[24] J. Jin, B. Z. Allison, E. W. Sellers, C. Brunner, P. Horki, X. Wang, and C. Neuper, "An adaptive p300-based control system", *Journal of neural engineering*, vol. 8, no. 3, p. 036 006, 2011.

[25] M. Murugappan, "Human emotion classification using wavelet transform and knn", in *2011 International Conference on Pattern Analysis and Intelligence Robotics*, IEEE, vol. 1, 2011, pp. 148–153.

[26] Q. Li, *Digital sonar design in underwater acoustics: principles and applications.* Springer Science & Business Media, 2012.

[27] P. Natarajan, N. Krishnan, N. S. Kenkre, S. Nancy, and B. P. Singh, "Tumor detection using threshold operation in mri brain images", in *2012 IEEE International Conference on Computational Intelligence and Computing Research*, IEEE, 2012, pp. 1–4.

[28] J. J. Shih, D. J. Krusienski, and J. R. Wolpaw, "Brain-computer interfaces in medicine", in *Mayo Clinic Proceedings*, Elsevier, vol. 87, 2012, pp. 268–279.

[29] B. B. Briesemeister, S. Tamm, A. Heine, A. M. Jacobs, *et al.*, "Approach the good, withdraw from the bad—a review on frontal alpha asymmetry measures in applied psychological research", *Psychology*, vol. 4, no. 03, p. 261, 2013.

[30] N. Gordillo, E. Montseny, and P. Sobrevilla, "State of the art survey on mri brain tumor segmentation", *Magnetic resonance imaging*, vol. 31, no. 8, pp. 1426–1438, 2013.

[31] S. A. Hosseini, M. Akbarzadeh-T, and M. B. Naghibi-Sistani, "Qualitative and quantitative evaluation of eeg signals in epileptic seizure recognition", *International Journal of Intelligent Systems and Applications*, vol. 5, no. 6, p. 41, 2013.

[32] C. Benson and V. Lajish, "Morphology based enhancement and skull stripping of mri brain images", in *2014 International Conference on intelligent computing applications*, IEEE, 2014, pp. 254–257.

[33] R. Yuvaraj, M. Murugappan, N. M. Ibrahim, M. I. Omar, K. Sundaraj, K. Mohamad, R. Palaniappan, E. Mesquita, and M. Satiyan, "On the analysis of eeg power, frequency and asymmetry in parkinson's disease during emotion processing", *Behavioral and brain functions*, vol. 10, no. 1, p. 12, 2014.

[34] A. Bhardwaj, A. Gupta, P. Jain, A. Rani, and J. Yadav, "Classification of human emotions from eeg signals using svm and lda classifiers", in *2015 2nd International Conference on Signal Processing and Integrated Networks (SPIN)*, IEEE, 2015, pp. 180–185.

[35] P. A. Abhang, B. W. Gawali, and S. C. Mehrotra, *Introduction to EEG-and speech-based emotion recognition.* Academic Press, 2016.

[36] M. S. Kalas and B. Momin, "Stress detection and reduction using eeg signals", in *2016 International Conference on Electrical, Electronics, and Optimization Techniques (ICEEOT)*, IEEE, 2016, pp. 471–475.

[37] 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*, 2016, pp. 53–60.

[38] M. O. Krucoff, S. Rahimpour, M. W. Slutzky, V. R. Edgerton, and D. A. Turner, "Enhancing nervous system recovery through neurobiologics, neural interface training, and neurorehabilitation", *Frontiers in neuroscience*, vol. 10, p. 584, 2016.

[39] A. V. Kyrpa, “European clubs or euroclubs as forms of introduction of extracurricular education”, *European Journal of Education and Applied Psychology*, pp. 45–47, 2016. DOI: 10.20534/ejeap-16-2-45-47.

[40] C. Saitis and K. Kalimeri, “Identifying urban mobility challenges for the visually impaired with mobile monitoring of multimodal biosignals”, in *International Conference on Universal Access in Human-Computer Interaction*, Springer, 2016, pp. 616–627.

[41] S. Bose, V. Rama, N. Warangal, and C. R. Rao, “Eeg signal analysis for seizure detection using discrete wavelet transform and random forest”, in *2017 International Conference on Computer and Applications (ICCA)*, IEEE, 2017, pp. 369–378.

[42] A. R. Subhani, W. Mumtaz, M. N. B. M. Saad, N. Kamel, and A. S. Malik, “Machine learning framework for the detection of mental stress at multiple levels”, *IEEE Access*, vol. 5, pp. 13 545–13 556, 2017.

[43] Y. Tian, H. Zhang, W. Xu, H. Zhang, L. Yang, S. Zheng, and Y. Shi, “Spectral entropy can predict changes of working memory performance reduced by short-time training in the delayed-match-to-sample task”, *Frontiers in human neuroscience*, vol. 11, p. 437, 2017.

[44] Z. Koudelková and M. Strmiska, “Introduction to the identification of brain waves based on their frequency”, in *MATEC Web of Conferences*, EDP Sciences, vol. 210, 2018, p. 05 012.

[45] C. Saitis and K. Kalimeri, “Multimodal classification of stressful environments in visually impaired mobility using eeg and peripheral biosignals”, *IEEE Transactions on Affective Computing*, 2018.

[46] C. Saitis, M. Z. Parvez, and K. Kalimeri, “Cognitive load assessment from eeg and peripheral biosignals for the design of visually impaired mobility aids”, *Wireless Communications and Mobile Computing*, vol. 2018, 2018.

[47] R. Carter, *The human brain book: An illustrated guide to its structure, function, and disorders*. Penguin, 2019.

[48] H. Jebelli, M. M. Khalili, and S. Lee, “Mobile eeg-based workers’ stress recognition by applying deep neural network”, in *Advances in Informatics and Computing in Civil and Construction Engineering*, Springer, 2019, pp. 173–180.

[49] 2020. [Online]. Available: http://www.who.int/mediacentre/factsheets/fs282/en/Available.

[50] 2020. [Online]. Available: https://letstalkscience.ca/educational-resources/backgrounders/brain-architecture.

[51] 2020. [Online]. Available: https://qbi.uq.edu.au/brain/brain-anatomy/lobes-brain.

[52] 2020. [Online]. Available: https://human-memory.net/occipital-brain-lobe/.

[53] 2020. [Online]. Available: https://brainmadesimple.com/cerebellum/.

[54] 2020. [Online]. Available: https://www.hopkinsmedicine.org/health/conditions-and-diseases/anatomy-of-the-brain.

[55] 2020. [Online]. Available: https://en.wikipedia.org/wiki/Brain_computer_interface.

[56] 2020. [Online]. Available: https://images.app.goo.gl/JL3NAXGNTaAXXTTC8.

[57] 2020. [Online]. Available: https://blog.santelog.com/2020/08/05/epilepsie-lia-pour-detecter-la-crise-avant/.

[58] 2020. [Online]. Available: https://www.kidshealth.org.nz/eeg-electroencephalogram.

