M.Sc. Engg. Thesis

REVEALING ASSOCIATIONS AMONG NEGATIVE FEELINGS AND EEG-BASED BRAINWAVE SIGNALS IN ROHINGYA REFUGEES

by

Kazi Sharmin Dina (1015052070)

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Dedicated to my loving parents

AUTHOR'S CONTACT

Kazi Sharmin Dina

Email: kazi.sharmin.dina@gmail.com

The thesis titled REVEALING ASSOCIATIONS AMONG NEGATIVE FEELINGS AND EEG-BASED BRAINWAVE SIGNALS IN ROHINGYA REFUGEES, submitted by Kazi Sharmin Dina, Roll No. **1015052070**, Session October 2015, to the Department of Computer Science and Engineering, Bangladesh University of Engineering and Technology, has been accepted as satisfactory in partial fulfillment of the requirements for the degree of Master of Science in Computer Science and Engineering and approved as to its style and contents. Examination held on February 28, 2022.

Board of Examiners

1. ______________________________

Dr. A. B. M. Alim Al Islam — Chairman (Supervisor)
Professor
Department of Computer Science and Engineering
Bangladesh University of Engineering and Technology, Dhaka.

2. ______________________________

Dr. A.K.M. Ashikur Rahman — Member (Ex-Officio)
Head and Professor
Department of Computer Science and Engineering
Bangladesh University of Engineering and Technology, Dhaka.

3. ______________________________

Dr. Mahmuda Naznin — Member
Professor
Department of Computer Science and Engineering
Bangladesh University of Engineering and Technology, Dhaka.

4. ______________________________

Dr. Mohammad Saifur Rahman — Member
Associate Professor
Department of Computer Science and Engineering
Bangladesh University of Engineering and Technology, Dhaka.

4. ______________________________

Dr. Muhammad Tarik Arafat — Member (External)
Associate Professor
Department of Biomedical Engineering
Bangladesh University of Engineering and Technology, Dhaka.

Candidate's Declaration

This is hereby declared that the work titled REVEALING ASSOCIATIONS AMONG NEGATIVE FEELINGS AND EEG-BASED BRAINWAVE SIGNALS IN ROHINGYA REFUGEES, is the outcome of research carried out by me under the supervision of Dr. A. B. M. Alim Al Islam, in the Department of Computer Science and Engineering, Bangladesh University of Engineering and Technology, Dhaka 1000. It is also declared that this thesis or any part of it has not been submitted elsewhere for the award of any degree or diploma.

Kazi Sharmin Dina.

Kazi Sharmin Dina

Candidate

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Abstract

Negative feelings, e.g., hopelessness, helplessness, sadness, etc., often result in a loss of purpose and meaning in life, which can get associated even with lethal outcomes such as suicides. The negative feelings are generally analyzed through interviews that become extremely difficult in the contexts of marginalized communities such as refugees. The difficulties arise due to diversified barriers covering language and cultural barriers, lack of literacy and technological skills, lack of trust to reveal sensitive information to a stranger, etc. To overcome the barriers, we propose using non-verbal biomarkers such as non-invasive electroencephalogram (EEG) brainwave signals and head movement data for the purpose of revealing and analyzing negative feelings. To do so, in this study, we collect EEG and head movement data along with conducting interviews on negative feelings over Rohingya refugees (n = 135). Then, we analyze associations among different negative feelings based on the collected interview data through applying graph theoretic approaches to develop various models of associations. Besides, we use various statistical measures to identify potential neurobiological markers. We also leverage machine-learning algorithms for classifying the negative feelings. Our study demonstrates novel outcomes on the associations over different negative feelings. Besides, our study also presents substantial (up to 95%) accuracy in classifying negative feelings based on EEG signals and head movement data in isolation and in combination.

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Chapter 1

Introduction

The feeling is often defined as a sensation that is checked against previous experiences [5]. Feelings are biographical as well as personal, as every person has a distinct set of previous sensations from which s/he can interpret and label own feelings [5]. Feelings can also be considered as conscious experiences. Feelings are generally fueled by a mix of emotions and last for longer than emotions. Feelings can be categorized as positive or negative [6, 7, 8]. Prominent negative feelings include helplessness [9], hopelessness [10, 11], worthlessness [12], feeling of failure, feeling of nothing to look forward to, unhappiness, depression, sadness, etc. Such negative feelings are core components of several psychological disorders covering PTSD, hypochondria, etc., which can get associated even with lethal outcomes such as suicides or involvement in criminal activities [13, 14, 15]. Therefore, rigorous analysis of the negative feelings is of utmost importance in the road to combat such unexpected outcomes.

As refugees are known to have higher rates of psychological disorders, in particular PTSD [4], anxiety disorders, depression [16], suicidal ideation [17], etc., compared to those usually found in the non-war affected general population [18, 19, 20, 21, 22], they are more prone to experience negative feelings. Rohingya refugees are no exception in this case [23]. The Rohingya people, an ethnic minority in the Rakhine state of Myanmar, have a long history of exposure to human rights violations and systematic discrimination [24]. Over the last few years, discrimination and oppression have resulted in their mass forced displacement from and within Myanmar. Bangladesh has been hosting the forcefully displaced Rohingya refugees for decades. The latest exodus in this regard began in August 2017, when violence broke out in Myanmar's Rakhine state, driving more than 742 thousand to seek shelter in

Bangladesh [25, 24]. At the peak of the crisis, thousands were crossing into Bangladesh daily. Most of them walked for days through jungles and mountains, or dangerous sea voyages across the Bay of Bengal. These bitter experiences unavoidably result in mental distress over the forcefully displaced Rohingya refugees. Accordingly, recent research studies conducted over Rohingya refugees reported different risk factors pertinent to mental distress including exposure to traumatic events (such as torture, rape, physical violence, etc.) [26], poverty, shortage of food and shelter, lack of access to medical care, loss of identity and exclusion, and so on [4]. These factors, in turn, contribute to mental health problems including PTSD, anxiety, depression, and suicidal ideation [17]. As such, an inevitable consequence is the potential widespread existence of negative feelings among the Rohingya refugees.

Negative Feelings among The Rohingya Refugees

As the Rohingya refugees face countless trauma events during their migrations and still struggling for their living, this community appears to be of utmost importance for getting their negative feelings thoroughly analyzed. As similar psychological aspects are known to be potentially associated with brainwaves such as non-invasive electroencephalogram (EEG) signals [4] and head movement data [27], the analysis of negative feelings over Rohingya refugees can be augmented with the use of EEG and head movement data.

EEG generally refers to a physiological method for measuring electrical activities generated by a brain. Our motivation behind exploring EEG in our study is that it offers excellent temporal and spatial resolutions for the assessment of brain activities [28]. Besides, a study over these brain activities points towards a gleaming prospect of characterizing and detecting associations of them with various emotions [29]. Additionally, being a spontaneous phenomenon [30], EEG is less susceptible to conflicts and confusions associated with responses collected from the participants through conducting traditional questionnaire-based interviews used for understanding negative feelings. Moreover, EEG signals have the capability to identify and differentiate potential neurobiological markers of disorders even at rest state [31, 32, 33]. Thus, the use of EEG may avoid issues and challenges associated with human interaction and communication, which include language and cultural barriers, lack of technological skills, lack of trust to reveal sensitive information to a stranger, etc. However, there can arise some consequences too. For example, EEG devices used for collecting EEG signal data might have chances to create confusion regarding data collection and participants might not be comfortable in wearing an EEG signal collecting device during interview session. These aspects need to be focused during a study incorporating EEG data collection, which we do in this work.

In addition to EEG, we also consider head movement data of our participants in analyzing negative feelings. In case of capturing head movement, accelerometer and gyroscope data are mostly used. Such data, used in tracking head movements, often work as features for human activity classification [34, 35], respiration rate monitoring [36, 37], jaw clenching [38], psychological activity analyzing [39, 40, 41], etc. In this regard, similar to EEG, head movement tracking may also help us to avoid issues and challenges associated with human interaction and communication.

Our Analyses and Classification over Negative Feelings

Considering the above aspects, in this study, we attempt to find associations among our considered eight different negative feelings by conducting interviews over Rohingya refugees (n = 135) and subsequent analysis over the collected interview data. We also augment our analysis and classification of negative feelings through leveraging EEG and head movements to overcome the limitations of questionnaire-based interviews and analyses based on them. To do all the analyses, in our study, we exploit graph-theoretic approaches, statistical analysis, and machine learning-based analysis.

From our interview data, first, we generate various association models through exploring graph theoretic approaches. The approaches we adopt subsume the notions of correlation network, partial correlation network, and regulatory network, which help us to explore associations among our considered negative feelings. Besides, in our study, we collect a sufficient amount of EEG brainwave signal data and head movement data, and label them by our considered eight different negative feelings. Subsequently, we perform statistical analysis over the labeled data and explore machine learning algorithms for conducting classifications over negative feelings based on the labeled data. In our exploration, we achieve noteworthy accuracy in classifying the negative feelings.

Our Contributions

Accordingly, in this study, we make the following set of contributions.

- We conduct an on-field interview on different negative feelings over Rohingya refugees. We also collect EEG brainwave signals and head movement (using three-axis accelerometer and three-axis gyroscope) data from the participants while participating in the interview sessions. In total, we collect such interviews as well as EEG brainwave and head movement data from 135 Rohingya refugees.

- For finding associations among our considered eight different negative feelings (worthlessness, feeling of nothing to look forward to, helplessness, sadness, feeling of failure, depression, unhappiness, and hopelessness), we generate several association models from the negative feelings by applying graph theoretic approaches over our collected interview data. We find several noteworthy associations among our considered negative feelings from our analyses.

- Later, for overcoming the drawbacks of interview-based determination of negative feelings, we study the appropriateness of using EEG brainwave signals and head movement data in revealing negative feelings. To do so, we conduct statistical analyses (F-test and t-test with necessary corrections) over our collected data. From the analyses, we find out statistically significant similarities between the negative feelings and EEG brainwave data. We also find out statistically significant similarities between the negative feelings and head movement data.

- Being inspired by the statistically significant similarities, we explore different machine learning algorithms (in Weka toolkit [42]) over both EEG brainwave and head movement data in isolation and in combination for classifying our considered negative feelings. We achieve substantial accuracy in the machine learning-based classification tasks. We achieve up to 87% and 92% accuracy in classifying negative feelings using EEG brainwave and head movement data in isolation respectively. Further, when we consider both EEG brainwave and head movement data in combination, we get better accuracy for seven of our negative feelings compared to what we get for them based on EEG brainwave and head movement data in isolation. Finally, we point out the best method (only EEG brainwave, only head movement data, or both of them in combination) of classifying each of the negative feelings.

Chapter 2

Background of Our Study

In our study, we work on the negative feelings of Rohingya refugees by collecting interview data as well as EEG brainwave signal data and head movement data. Accordingly, as negative feelings are of utmost importance in our study, we present a brief background on them in this chapter. Besides, as the notion of feelings is closely related to that of emotions, we first present a brief overview over them.

Emotions and Feelings

Emotions and feelings are closely related, however, they present separable phenomena [43]. Emotions are often regarded as perceptions of patterned changes in the body [44, 45]. We can also define emotions as a patterned collection of chemical and neural responses as produced by the brain as soon as it detects the presence of an emotionally competent stimulus [43]. Emotions result in emotional responses, which pertain to a mode of reaction of brains. The brains are prepared through evolution in responding to certain classes of objects and events with certain repertoires of actions [43]. Thus, brains can govern emotional responses that can in turn engender bodily perceptions. The bodily perceptions constituting emotions can occur unconsciously, subconsciously, and consciously. Only the conscious perceptions of the body generated from emotions qualify as feelings [45].

Feelings can be defined as a mental representation of the physiological changes that characterize emotions [43]. Whereas emotions are scientifically known to be public, feelings are regarded as private while being direct consequences of emotions [43]. Nonetheless, feelings are as amenable to scientific analysis as any other cognitive phenomenon. Feelings have the potentials to amplify the impact of a given situation, enhance learning, and increase the probability of anticipating comparable situations. Being a reflective outcome, our feelings help us to identify what is going on inside of us emotionally. Besides, it is worth mentioning that feelings present broader aspect than emotions from a semantic perspective, as there exist somatic feelings such as chilliness [45].

Differences between Emotions and Feelings

Emotions and feelings are closely related to each other. They are so close that sometimes they are referred interchangeably. However, an interesting reality is that, even though all languages have a word for 'feeling', some languages lack a word for 'emotion' [46, 45]. This, from the linguistic perspective, makes a difference between emotions and feelings. Besides, there also exist other scientific differences between them. Examples of the differences include the following.

1. Feelings are regarded as direct consequences of emotions [43]. Thus, emotions present the cause and feelings exhibit impacts.

2. Emotional responses can generate bodily perceptions, which can be unconscious, subconscious, and conscious. On the other hand, feelings refer to only the conscious bodily perceptions generated from emotions [45].

3. Emotions are scientifically known to have the potential to be public. On the other hand, feelings are treated as private [43].

4. Feelings measure emotional experiences as well as physical sensations such as hunger or pain. As such, there exist somatic feelings (such as chilliness) that are not related to emotions [45].

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Types of Emotions and Feelings

Emotions can be of two different types - positive and negative [47]. In the case of positive emotions, we typically find pleasurable while experiencing. Thus, we experience pleasant of desirable situational responses in the case of positive emotions [47, 48]. Some common positive emotions include love, joy, satisfaction, interest, amusement, etc., [47].

On the other hand, negative emotions are those that we typically do not find pleasurable to experience [47]. Thus, negative emotions refer to unpleasant emotions resulting in expressing a negative

Table 2.1: Examples of negative feelings

Negative Feeling	Example Case/Scenario
Worthlessness	Feeling like we have nothing to offer the world [54]
Feeling of nothing to look forward to	When we get demoralized and have no vision for life [55]
Helplessness	Feeling of being powerless to progress and make changes [56]
Sadness	When a family member dies [57]
Feeling of failure	Suffering from lack of confidence having a feeling like not doing things as well as we are used to [58]
Depression	The death of a close family member or friend, which goes beyond normal grief and leads to depression [59]
Unhappiness	When a bus driver arrives late [57]
Hopelessness	Feeling like "Why should I even bother" [58]

effect towards a person or an event [49]. Negative emotions eventually engender bad feelings for us, lessen our energy, and lower the level of our self-esteem. Examples of some negative emotions are anger, emptiness, frustration, inadequacy, etc., [50].

Similar to emotions, feelings can also be categorized as positive and negative [51, 8, 7]. Between the two types, negative feelings alone exhibit substantial significance to be analyzed and studied [7]. Accordingly, we focus on negative feelings and dig into it from the perspective of revealing their inherent associations as well as their associations with brainwave signals and head movement data. Before, presenting our study, we present a brief overview on negative feelings next.

Negative Feelings

In our study, we consider eight different negative feelings. The negative feelings under our consideration are worthlessness, feeling of nothing to look forward to, helplessness, sadness, feeling of failure, depression, unhappiness, and hopelessness. We consider these negative feelings following the assessment measures adopted by American Psychiatric Association [52]. More specifically, we adopt these negative feelings from the ones utilized in Level 2 cross-cutting symptom measures for emotional distress [53].

We present a glimpse of our adopted negative feelings in Figure 2.1. We also briefly present an overview for each of them in the following subsections. Besides, in Table 2.1, we present examples of our considered eight different negative feelings.

Worthlessness

Worthlessness refers to a negative feeling that may work behind an individual to feel like, s/he has no significance or purpose in his/her own life. Feeling worthless can create significant distress and make

Figure 2.1: Different negative feelings under our consideration [1]

it difficult to function normally in daily life. We might find it difficult to feel motivated to pursue our goals when we feel that nothing we do is right or that none of our efforts will make a difference [60].

Worthlessness has lots of significant negative effects on mental health. A study [61] finds that feelings of worthlessness are remarkably associated with lifetime suicide attempts [62] in adults who indicated major depression and had experienced trauma. Further, the study concludes that, among diversified symptoms of depression, worthlessness exhibits the strongest association with lifetime suicide attempts. Nonetheless, people who experience worthlessness may find it difficult to see any aspect of life as positive and may believe that there is no scope for improvement ahead. This perception is generally a perverted one and is often likely to result from radical conditions such as depression [63], anxiety, and stress. The longer one experiences worthlessness, the more difficult it may be to overcome the feelings without help from others. In the diagnostic manual, worthlessness is associated mainly with depression [63]. However the feeling might also appear as a symptom of schizophrenia or certain personality spectrum's [61].

Feeling of Nothing to Look Forward to

When people get demoralized and have no vision for life, that scenario portrays one of our considered negative feelings called feeling of nothing to look forward to. It can also cause other negative feelings such as stress, depression, and anxiety [55]. The existence of feeling of nothing to look forward to for a long period of time may indicate that overcoming the feeling alone may be difficult. Besides, it may have some bad impacts on mental health. Nonetheless, feeling of nothing to look forward to is considered as a symptom of other psychological disorders such as depression [64].