[59] 2020. [Online]. Available: https://www.epilepsy.com/learn/diagnosis/eeg.

[60] 2020. [Online]. Available: https://www.mayoclinic.org/tests-procedures/eeg/about/pac-20393875.

[61] 2020. [Online]. Available: https://www.hopkinsmedicine.org/health/treatment-tests-and-therapies/electroencephalogram-eeg.

[62] 2020. [Online]. Available: https://www.nhs.uk/conditions/electroencephalogram/.

[63] 2020. [Online]. Available: https://brainworksneurotherapy.com/what-are-brainwaves.

[64] 2020. [Online]. Available: http://neurofeedbackalliance.org/understanding-brain-waves/.

[65] 2020. [Online]. Available: https://owlcation.com/social-sciences/The-Effect-of-Binaural-Beats-on-Memory-through-the-Induction-of-of-Gamma-Brain-Waves.

[66] 2020. [Online]. Available: https://www.javatpoint.com/dip-introduction-to-frequency-domain.

[67] 2020. [Online]. Available: https://www.mathworks.com/help/signal/ug/practical-introduction-to-frequency-%20domain-analysis.html;%20jsessionid=e8970524ca33e034f77ed7828f7f.

[68] 2020. [Online]. Available: https://www.wavemetrics.com/products/igorpro/dataanalysis/signalprocessing/fouriertransforms.

[69] 2020. [Online]. Available: http://hyperphysics.phy-astr.gsu.edu/hbase/Math/fft.html.

[70] 2020. [Online]. Available: https://www.wavemetrics.com/products/igorpro/dataanalysis/signalprocessing.

[71] 2020. [Online]. Available: https://www.originlab.com/doc/Origin-Help/IFFT.

[72] 2020. [Online]. Available: https://www.r-bloggers.com/2017/08/radial-kernel-support-vector-classifier/.

[73] 2020. [Online]. Available: https://en.wikipedia.org/wiki/Random_forest.

[74] 2020. [Online]. Available: https://www.freecodecamp.org/news/how-to-use-the-tree-based-algorithm-for-machine-learning/.

[75] 2020. [Online]. Available: https://en.wikipedia.org/wiki/Linear_discriminant_analysis.

[76] 2020. [Online]. Available: https://medium.com/towards-artificial-intelligence/%20machine-learning-dimensionality-reduction-via-linear-%20discriminant-analysis-cc96b49d2757.

[77] 2020. [Online]. Available: https://www.thoughtco.com/how-to-calculate-standard-deviation-608322.

[78] 2020. [Online]. Available: https://www.who.int/blindness/publications/globaldata%20/en/?fbclid=IwAR0Pc_l-I_gMki_aebKcKRV8F9gvGFqp3UKcrLZ%206VNnrGemzE8aKCv3MJAA.

[79] S. American, *What is the function of the various brainwaves?*, 2020. [Online]. Available: https://www.scientificamerican.com/article/what-is-the-function-of-t-1997-12-22/.

[80] J. Brownlee, *Linear discriminant analysis for machine learning*, 2020. [Online]. Available: https://machinelearningmastery.com/linear-discriminant-analysis-for-machine-learning/.

[81] R. Garg, R. Garg, and R. Garg, *7 types of classification algorithms - analytics india magazine*, 2020. [Online]. Available: https://analyticsindiamag.com/7-types-classification-algorithms/.

[82] T. Hubing, *Learnemc - time/frequency domain*, 2020. [Online]. Available: https://learnemc.com/time-frequency-domain.

[83] Z. Little, *Stratifiedkfold v.s kfold v.s stratifiedshufflesplit*, Jan. 2020. [Online]. Available: https://medium.com/@xzz201920/stratifiedkfold-v-s-kfold-v-s-stratifiedshufflesplit-ffcae5bfdf.

[84] P. Raphael Vallat, *Bandpower of an eeg signal*, 2020. [Online]. Available: https://raphaelvallat.com/bandpower.html.

[85] R. Sharma and K. Chopra, "Eeg signal analysis and detection of stress using classification techniques", *Journal of Information and Optimization Sciences*, vol. 41, no. 1, pp. 229–238, 2020.

[86] B. Tool, P. Search, R. Designs, T. Articles, I. Articles, T. Equipment, I. Days, I. Training, I. Webinars, and D. e. a. ICrsquo;s, *An introduction to digital signal processing - technical articles*, 2020. [Online]. Available: https://www.allaboutcircuits.com/technical-articles/an-introduction-to-digital-signal-processing/.

Appendix
Stratified 10 Fold CV Graphs

SVM

Environment Doors

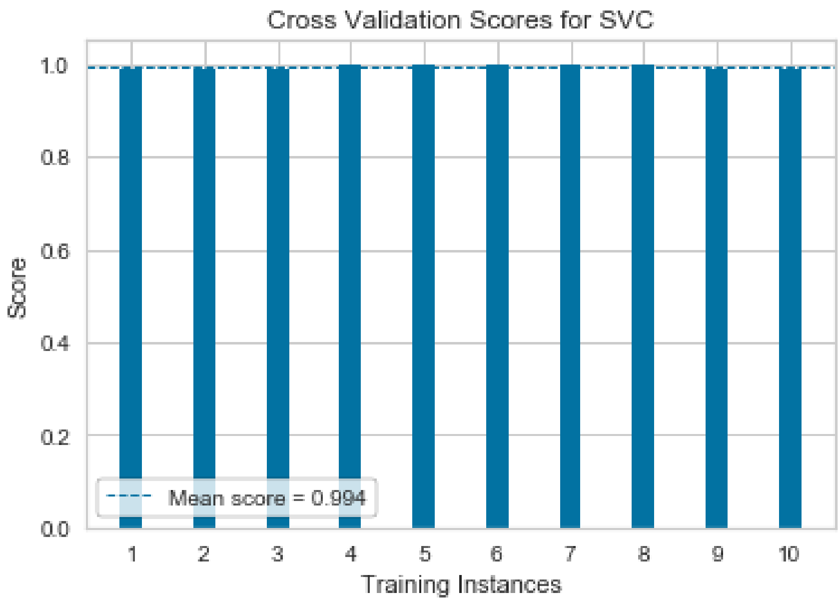

Figure 6.1: Stratified 10 Fold CV (SVM) for Environment 'Doors'