Helplessness

Helplessness refers to feeling like having no power to progress ahead or make changes. Feeling helpless can be a cause of other negative feelings such as stress or depression [56]. This happens as helplessness presents a belief of having nothing that anyone else can do to improve the sufferer's bad conditions. The cause of helplessness cannot always be determined. For example, whenever one experiences negative emotions for a prolonged period of time, it can cause some disappointment in life and it can lead to uncomfortable mental as well as emotional states. Besides, helplessness can be associated with several different psychological disorders such as anxiety, phobia, shyness, and loneliness - all of which can be enhanced by helplessness [65].

Sadness

Sadness is the feeling when someone loses something important for him/her such as own family member(s) [57]. People who are sad are essentially trying to deal with their important losses and to accommodate in life without the lost beloved ones or things. Depending on the weight of the loss, this can take time to recover. Sad people often have the urge to stop their regular activities and to reflect on their situation [66]. Feeling sad is a natural reaction to situations that can cause emotional pain [67]. Some examples of common causes of feeling sadness include rejection by a friend or lover, endings and goodbyes, sickness or death of a loved one, the loss of some aspect of identity (e.g., transition of home, work, or life stages), being disappointed by an unexpected outcome, etc., [68].

Feeling of Failure

Feeling of failure often refers to a scenario of suffering from lack of confidence along with having a feeling like not doing things as well as we are used to [58]. Feeling of failure often presents one of the most common causes for depression [69]. When we feel that we will never be good enough to achieve our goals or suffer from a lack of belief within own, all these make us feel like a failure. When we hold a negative perception within own, it is not surprising that we feel quickly defeated while facing challenges. Each obstacle, mistake, or failure can seem like proof of what we already know – that we will not succeed and that we are not good enough [70]. Feeling of failure can be like a stab in the gut and moral, and if nothing is done about it, it becomes a wound that can persist for the whole remaining life. At the worst, feeling of failure can even be a cause of attempting suicide [69]. Besides, feeling a sense of futility about life and a sense of loss of purpose are some common impacts of the feeling of failure [69].

Depression

Depression can occur for various reasons such as death of a close family member or friend, which goes beyond normal grief [59]. Experiencing depression is common at some points in life. However, if this lingers for long time, and accompanies other painful feelings such as worthlessness and hopelessness, it may become a serious problem in the long run. People react to depression in different ways. However, typically those who are depressed feel hesitation for the majority of their days. A lot of general things might start to be thought of as completely meaningless while experiencing depression. Example thoughts in this regard include *"What's the point of going to work?", "Why get out of bed?", "Who cares?", "It doesn't matter what I do", etc.* In more extreme cases, depression can even lead to suicidal thoughts [71, 72].

Unhappiness

Unhappiness can occur if something expected is not obtained. An example case could be the scenario where we get a bus driver late [57]. Besides, we can define unhappiness by a feeling of being heart-burning, as unhappiness is all about being unhappy. Unhappiness can happen for several reasons such as lack of belonging/connection, loud noise, insecurity, pollution, frustration, hunger, anger, unhealed trauma, low self-esteem, poor health, wealth inequality, child abuse, sexual abuse, being in a dangerous environment, being the victim of violence, lack of control at work, unloving parents, physical pain, unavoidable toxic people, being harassed, shamed, demeaned, threatened or intimidated, etc., [73]. Unhappiness may not directly affect life by sickness, however, it can be toxic for surrounding people [74].

Hopelessness

Hopelessness often refers to a scenarios when we feel like "Why should I even bother?" [58]. Some common examples of hopelessness are feeling like life has no hope, feeling hard to imagine that everything will get better, etc. When people go through some sort of difficulties or painful experiences, hopelessness can happen. A psychological disorder can also be a reason behind hopelessness [58]. Hopeless feelings fuel hopeless thoughts and it is easy to get caught up in a negative cycle that makes it hard to see that things can get better in future [75]. It is common to have these feelings for a short period of time, however, when hopelessness lasts for a long period or it troubles a lot, then it could be a cause of several psychological disorders. Examples of the engendered psychological disorders include depression, anxiety, etc., [58]. Besides, it is common that people experiencing hopelessness make statements such as - *"My situation will never get better", "I have no future", "No one can help me", "I feel like giving up"*, etc. Hopelessness sometimes can cause thoughts of wishing like never getting up from sleep, planning to harm, or even committing suicide [76, 58].

Similarities and Dissimilarities among Different Negative Feelings

There exist similarities and dissimilarities among our considered negative feelings. As already elaborated with examples above, different negative feelings can be associated with each other, or even sometimes appear together. However, there also exist dissimilarities between them.

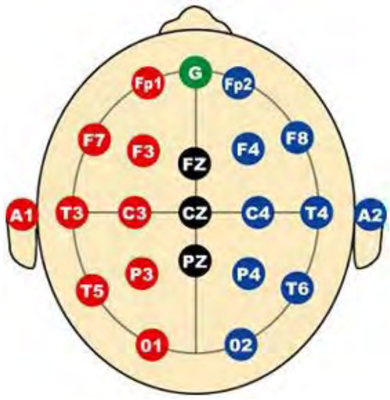
For example, sadness contains some similarities with the feeling of unhappiness. Events that work behind making someone sad can also make them unhappy in some cases. However, these feelings can appear in isolation too, as there also exist some differences between them. To exemplify, we present the following different scenarios when the feelings appear in isolation. It is worth mentioning that these scenarios are not universal and always applicable, however, these can certainly appear in reality for different people at different points of time in their lives.

- **Sadness without unhappiness:** Suppose a family member, who is suffering from illness and completely bedridden for long, dies. In such a case, it can happen that we feel sad, however, we do not feel unhappy considering the past sufferings of the dead family member [77]. Besides, it can happen that we get a promotion in our work that needs leaving our family members. In such a case, it can happen that we feel sad, however, we do not feel unhappy considering the future progression of our carrier.
- **Unhappiness without sadness:** Suppose we have a bus driver late in appearing as per his schedule. In such a case, we may feel unhappy, however, we generally do not feel sad in experiencing so [57]. This happens as getting a bus driver late may not be that important to us to be sad. Besides, it can happen that we do not get expected level of work from our office employees. In such a case, it can happen that we feel unhappy, however, we may not feel sad considering the fact that the work from our office employees may not be that important to us to be sad.

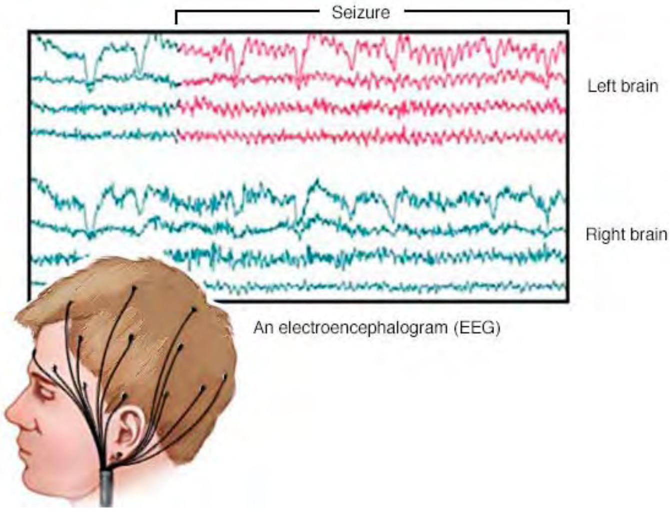
In a similar way, we can find situations when sadness and depression come together. However, they can also be differentiated in some cases [78]. Besides, depression can accompany other painful feelings as symptoms such as worthlessness and hopelessness [79]. Additionally, feeling worthless and feeling of failure often involves a sense of hopelessness [60]. Nonetheless, even though worthlessness and hopelessness can appear together, they can also be distinct [79].

EEG Brainwave Signals

In our study, we consider EEG brainwave signal data in investigating the negative feelings of Rohingya refugees. The electroencephalogram (EEG) is a recording of the electrical activity of the brain, and collects the electrical activity from the scalp. EEG measures refer to changes in the electrical activity that the brain produces. These changes in turn refer to voltage changes that come from ionic current within and between some brain cells known as neurons [80]. Our brain consists of billions of cells. Half of them are neurons, and the rest half help and facilitate the activity of neurons. Besides, neurons are very closely interconnected via synapses. Here, synapses act as a gateway of excitation and inhibition activities [81]. However, synaptic activity produces an exquisite electrical impulse referred as a postsynaptic potential. Whenever thousands of neurons fire, they produce a strong electrical field that spread through tissue, bone, and skull. Eventually, the produced electrical fields can be



(a) Locations of EEG electrodes [82]



(b) Measurements of EEG waves [83]

Figure 2.2: Overview of EEG brainwave signal collection and measurements

measured from the head surface area [81], and the measured values represent brainwave. An EEG machine measures the brainwave from the outer layer of the brain, known as the cerebral cortex. For measuring EEG brainwave signal, sensors or electrodes are placed on the surface area of the head and the electrodes non-invasively detect brainwaves from the head. In this way, EEG sensors can record up to several thousands of snapshots of the electrical activity generated in the brain within a single second. In Figure 2.2, we present an overview of EEG brainwave signal collection and measurements.

Types of EEG Brainwaves

Electroencephalography (EEG) is a technique to collect the electrical activity of the brain [84]. However, electrical activity capture from electrodes of an EEG device expresses various EEG frequencies. Here, frequency refers to the speed of electrical oscillations and measure in cycle per second. EEG brainwaves are categorized by frequency into five main types, these are alpha, beta, delta, theta, and gamma [85].

Delta

Delta waves present a low-frequency wave and contain a frequency range over 0 to 4 Hz. Delta waves are mostly associated with deep stages of sleep. Besides, delta waves are the slowest recorded brain waves in human beings. Mostly, they are found in infants and young children and are associated with the deepest levels of relaxation and, healing sleep. Additionally, delta waves are prominently seen in cases of brain injuries, learning problems, inability to think, etc. Other than that, suppression of this wave leads to an inability to rejuvenate the body and revitalize the brain, which can effectively result in poor sleep [86].

Theta

Theta waves generally exhibit a frequency range between 4 to 7 Hz. Theta waves are often found in young adults, particularly over the temporal regions and during hyperventilation [87]. Besides, theta waves occur during sleep or dreaming. However, they do not occur during the deepest phase of sleep. Other than that, theta waves also occur in a very deeply relaxed state of mind [87].

Alpha

Alpha frequency is defined in terms of peak or gravity frequency within the traditional alpha frequency range of about 7.5 – 12.5 Hz. Alpha frequency reflects cognitive and memory performance [88]. However, often alpha waves are associated with a relaxed and calm state of mind. The alpha waves can be induced by closing the eye and relaxing. Besides, alpha waves rarely present intense cognitive processes such as thinking, mental calculus, and problem-solving [80]. Most alpha waves are found in the occipital and posterior regions of the human brain.

Beta

Beta frequency generally ranges from 13 to 30 Hz. Beta waves are known as high-frequency, and low-amplitude brain waves that are commonly observed in an awaken state. Mostly beta waves are involved in conscious thought and logical thinking and tend to have a stimulating effect. Other than that, the prominence of this wave can be caused by anxiety, high arousal, stress, and an inability to relax. Besides, its suppression can lead to daydreaming, depression, and poor cognition. Additionally, beta waves appear in conscious focus, memory-related activity, and problem-solving [86].

Gamma

Gamma waves exhibit the highest frequency among all the EEG brainwaves and are considered to be the fastest brain activity. Gamma frequency ranges from 30 to 80 Hz. Research studies report that gamma waves are involved in attention, working memory, long-term memory processes, etc. Other than that, gamma waves are also involved in psychiatric disorders such as schizophrenia, hallucination, Alzheimer's disease, and epilepsy [89]. In general, gamma waves are associated with attention, focus, binding of senses, consciousness, mental processing, etc., [90].

Head Movement Data

Currently, head movement data are widely explored in the various research field. Among them, identifying psychological as well as behavioral dissimilarities are common in using head measurement data [91]. We can easily capture head movement data using an accelerometer and gyroscope sensors. In our study, we use the eSense earbud device [92] to collect head movement data from our interviewees. eSense earbud is very lightweight and very easy to use. In eSense earbuds, accelerometer and gyroscope sensors are integrated.

The accelerometer sensor used in capturing head movement data measures the acceleration exerted upon the sensor. Here, in our study, we use the acceleration that gives three-axis vector components to eventually make up the sum/net acceleration. Besides, the gyroscope sensor used in capturing head movement data can measure and maintain the orientation and angular velocity of the head under measurement. The gyroscope provides a more advanced feature than the accelerometer. For example, gyroscope measures the tilt and lateral orientation of the head whereas, an accelerometer can only measure the linear motion. From the eSense earbud, we can collect three-axis data by its gyroscope. Over the collected data different types of analyses can be attempted. Examples of such analyses include Bayesian Network based analysis, statistical analysis, etc.

Bayesian Network

A Bayesian network refers to a probabilistic graphical model. The model presents conditional dependencies of a set of variables through a directed acyclic graph (DAG). Here, nodes represents the variables and edges between nodes represents causal relationships over the nodes considering a conditional probability distribution for each node [93]. In our study, for exploring diversified negative feelings along with substance usage, a Bayesian network may help to evaluate different hypothesis about which negative feelings are directly affected by other negative feelings and so on. Besides, a Bayesian network can facilitate representing probabilistic relationships among our considered eight different negative feelings along with substance usage. In such a Bayesian network, nodes may represent negative feelings and substance usage, and edges may represent conditional dependencies between them.

Centrality

While a network represents relationships among entities/nodes, measurement of the importance of each node in the networks often becomes important to be determined. Centrality refers to one such measurements of importance of the nodes. There are various measures of centrality. For our analysis, we use the following two measures:

- Betweenness centrality measures the number of times a node lies on the shortest path between other nodes. This measure shows which nodes are 'bridges' between other nodes in a network. This measurement is used to find the individuals who influence the flow around a network. A high betweenness indicates that the associated node perhaps holds authority over other nodes in a network.

- Strength centrality of a particular node in a weighted network refers to the sum of weights of all the edges incident to it. It reflects the overall strength of association associated with a particular node. The more neighbors a given node has, the greater is its influence in a network. This often leads to the idea of degree centrality, which refers to the degree of a given node in the network. Here, the degree of a node is the number of edges connecting it.

Hypothesis Testing

A statistical Hypothesis generally presents a belief about a population parameter. This belief may be right or the other way around. Hypothesis testing is a process used by scientists to support or reject statistical hypotheses. A hypothesis test helps in making a decision on which statement about a population is best supported by available sample data.

A null hypothesis is generally regarded as a type of hypothesis in statistics that proposes having no difference between different population parameters. The alternate hypothesis will just be the opposite of the null hypothesis.

In a statistical test, a p-value helps to determine the significance of the results in relation to the null hypothesis. A p-value or probability value is a number that describes the probability of having observed difference between the population parameters in a random manner. The level of statistical significance is expressed as a p-value over the range [0, 1]. The smaller the p-value, the stronger the evidence that we should reject the null hypothesis. A p-value less than 0.05 is often considered to be statistically significant. It indicates strong evidence against the null hypothesis, as there is less than 5% cases where the null hypothesis is correct. Therefore, in this scenario, we reject the null hypothesis and accept the alternative hypothesis.

F-test and t-test present two different techniques of hypothesis testing. F-test is utilized for understand if there is any variance inside the available samples. Besides, t-test is utilized to understand whether there is any similarity between two groups of available samples.

F-Test

The F-test is designed to test if variances of two population are equal or not. F-test compares the ratio of the two variances. Therefore, if the variances are equal, the ratio of the variances will be 1.

t-test

A t-test is a statistical test that is used to compare the means of two groups of population. It is often used in hypothesis testing to determine whether a process actually has an effect on the population of interest, or whether two groups are different from one another. A t-test can only be used when comparing the mean values of two groups.

False Discovery Rate

False Discovery Rate (FDR) refers to the proportion of false positive cases. A false positive case occurs when we incorrectly reject the null hypothesis. In the case of repeating a test more and more times, chances increase to get a number of false positives. Besides, in the case of testing over multiple hypotheses, it is well practiced by the data scientists to control FDR that can occur owing to randomness in results. In such a context, Benjamini-Hochberg correction is generally used for the purpose of controlling FDR [94, 95]. The Benjamini-Hochberg correction [96] orders the hypotheses and then accepts or rejects them based on p-values in road to controlling the FDR. An alternative here is Bonferroni correction [97]. Bonferroni correction presents a multiple comparison test that attempts to prevent data from incorrectly appearing as statistically significant. This offers a conservative approach and it is appropriate when each false positive case is desired to be removed. In the process of this correction, the original alpha level gets divided by the number of tests being performed to get the Bonferroni-corrected p-value. The corrected p-value becomes the new threshold, which needs to be reached by a test to be significant.

Chapter 3

Related Work

Our study pertains to three different types of research areas encompassing negative feelings, EEG brainwave signals, and head movements. Therefore, we present relevant research studies on these research areas below.