Environment Elevator

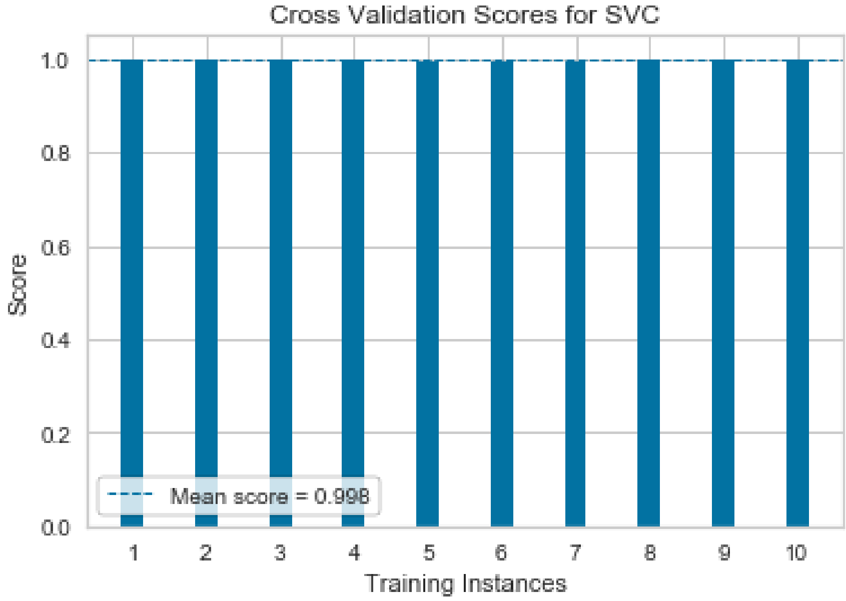

Figure 6.2: Stratified 10 Fold CV (SVM) for Environment 'Elevator'

Environment Moving

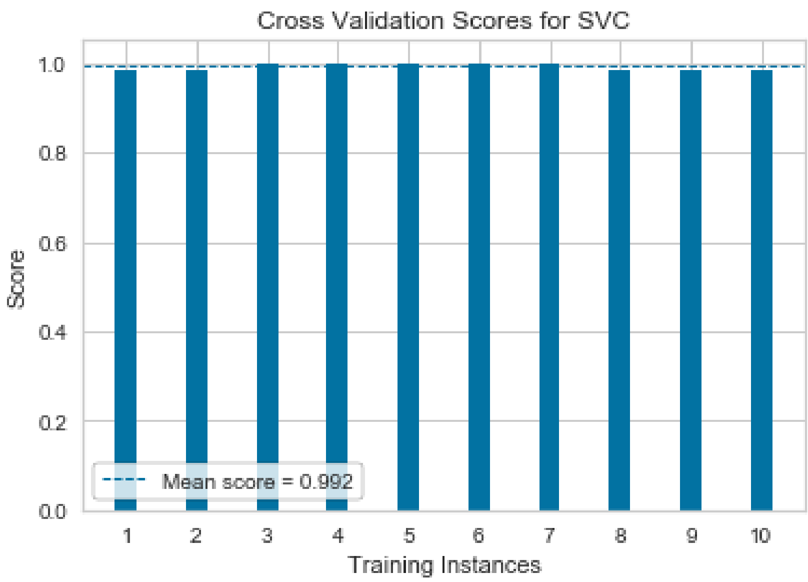

Figure 6.3: Stratified 10 Fold CV (SVM) for Environment 'Moving'

Environment Open Space

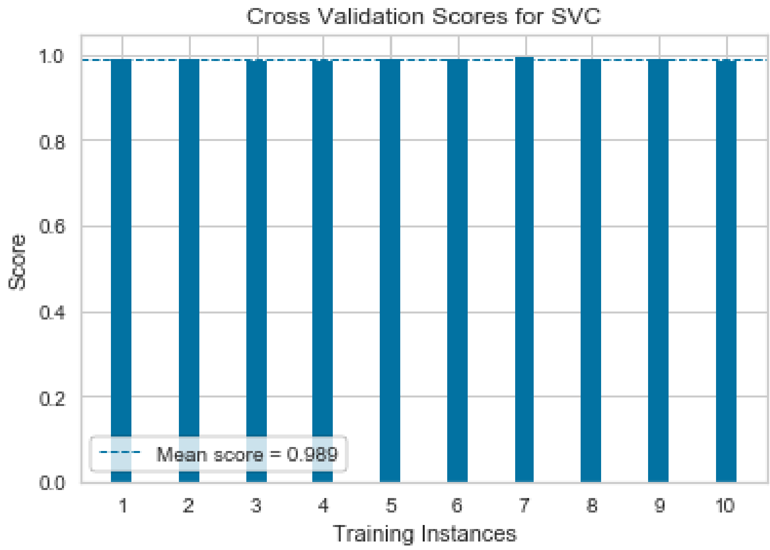

Figure 6.4: Stratified 10 Fold CV (SVM) for Environment 'Open Space'

Environment Sounds

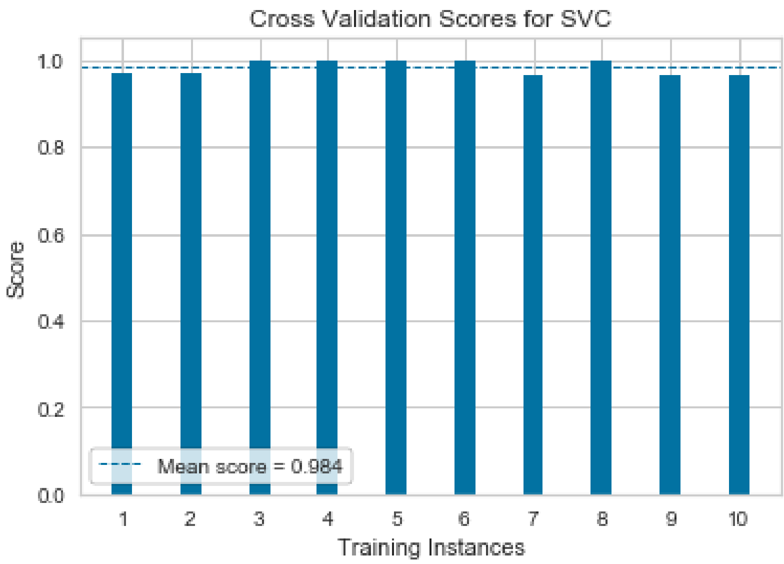

Figure 6.5: Stratified 10 Fold CV (SVM) for Environment 'Sound'