Negative Feelings

Several research studies conducted on various negative feelings and their relationships with different psychological disorders. In this regard, Simister [98] the effects of stressful 'life events' on mental health and found that feeling worthless shows the slowest recovery. Tadesse et al., [99] examined the Reddit user's posts to detect factors that may reveal depression attitudes of online users such as feeling loneliness, feeling hopelessness, feeling helplessness, or failure, etc. Berardelli et al., [14] revealed that, negative feelings such as hopelessness and helplessness exhibits diversified mental health concerns, which could be frequently related to lethal outcomes such as suicides. Their findings suggested that demoralization was prevalent in patients with schizophrenia. Their findings also supported the hypothesis that the relationship between depression and suicide was moderated by hopelessness. Arslanoglou et al., [15] analyzed relationships over negative emotions and non-emotional symptoms. They also analyzed the course of depression in suicidal older adults with major depression and cognitive impairment. This study showed among participants with suicidal ideation that the reduction in negative emotions was significantly associated with the reduction in non-emotional symptoms of depression. Besides, a study [100] showed that, data from phone usage along with the results from functional Magnetic Resonance Imaging (fMRI) [101] scans confirmed about passively collected information could mirror activities in the brain, which were linked to traits such as anxiety. Additionally, predictions based solely on data collected through smartphones [100] can substantially match with those based on brain scans. Most of these studies, particularly focused on negative feelings grounded over interview-based analyses. Nonetheless, Skjerdingstad et al., [102] investigated on depressive symptoms and found that feeling worthless was the most influential feeling. However, there exists no analysis on diversified negative feelings and associations among them in the literature to date to the best of our knowledge. Moreover, none of these existing studies presented any analysis on relating the negative feelings with a non-verbal biomarker such as EEG brainwave signals or head movements.

EEG Brainwave Signals

Various research studies investigated using EEG as a neurological biomarker for diagnosing psychological disorders such as PTSD, depression, etc. In this regard, Neto et al., [103] worked on a review of recent studies that used non-invasive EEG to detect depression biomarkers. Shahid et al., [4, 23] worked on diagnosing PTSD for Rohingya refugees and explored EEG as a neurological biomarker for diagnosing PTSD. In their first study, they proposed a diagnosis of PTSD using a short inexpensive questionnaire to determine its prevalence and low-cost nature of portable EEG headset to identify potential neurological markers of PTSD based on EEG. In their second study, they showed a method to screen potential cases of PTSD based on free-hand sketches as well as EEG. In both studies, authors tried to use EEG brainwave signals for finding potential biomarkers for PTSD.

Besides, Wang et al., [104] worked on the relationship between emotional states and brain activity by integrating the advantage of dynamical graph convolution neural networks and broad learning systems. They proposed a novel architecture, called a broad dynamical graph learning system (BDGLS) for extracting features from EEG signals. In this work, the authors used the SJTU emotion EEG dataset and performed recognition with an average accuracy of 93.66%. Similarly, Gupta et al., [105] worked on neuronal activities in the brain to get information about the human emotional states using EEG signals. They comprehensively investigated the channel-specific nature of EEG signals to provide an effective method, based on flexible analytic wavelet transform (FAWT), for the recognition of emotion. Authors used two different publicly available databases, which were SJTU emotion EEG dataset (SEED) and database for emotion analysis using physiological signal (DEAP), and showed better performance for human emotion classification as compared to the existing methods.

Additionally, Yang et al., [106] worked on classifying human emotional states by effectively learning compositional spatio-temporal representation of raw EEG streams though using a convolutional neural network (CNN) and a recurrent neural network (RNN). This study showed 90.80% and 91.03% accuracy in classifying valence and arousal. On the other hand, Ullah et al., [107] proposed an ensemble learning algorithm for automatically computing the most discriminative subset of EEG channels for internal emotion recognition.

Wen et al., [108] proposed an end-to-end model based on convolutional neural networks (CNNs) to reduce the manual effort for identifying features used in EEG-based emotion recognition and improved the performance. Other than that, Wu et al., [109] proposed a novel method for emotion recognition using fewer channels of frontal EEG signals and attained a maximum accuracy of 76.34%. In all these studies, authors attempted to use EEG signals for emotion recognition. Besides, Sakalle et al., [110] worked on emotion recognition using EEG brainwave signals. Additionally, Kora et al., [111] investigated on humane brain activity recognition during yoga meditation through EEG brainwave signals. Nonetheless, Klibi et al., [112] worked on emotional behavior analysis using EEG brainwave signals along with conducting machine learning-based analysis.

Additionally, Jiang et al., [113] proposed depression classification based on EEG data and achieved noteworthy classification accuracy. This study also evaluate classification performances for individual frequency bands and found that gamma band shows best performance. Besides, Kasuga et al., [114] worked on positive and negative emotions classification from EEG signal collected by using 14 electrodes. Other than that, Zhang et al., [115] explore on emotion classification based on AI technique LSTM. Nonetheless, Oh et al., [116] worked on emotion classification based on facial expressions and physiological signals using AI technique deep learning and found noteworthy accuracy for facial expressions and physiological signals in isolation and in combination. However, to the best of our knowledge, there exists no analysis on diversified negative feelings and associations among them. Moreover, there exists no analysis on relating the negative feelings with non-verbal biomarkers such as EEG.

Head Movements

Different research studies investigated head movement and other movement tracking. For example, Röddiger et al., [37] worked on respiration rate monitoring by accelerometer and gyroscope-based sensing. Additionally, Ferlini et al., [117] worked on head motion tracking using an accelerometer and gyroscope. Besides, Jain et al., [34] worked on human activity classification based on accelerometer and gyroscope.

However, Huang et al., [91] proposed a new human activity recognition method using an accelerometer and gyroscope with a two-stage end-to-end convolutional neural network and a data augmentation method that achieves significantly improved recognition accuracy and reduce computational complexity. Zhang et al., [118] worked on a multimodal system that integrates a head-motion module using accelerometer and gyroscope data, a pen-motion module, and a visual-focus module to accurately analyze students' attention levels in the class. These modules collected information via camera, accelerometer, and gyroscope integrated into wearable devices to recognize students' behaviors. Abdelfatah et al., [119] proposed a tracking system that involves determining the position and attitude angles of the unmanned aerial vehicles (UAVs) in real-time. In this work, sensor fusion of an accelerometer, a gyroscope, a magnetometer, and a real-time kinematic global positioning system (RTK-GPS) sensors implemented to decrease the uncertainty in position and attitude angles, and establish the UAV's location more precisely.

Additionally, Ma et al., [120] proposed a novel attention-based (accelerometer and gyroscope) multimodal neural network model called AttnSense for multimodal human activity recognition. Furthermore, Radhakrishnan et al., [121] explored the use of the wearable device (eSense earbud with three-axis accelerometer and three-axis gyroscope sensor) while performing gym exercises by users for providing personalized and quantified insights along with the feedback. Besides, Prakash et al., [122] worked on counting the number of steps a user walk by using eSense earbud and found 95% step-count accuracy. Among all these studies, there exists no analysis on associating negative feelings with gyroscope and accelerometer. Moreover, none of the studies used a gyroscope and accelerometer for classifying negative feelings.

Other Related Research Studies

Various research studies investigated emotion detection using different other modalities of processing such as image processing, audio, and video analysis, text analysis, etc. In this regard, Pandeya et al., [123] worked on music video based emotion analysis. According to the study, such an analysis on emotions is complex because of the diverse textual, acoustic, and visual information, which are related with lyrics, singer voice, sounds from the different instruments, and visual representations. Therefore, the study could classify emotions with 77% accuracy. Besides, Wijayasingha et al., [124] explored reducing adverse effects of noise on speech based emotion classification. Additionally, Nandi et al., [125] investigated real time emotion classification by using EEG data stream in E-Learning context.

Research studies also explored other domains of sensing for similar purposes. For example, Naqvi et al., [126] explored gaze-based drivers' real-time emotion classification to prevent traffic accidents. Besides, Goshvarpour et al., [127] analyzed emotion state classification using eye-blinking analysis. Nonetheless, Acheampong et al., [128] investigated text-based emotion detection. Among all these studies, there exists no analysis on associating negative *feelings* with non-verbal biomarkers such as EEG or head movements.

Chapter 4

Methodology

As negative feelings are very important inroad to ensuring mental well-being, determining or revealing negative feelings is worth investigating. The task of revealing negative feelings often relies on either interview or self-report-based measures. Therefore, first, for the qualitative measure of eight different negative feelings, we conduct interview-based data collection from Rohingya refugees where the participants report themselves about their experiences of negative feelings. Second, for quantitative measures of associations among the negative feelings, we analyze outcomes of the interview following graph-theoretic approaches along with statistical analyses. Third, we choose a low-cost consumer-grade EEG device [129, 130] and eSense [92], a representative earable device that can track head movements, to collect EEG brainwave and head movement data from our participants while participating in our interviews. We analyze the EEG brainwave data and head movement data through another set of statistical analyses and machine learning-based analyses to classify the negative feelings based on the EEG brainwave and head movement data. Using this methodology, we attempt to figure out potential neurobiological markers of eight different negative feelings as well as to explore different models that could reflect possible interactions among those negative feelings. We present an overview of the methodology in Figure 4.1. We elaborate on the methodology in detail below.

Questionnaire for Conducting Interview on Negative Feelings

In our study, we performed interview-based (semi-structured interview) data collection from Rohingya refugees. Our ground truth is self-reported interview data. We interviewed 135 Rohingya refugees from Kutupalong [131, 132] refugee camp in Ukhia, Cox's Bazar. In our interview session, we collected

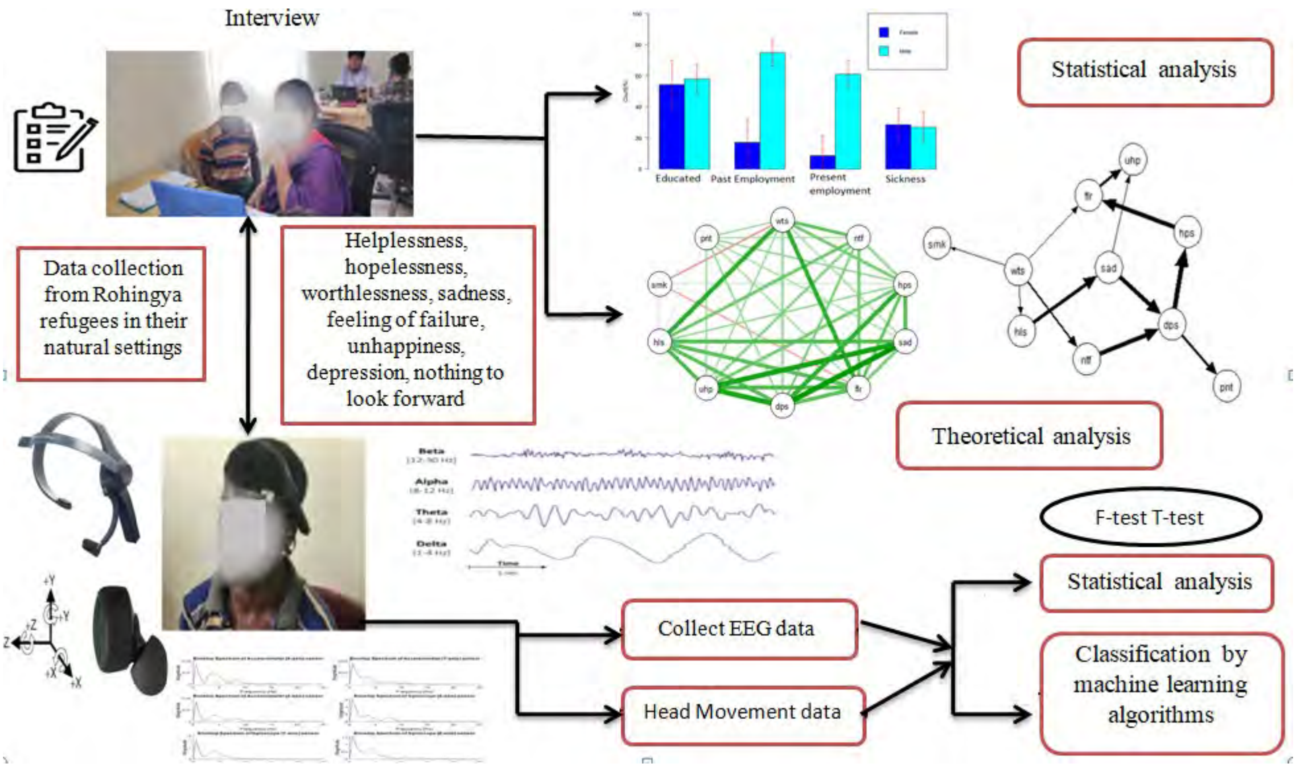


Figure 4.1: An overview of our methodology

demographic data and also collected data for our considered eight different negative feelings along with some other aspects such as intake of substance. We asked eight questions that can be answered by responding with either yes or no. Though in the refugee context, getting properly formatted data is not so easy because of language and cultural barriers, we tried to get answers from their reactions and explanations in their natural setting onboarding their familiar faces alongside.

We asked eight questions on the eight different negative feelings as follows: (1) Did you feel worthless? (2) Did you feel that you have nothing to look forward to? (3) Did you feel helpless? (4) Did you feel sad? (5) Did you feel like a failure? (6) Did you feel depressed? (7) Did you feel unhappy? (8) Did you feel hopeless? To conduct the interview, we translated the questions in Bangla and then to the local dialect using people having experience with similar local dialects. Local agent renowned as 'majhi' helped us to elaborate the negative feelings to our participants during the interview session.

For a concise presentation of our interview feedback, in this study, we used short forms of negative feelings under our consideration. Table 4.1 shows the short forms for our considered eight negative feelings along with usage of substance betel leaf (we chose its short form following its Bangla meaning)

Table 4.1: Abbreviated terms or short forms for different feelings or contexts

Abbreviation	Feeling/Context	Abbreviation	Feeling/Context
wts	Worthlessness	ntf	Feeling of nothing to look forward to
hps	Helplessness	sad	Sadness
flr	Feeling of failure	dps	Depression
uhp	Unhappiness	hls	Hopelessness
smk	Substance smoking	pnt	Substance betel leaf

and smoking.

It is worth mentioning that, our questionnaire for interviewing on negative feelings is adopted from a standard questionnaire [133] developed by American Psychiatric Association (APA). As per the procedure followed by the APA, ground truth data are collected through interviewing the participants using such a questionnaire, and we have done the same in our study.

Interview Session with Rohingya Refugees

To collect data from our population of interest, i.e., Rohingya refugees, seven members from our team (four postgraduate students and two undergraduate students along with a professor) visited Kutupalong [131, 132] refugee camp in Ukhia, Cox's Bazar. The Kutupalong camp is the world's largest reported refugee camp with an estimated population of about 600,000 [131] refugees, where the total number of Rohingya refugees in Bangladesh is around 900,000 [134, 135]. The majority of this large population migrated to Bangladesh after the violence escalated in 2016 - 17 in the Rakhine state of Myanmar [131]. The permission for our data collection was officially granted by the District Commissioner (DC) of Cox's Bazar. Besides, our study was approved by the authority of the university of the corresponding author.

Our interviewers, occasionally accompanied by camp officials, invited refugees within the camp area to participate in the interview while they were engaged in their daily activities. Some of the interviewers had experiences with local dialects that facilitated communication with the refugee participants. During the interview process, we invited 135 refugees at random within the camp area. Participants' age range spans over 10 years to 60 years. We interviewed 100 male (74.07%) and 35 female (25.93%) participants. Thus, we can say that our collected data from Rohingya refugees cover different groups of participants.

As we have more males than females among the participants, we acknowledge that there remains an extent of gender bias over the participants. Nonetheless, note that even to compare the neurobiological characteristics of the refugee group with that of another comparison group, we need at least 34 participants in each group for 90% power at a minimum of 0.05 level of significance [4]. In our case, the minimum participant count for any gender (female) is 35, which crosses the bar of 34. Thus, our dataset comprises data from both genders that are sufficient to be compared to another comparison group. Here, it is worth mentioning that recruiting female participants were more challenging for us owing to the conservative social and cultural norms of Rohingya refugees [136]. We attempted to overcome such barriers in recruiting female participants through engaging our female data collectors.

Our participant refugees came to the camp area for their regular work and participated in this interview after acknowledging the full process of our interview session. we conducted interviews with them at the camp registration office, where most of the refugees registered themselves as residents of different camps. Therefore, the office was a familiar place for them and they felt comfortable there. We took the participants' oral consent about participation before conducting our interviews in the office. We conducted the interviews back in August 2019. It is worth mentioning that camp 'majhi' (local leader from the refugees) [137] helped us to collect interviewees from the beginning. 'Majhi' is the most reliable person for refugees in the camp. Therefore, camp 'majhi' asked refugees to participate in our interview and assured them that our team and our interview would not harm them anyway. Refugees got started to rely on us and the number of interviewees increased over time. It is worth mentioning that, our local interviewers and 'majhi' helped us to elaborate the negative feelings to our participants during the interview sessions, which we found very much effective for getting the actual information from our participants.

Our interview session consisted of two parts. First, we collected data based on our selected question set. Second, during the whole interview session, we collected EEG brainwave signal and head movement (accelerometer and gyroscope) data from the interviewees. We collected EEG brainwave signals using Neurosky Mindwave devices [130], which were very light and easy to use. Besides, we collected head movement data using eSense earbuds [92], which were very easy to wear and light weight. We observed some sort of hesitation in wearing the devices among the participants who had participated at the beginning of our data collection. We understood that the reasons behind the hesitation include unfamiliarity with the devices and lack of confidence in wearing them. To overcome these, first, we briefed the participants about the devices to make the devices familiar to them.