Environment Stair

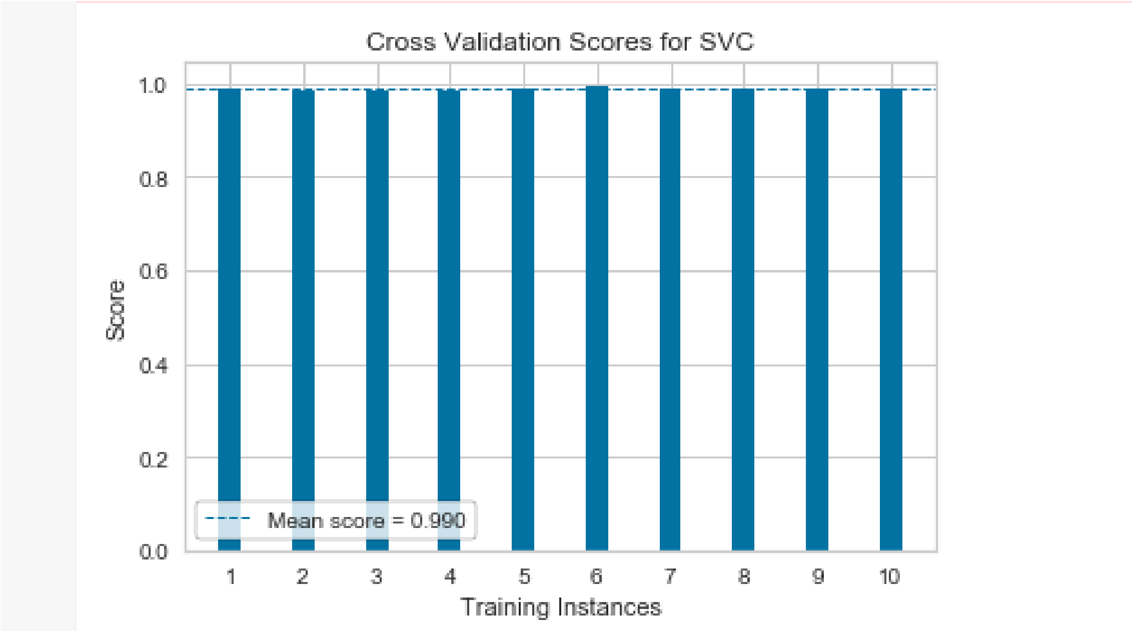

Figure 6.6: Stratified 10 Fold CV (SVM) for Environment 'Stair'

KNN

Environment Doors

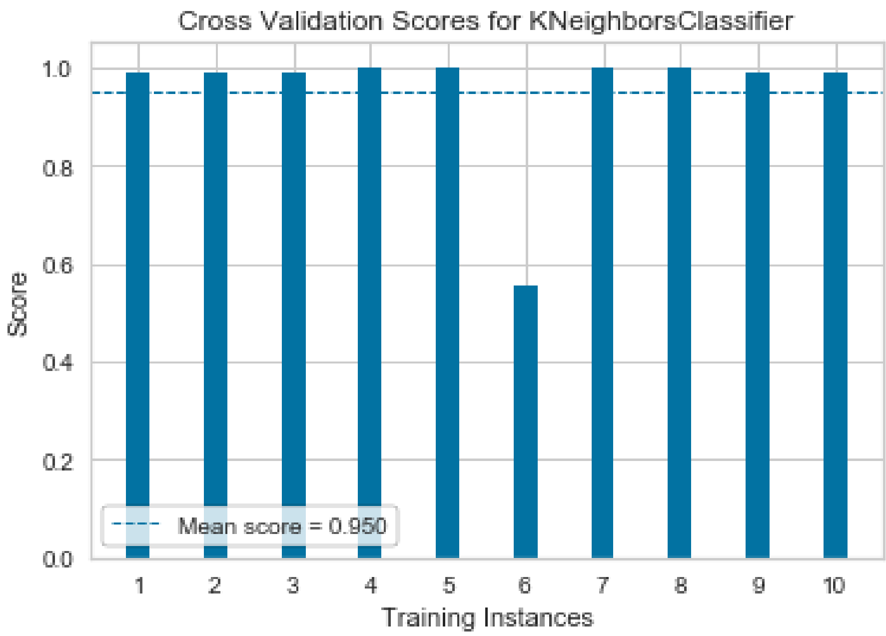

Figure 6.7: Stratified 10 Fold CV (KNN) for Environment 'Doors'

Environment Elevator

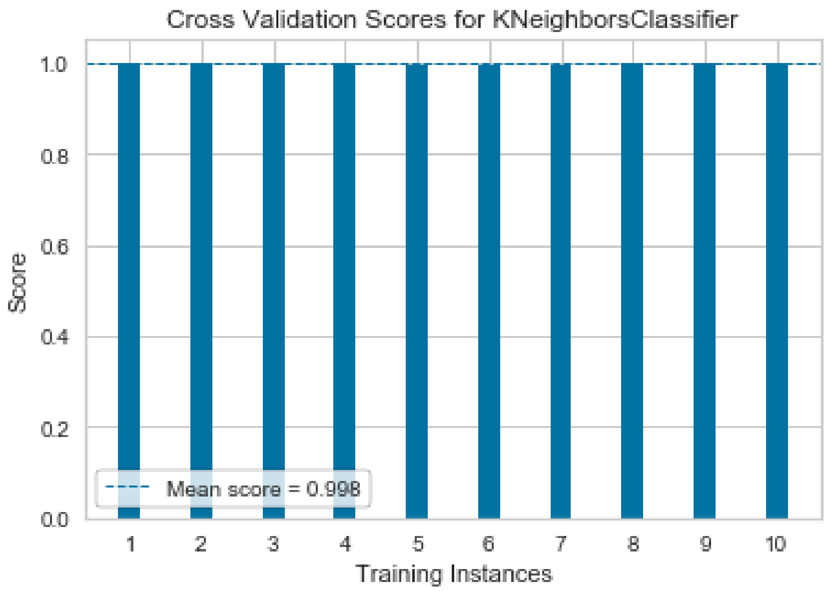

Figure 6.8: Stratified 10 Fold CV (KNN) for Environment 'Elevator'

Environment Open Space

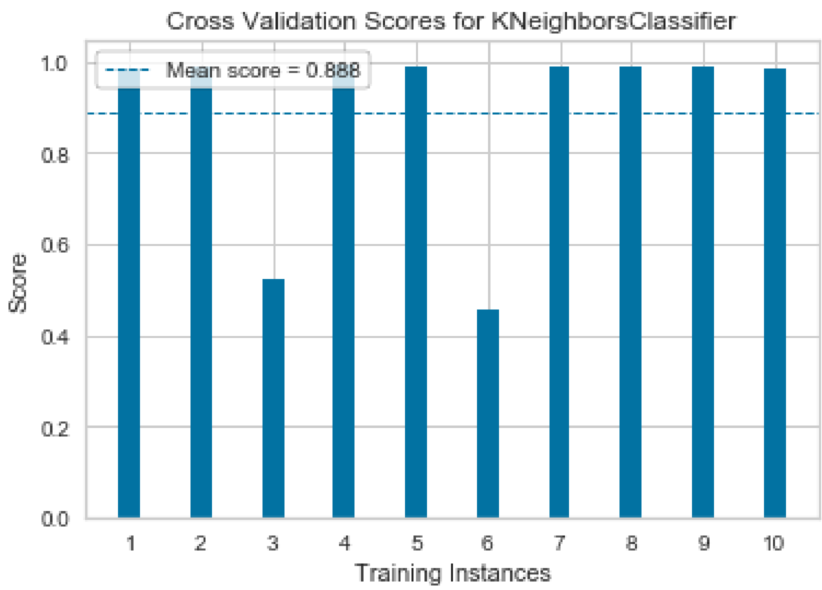

Figure 6.9: Stratified 10 Fold CV (KNN) for Environment 'Open Space'