Figure 4.2: A snapshot of conducting an interview session in Kutupalong camp office

Secondly, we onboarded a local leader (majhi) during our data collection to make the participants confident about using the devices. Thirdly, we put the devices at the proper places of the participants to make sure that they can participate in our data collection with ease. All these together removed the hesitation of the participants in wearing the devices, and afterward, we could collect the data smoothly. Additionally, after completing a couple of interviews, other participants also started to get used to the procedure of our interview.

Besides, we experienced concern about making interviewees comfortable while collecting data. To overcome the concern, we tried to make conversations with the interviewees during the interviews in the Chittagonian dialect. Chittagonian dialect is the language of a division of Bangladesh called Chittagong, which is hosting the Rohingya camps. Though the Rohingya dialect and Chittagonian dialect [17] were a bit different, the Chittagonian dialect was mostly understood by Rohingya refugees living in the camps. We had two interviewers in our team from Chittagong along with a local person, and they conversed fluently in Chittagonian dialect with the Rohingya refugees. It greatly helped us in overcoming the language barrier during the interviews and engaging the participants in interactive conversations. During our interview sessions, three teams worked as interviewers where each team consisted of two members from our side. Each team had one member from us or the local person who knows the local language and can be talked in the local language. The remaining member in each team entered data into a laptop and monitor the data collection process so that collecting credible data gets ensured and data interpretation error can be kept to a minimum.

Collection of EEG Brainwave Signals

We collected as well as recorded EEG brainwave signals by using the Mindwave mobile headset developed by Neurosky Mindwave [138]. Among various available brain-computer interfaces, Mindwave is one of the most affordable and user-friendly solutions for its comparatively cheaper price (100 USD) [138]. Therefore, we preferred this low-cost, easy-to-control, and wearable package considering the scarce-resource context of the refugees. This headset has only one main electrode that needs to be placed at the FP1 [139] site and a reference electrode that needs to be placed near the ear [140]. As a result, it requires less preparation time and setup time, and thus, remains easy to control. The Mindwave Neurosky device comes with thinkgear technology that collects brain-wave signals through attached sensors, amplifies them, removes ambient noise and muscle movements, and processes all of them on its chip. This device takes EEG signal as input and produced outputs for eight commonly recognized brainwaves, namely delta (0.5 to 2.75 Hz), theta (3.5 to 6.75 Hz), low alpha (7.5 to 9.25 Hz), high alpha (10 to 11.75 Hz), low beta (13 to 16.75 Hz), high beta (18 to 29.75 Hz), low gamma (31 to 39.75 Hz), and mid gamma (41 to 49.75 Hz) [4]. The output values have no units and are only meaningful when compared to each other and to themselves [138]. For our analysis, we tried to explore EEG brainwave signal data for several states of mind. Regarding that, we had collected background EEG activity from refugees for three different activities. The activities were talking, showing four different videos that generally impose four different states of mind [141], and sketching. We had short breakages in EEG data collection for restarting the devices while changing between successive activities for a participant. However, even with having the short breakages, no participant reported any discomfort or trouble while using the EEG headset during the data collection. We transferred the data, collected through EEG headsets following this process, to laptops via Bluetooth connections.

Collection of Head Movement Data

We collected head movement data using eSense [92] earable device, provided by Nokia Bell Labs. eSense is equipped with a six-axis IMU. The left earbud unit can connect via Bluetooth Low Energy (BLE).

We recorded the x, y, and z axes gyroscopes as well as the x, y, and z axes acceleration using the eSense device. We implemented a mobile application in java for Android, which connected through Bluetooth to the eSense earbuds. We stored the data in the Android phone and take the timestamp on a rolling basis as the Bluetooth packages arrive.

eSense earbuds are lightweight and easy to use. We placed one eSense earbud set [92] on one of the ears of the participant for collecting accelerometer and gyroscope data during the data collection sessions. Note that, placing two eSense earbuds on two ears of participants could provide more data enhancing the reliability of collected data. However, due to having a handful number of eSense earbud devices, we had to get limited in using one earbud device per participant. Thus, during our data collection sessions, we put one earbud to the ear of the participant and put the other earbud of the same set in the charging system. Here, we kept the charging system nearby so that the BLE pairing (available to one earbud in a set of eSense) is maintained.

Each interview spanned a time duration of around 15 to 20 minutes. During this duration, we also tried to collect head movement data as well as EEG brainwave signals. We took consent from participants about using these devices and motivated them to wear these during the interview sessions for research purposes. No participant reported any discomfort or trouble while wearing any of these devices. After completion of interviews in this way, we collected all our head movement data of participants from the Android device and stored it in our laptop.

Data Prepossessing

After collecting interview data, EEG brainwave signal data, and head movement data from Rohingya refugee participants, we conduct several analyses over the collected data. Before starting our analysis, we pre-processed all the data. For each of the Rohingya refugee participants, we collected demographic information and information regarding their negative feelings through conducting the interview. During this interview session, we parallelly collected EEG brainwave signal data through using Neurosky Mindwave device and head movement data through using eSense earbud device. Here, we recorded the EEG brainwave signal data from the headset to our laptop through connecting by Bluetooth. During the data collection, due to some technical difficulties, we lost some of the EEG data. Besides, the length of the collected EEG brainwave signal data points varies among different participants. Nonetheless, owing to difficulties in data retrieval maintaining personalized information, we excluded

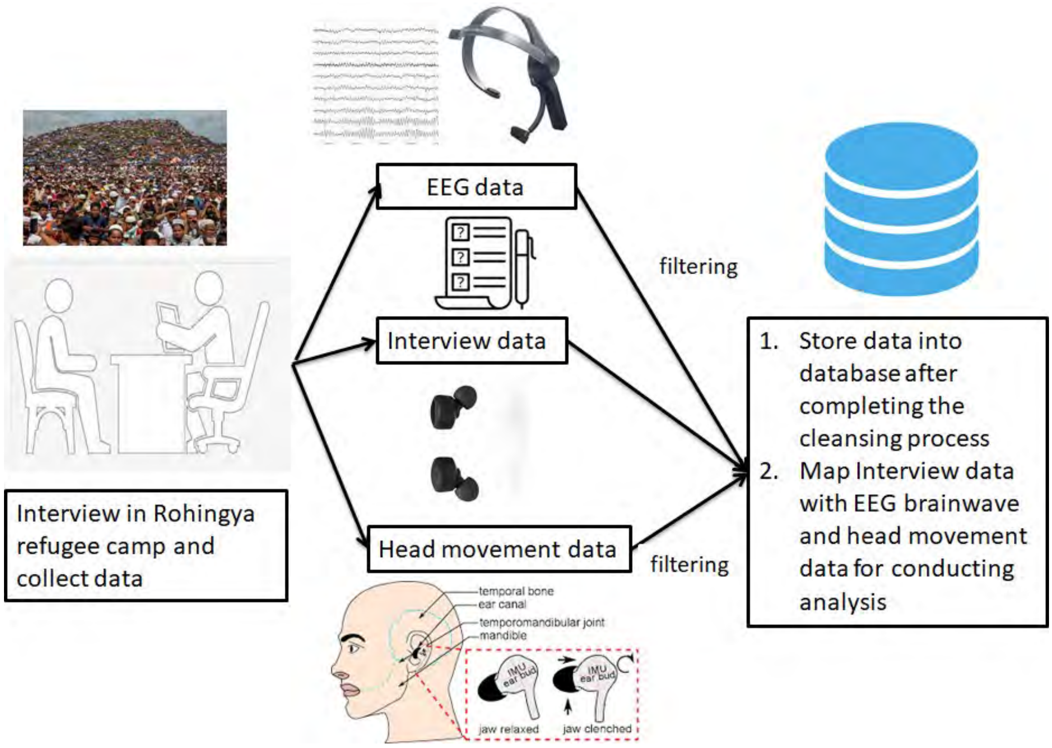


Figure 4.3: Overview of data preprocessing

some more EEG brainwave signal data points from our analysis.

Other than that, in the case of head movement data points pre-processing, we stored the head movement data points in an Android device during our interview sessions. After completing each interview session, we collected all the head movement data from an Android device to our laptop. Because of some technical difficulties, we lost some head movement data. Other than that, we also face similar difficulties in data retrieval maintaining personalized information. Accordingly, we excluded some more head movement data. Besides, the length of head movement data varies among different participants. We present an overview of the data pre-processing task in Figure 4.3.