Environment Stair

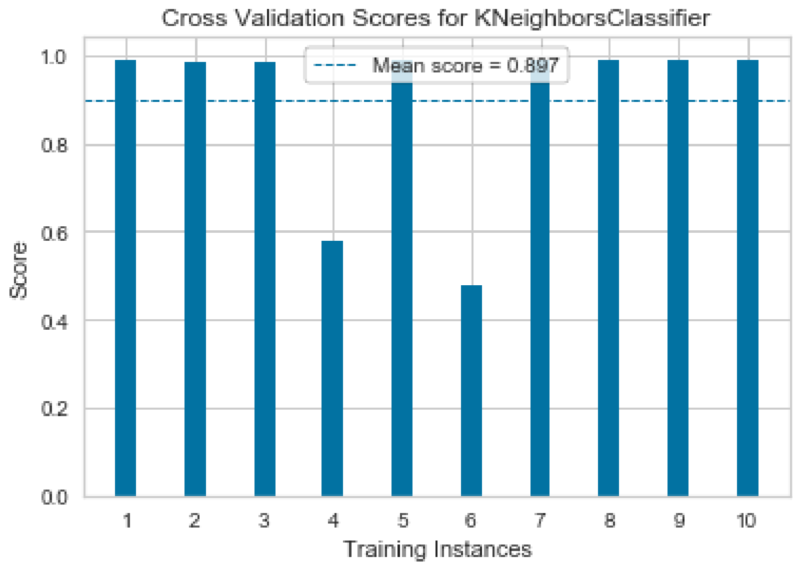

Figure 6.10: Stratified 10 Fold CV (KNN) for Environment 'Stair'

Environment Narrow Space

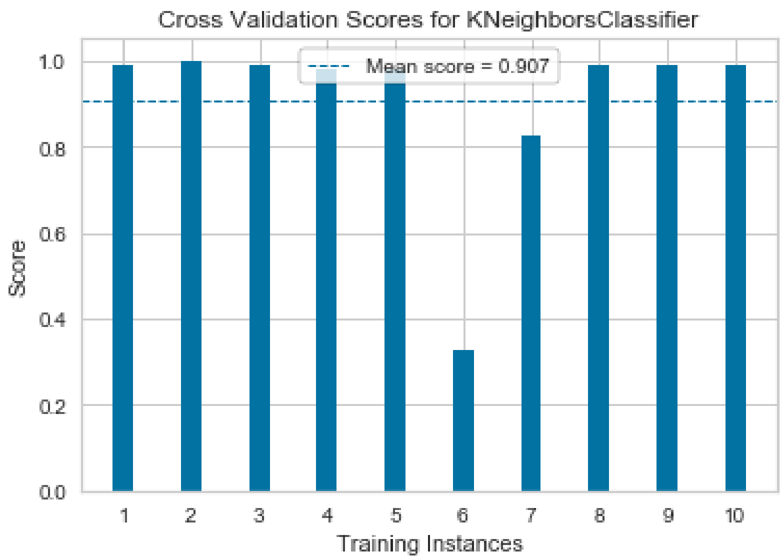

Figure 6.11: Stratified 10 Fold CV (KNN) for Environment 'Narrow Space'

Random Forest

Environment Doors

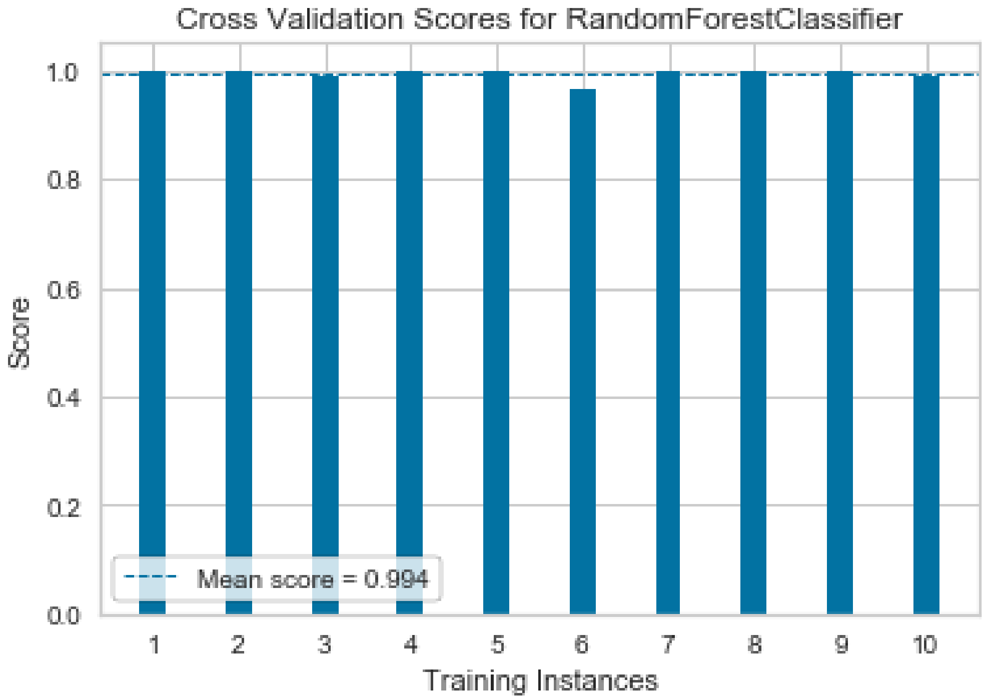

Figure 6.12: Stratified 10 Fold CV (RF) for Environment 'Doors'

Environment Elevator

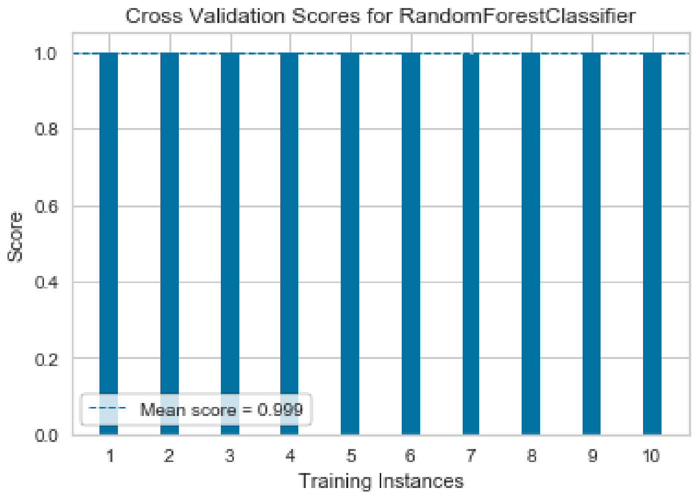

Figure 6.13: Stratified 10 Fold CV (RF) for Environment 'Elevator'

Environment Moving

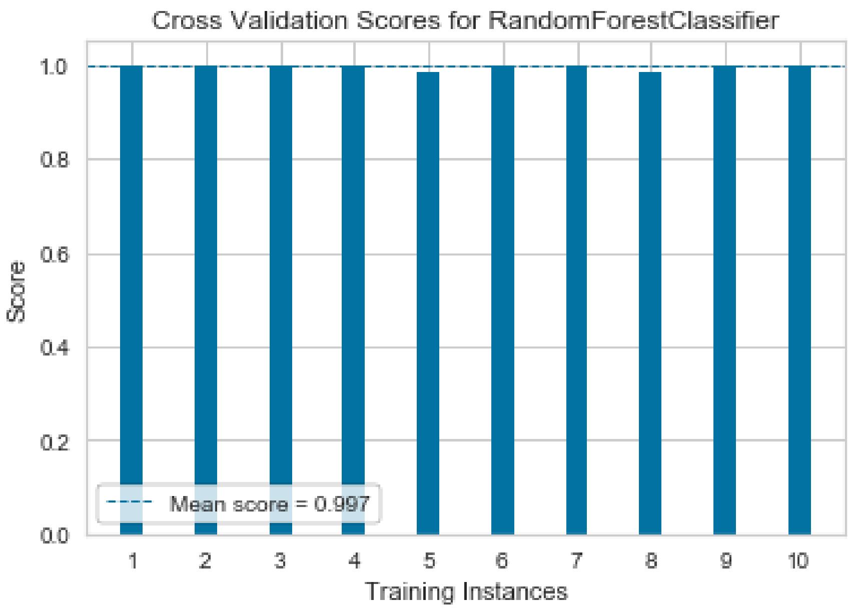

Figure 6.14: Stratified 10 Fold CV (RF) for Environment 'Moving'

Environment Open Space

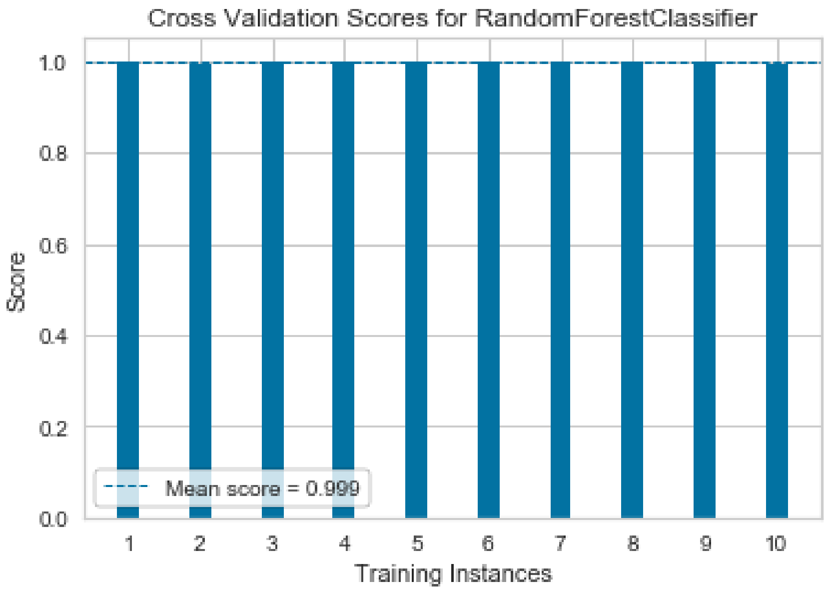

Figure 6.15: Stratified 10 Fold CV (RF) for Environment 'Open Space'

Environment Sounds

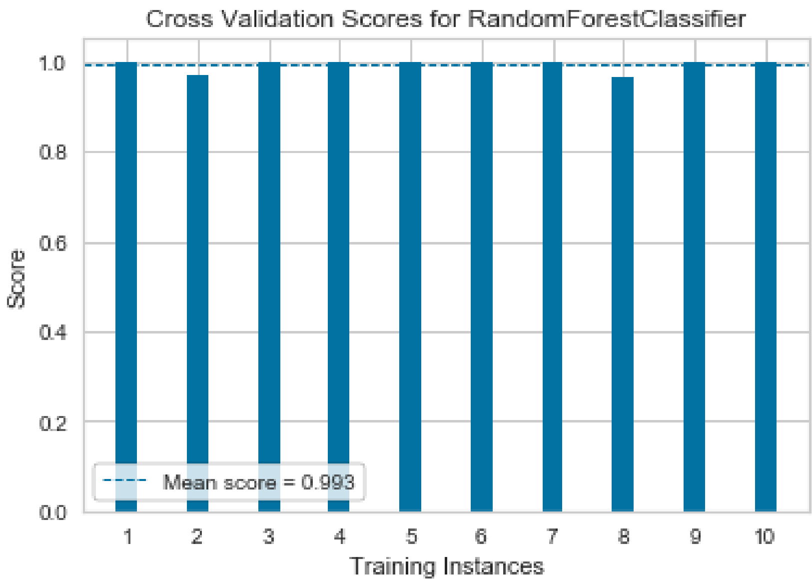

Figure 6.16: Stratified 10 Fold CV (RF) for Environment 'Sound'

Environment Stair

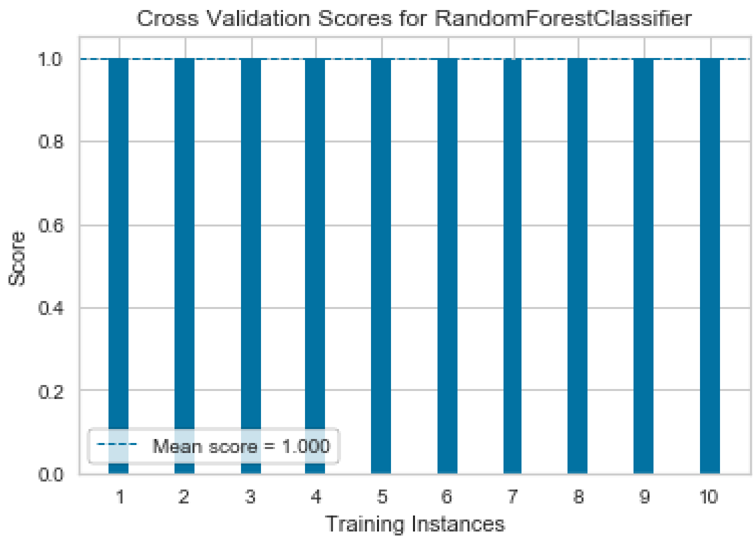

Figure 6.17: Stratified 10 Fold CV (RF) for Environment 'Stair'

Environment Narrow Space

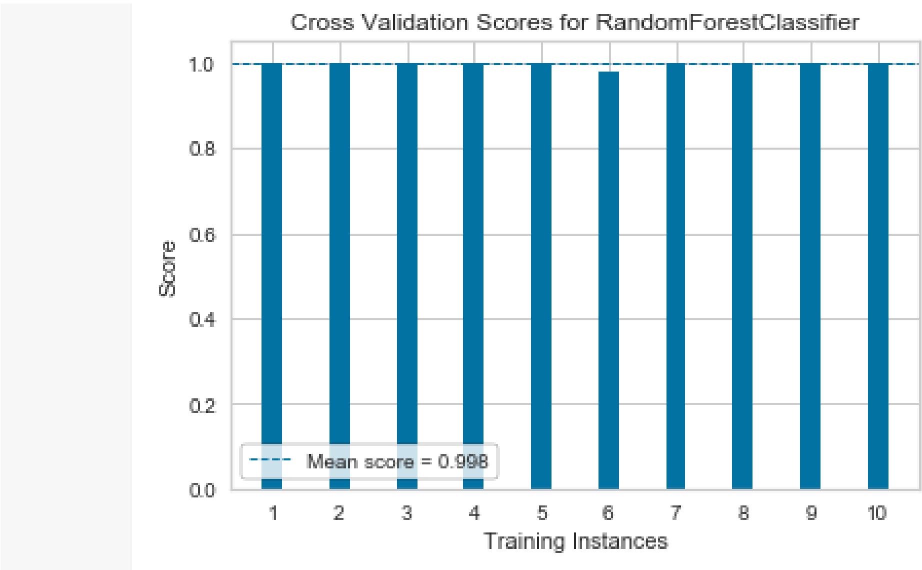

Figure 6.18: Stratified 10 Fold CV (RF) for Environment 'Narrow Space'

LDA

Environment Doors

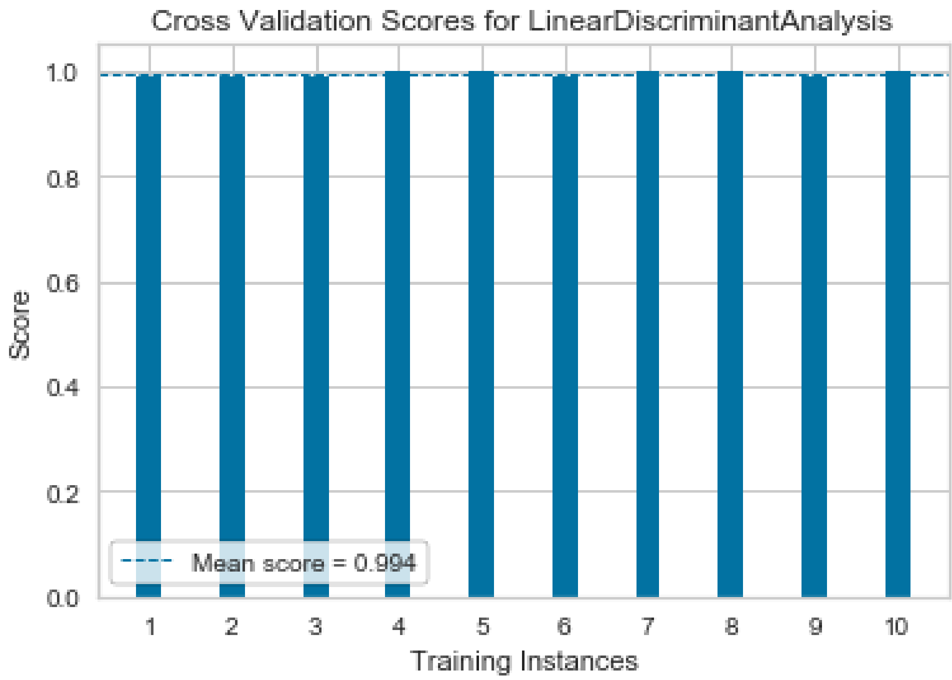

Figure 6.19: Stratified 10 Fold CV (LDA) for Environment 'Doors'

Environment Elevator

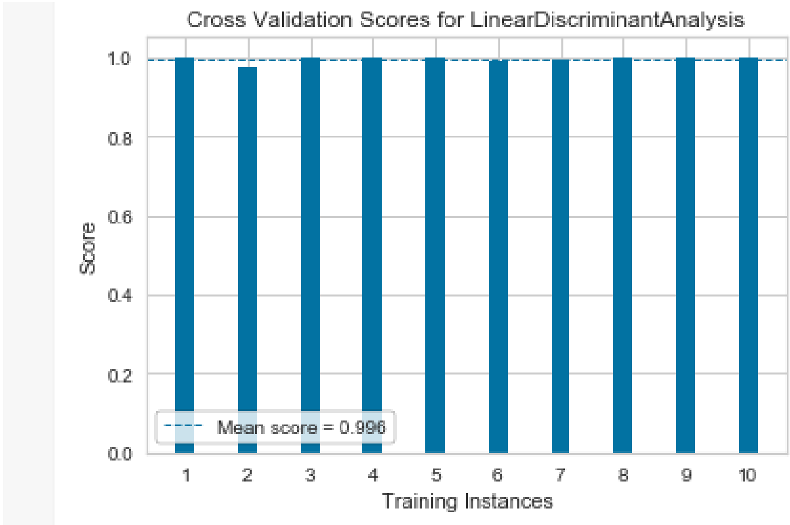

Figure 6.20: Stratified 10 Fold CV (LDA) for Environment 'Elevator'

Environment Moving

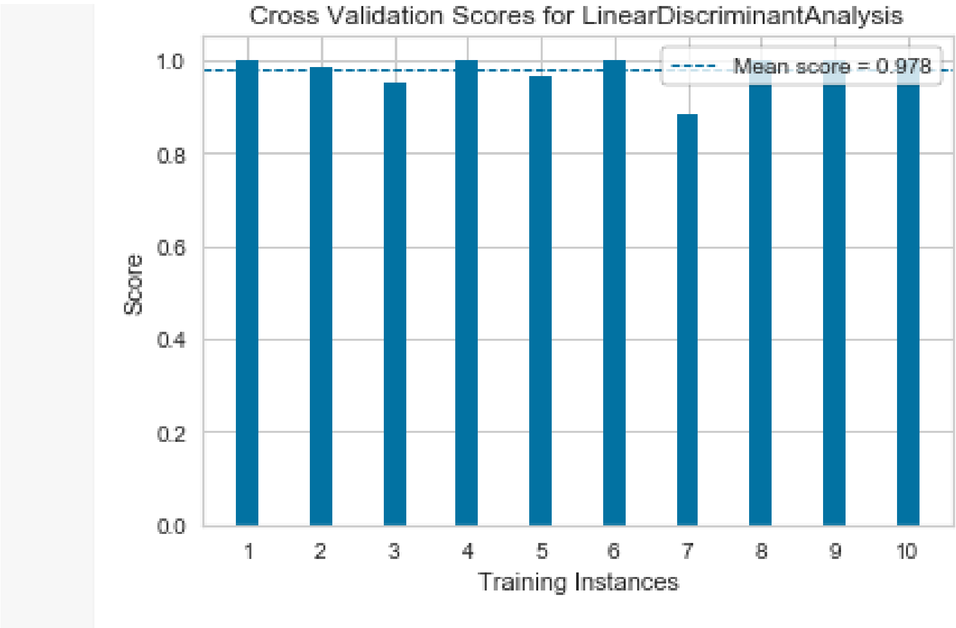

Figure 6.21: Stratified 10 Fold CV (LDA) for Environment 'Moving'

Environment Open Space

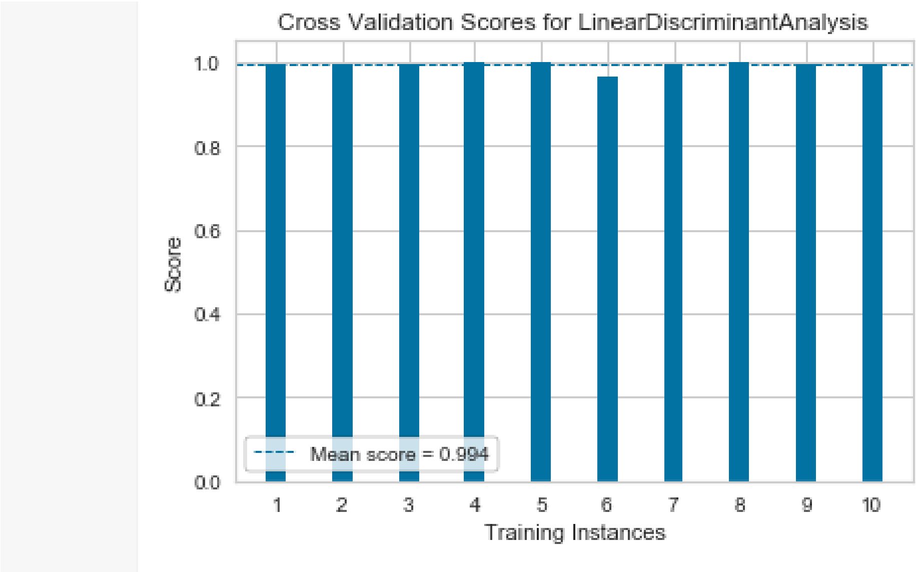

Figure 6.22: Stratified 10 Fold CV (LDA) for Environment 'Open Space'

Environment Sounds

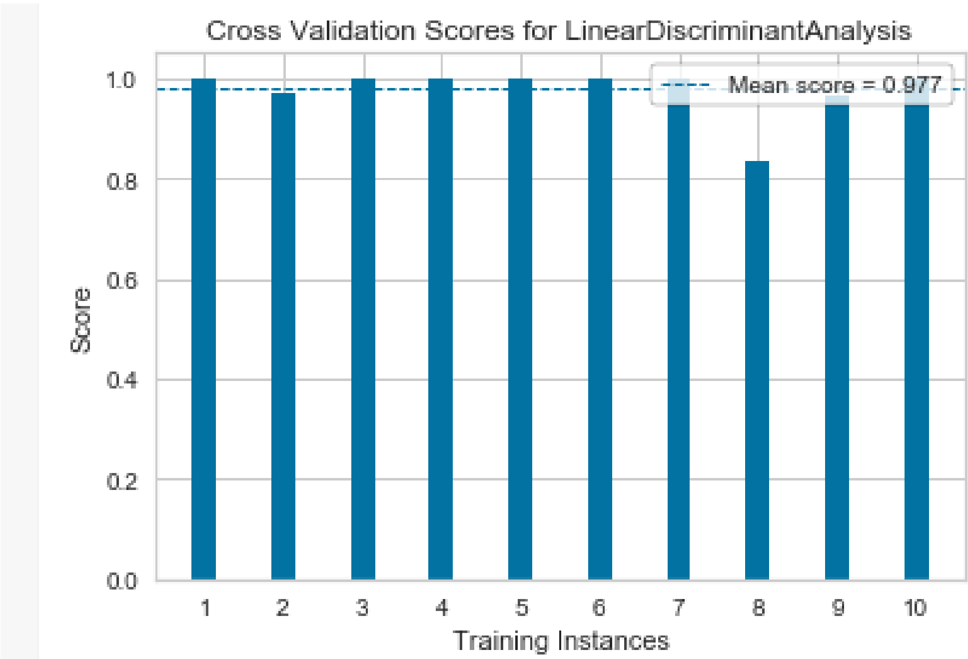

Figure 6.23: Stratified 10 Fold CV (LDA) for Environment 'Sound'

Environment Stair

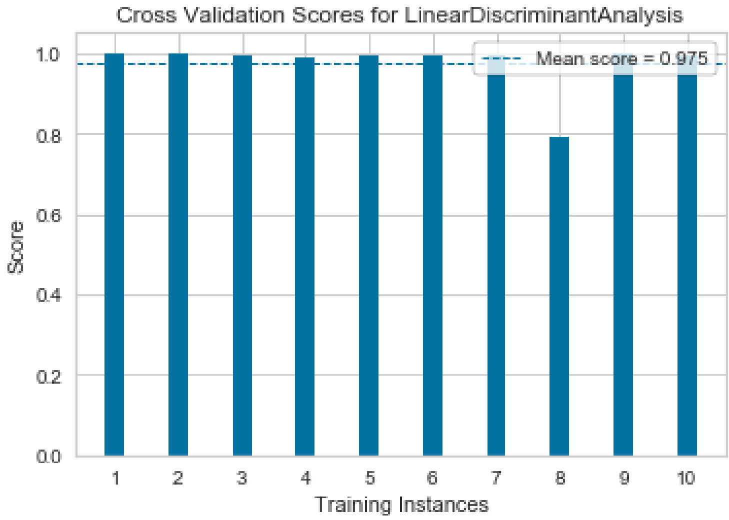

Figure 6.24: Stratified 10 Fold CV (LDA) for Environment 'Stair'

Environment Narrow Space

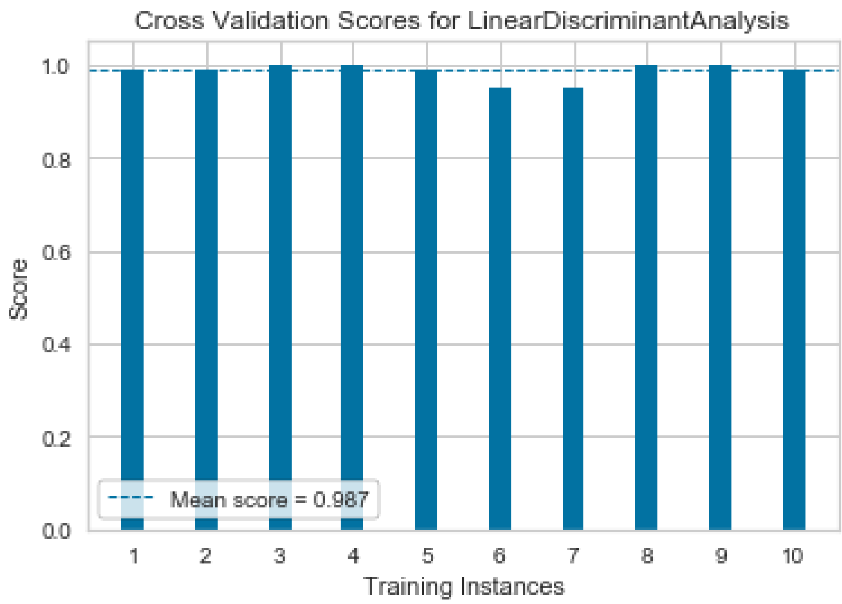

Figure 6.25: Stratified 10 Fold CV (LDA) for Environment 'Narrow Space'