After compromising the EEG and head movement data in this regard, we got interview data from a total of 135 refugees regarding demographic information and negative feelings, 58000 EEG brainwave signal data points, and 98000 head movement data points. After completing data pre-processing in this manner, we conduct various statistical and machine learning-based analyses over these datasets.

Analysis

Even though we faced various kinds of difficulties during the tasks from participant collection to data collection, we can manage a considerable number of interview data that should be enough to conduct qualitative and quantitative analyses. In addition, we perform different statistical analyses over the collected data using R [142]. Besides, we also perform graph-based analyses of the collected data.

Earlier studies identified that different socio-demographic factors such as age, gender, level of education, employment status, etc., work as significant mediators for different negative feelings [143, 144]. To extend the literature, we analyze the underlying structure of eight different negative feelings in this study and develop various association models [4]. We build all the models using the qgraph() package available in R [142]. To build one of the simplest models, called correlation network, we use Pearson's correlation test (corr.test()) from the R package named psych to identify how different negative feelings correlate with each other and whether there exists any statistically significant association between them or not.

Since a correlation network fails to differentiate between direct and indirect associations among our considered eight different negative feelings, we develop a partial correlation network to account for this difference. To develop this network, we use partial correlation that measures the degree of association between two entities while controlling the effects of other entities within the system. For this purpose, we use pcorr.test() method available in the R package called 'ppcor' to measure partial correlations among our considered eight different negative feelings.

However, both correlation network and partial correlation network fails to provide any useful cue about the direction of association between different negative feelings. Therefore, we develop a Bayesian regulatory network [4] to capture the underlying structure of associations for our considered eight different negative feelings having the directions of associations in our consideration. Here, to measure the degree of association between different negative feelings, we use greedy hill-climbing search along with Bayesian Information Criterion score (BIC) [145].

Additionally, we use measures of centrality to identify the influential negative feelings in our developed models of partial correlation network and regulatory network. Here, we use the centrality() method available in R package called qgraph to calculate different measures of centrality, such as strength and betweenness for each negative feeling, in the partial correlation network and regulatory network.

In addition to all these qualitative data on the mental health status of Rohingya refugees, we also have temporal data of background EEG activity of Rohingya refugees. We use F-test (var.test()) and t-test (t.test()) [4] from R stats package [142] to compare EEG activities between different groups of people classified based on negative feelings. Here, to control the false discovery rate, we use Benjamini-Hochberg correction [3, 4]. Further, to perform classification over our considered eight different negative feelings, we use a total of 45 different machine learning algorithms implemented in the Weka toolkit [42].

Nonetheless, we have data from the head movement of Rohingya refugees. We use F-test (var.test()) and t-test (t.test()) [4] from R stats package [142] to compare head movement activities between different groups of people classified based on negative feelings. Again, to control the false discovery rate, we use Benjamini-Hochberg correction [3, 4]. Further, to perform classification over our considered eight different negative feelings, we use a total of 38 different classification algorithms implemented in the Weka toolkit [42].

Finally, we combine EEG and head movement data and conduct machine learning-based analyses over them. We achieve good performance accuracy for some cases of classifying negative feelings from the combined data. We pinpointed the best method for conducting different classification tasks at the end. Next, we presented all our findings obtained through the methodology followed in this study.

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Chapter 5

Findings

We first conduct a demographic analysis of over 135 Rohingya refugee participants. We were able to collect EEG and head movement data from the participants. In our study, we conduct statistical and machine learning analysis over the dataset and present neurobiological characteristics obtained from the participants.

Rohingya Participants Profile

Among our 135 Rohingya refugee participants, the number of female participants was 35 (25.93%) and the number of male participants was 100 (74.07%). The number of unmarried participants was 31 (22.963%) and the number of married participants was 97 (71.85%). Other than that, 3 (2.22%) participants were divorced and 4 (2.96%) participants were widows. In Figure 5.1a, we present the numbers.

The age range of our participants starts from ten years. Among the Rohingya refugee participants, the number of participants having an age range between 10 years to 20 years was 38 (28.14%). 43 (31.85%) participants were in the age range between 21 years to 30 years. 29 (21.48%) participants were in the age range between 31 years to 40 years. 13 (9.63%) participants were in the age range between 41 years to 50 years. 12 (8.15%) participants were in the age range above 51 years. In Figure 5.1b, we present these numbers.

We also find that 15 (11.11%) participants reported their numbers of family members within the range between 2 to 3. 52 (38.52%) participants described their numbers of family members to be within the range between 4 to 5. 34 (25.19%) participants described their numbers of family members to be within the range between 6 to 7. 25 (18.52%) participants reported their numbers of family members to be within the range between 8 to 9. 6 (4.44%) participants mentioned their numbers of family members within the range between 10 to 12. 3 (2.22%) participants mentioned their numbers of family members within the range between 13 to 21. In Figure 5.1c, we present the numbers from where we can find that the number of family members for most of our participants was between 4 to 9. Besides, 29 (21.48%) participants migrated to Bangladesh from Buthidaung. 6 (4.44%) participants migrated to Bangladesh from Ladai. 21 (15.56%) participants migrated to Bangladesh from Maungdaw. 9 (6.67%) participants migrated to Bangladesh from Rathedaung. 71 (51.56%) participants migrated to Bangladesh from several other areas of Barma. In Figure 5.1d, we present the numbers.

Among our participants, 95 (69.63%) participants were living in Kutupalong. 9 (6.67%) participants were living in Camp 2. 5 (3.70%) participants were living in Camp 6. 5 (3.70%) participants were living in camp D4 and 22 (16.29%) participants living in other refugee camps. In Figure 5.1e, we present the numbers. From our participants, we find 77 (57%) to be educated refugees. Among them 58 (58% of total male participants) were male and 19 (54.2% of total female participants) were female refugees. We also find that 81 refugees among our participants were employed in the past. Among them, 75 (75% of total male participants) were male and 6 (17.14% of total female participants) were female. The number of currently employed refugees among our participants is 64 (47.4%) among which 61 (61% of total male participants) were male, 3 (8.57% of total female participants) were female. Besides, among our participants, 37 refugees reported several cases of sickness they were suffering from, and among them, 27 (27% of total male participants) were male and 10 (28.05% of total female participants) were female. In Figure 5.1f, we present these numbers.

Additionally, we also found that, among our 135 participants, 19 (14.07%) participants reported that they feel worthless, 20 (14.81%) participants reported that they feel nothing to look forward to, 59 (43.70%) participants reported that they feel helpless, 69 (51.1%) participants reported that they feel sad, 22 (16.29%) participants reported that they experience feeling like failure, 39 (28.89%) participants reported that they feel depressed, 36 (26.67%) participants reported that they feel unhappy, and 31 (22.96%) participants reported that they feel hopeless. In Figure 5.2, we present these numbers.

Note that more than 900,000 Rohingya refugees [134] are currently living in Bangladesh and among them only around 30,000 have official UNHCR [24] refugee cards at the time of conducting our interview sessions. Unofficial migrants are not allowed to work or get an education without an official UNHCR refugee card [4]. Therefore, we find Rohingya refugees highly unemployed and mostly dependent on relief provided by humanitarian agencies. Besides, movements of Rohingya refugees are highly restricted within the camp area, and also legal work permit is not easy to get, which also contributes to the high unemployment rate and lower education rate. Nonetheless, several existing research studies present a relationship between unemployment and mental health problems [146], which also play a vital role in the high rate of mental health problems in the Rohingya refugee context.

Nonetheless, Rohingya people are often found to be habituated with betel leaf [147]. Even when they meet with each other or visit others' places, offering betel leaf is a part of their culture. We found this prevalence of being habituated with betel leaf over our interviewed participants too. Accordingly, among our 135 participants, 112 (82.9%) participants reported their habit of taking betel leaf. Here, 27 (24.1%) participants were female and 85 (75.9%) participants were male. Besides, among these participants being habituated with betel leaf, 34 (30.3%) participants reported negatively on having any of the negative feelings. Other than that, 78 (69.6%) participants responded positively to having some of the negative feelings. Among these participants who reported positively about having some of the negative feelings, 18 (16.1%) participants had the feeling of worthlessness, 19 (16.9%) participants had the feeling like nothing to look forward to, 54 (48.2%) participants had the feeling helplessness, 54 (48.2%) participants had the feeling sadness, 21 (18.75%) participants had the feeling like failure, 37 (33.0%) participants had the feeling like depression, 34 (30.35%) participants had the feeling unhappiness, and 28 (25%) participants had the feeling hopelessness. Thus, from these numbers, we can infer that the existences of different negative feelings over the participants habituated with betel leaf substantially vary. Therefore, it is worth investigating whether there is an association between the existence of a negative feeling and usage of betel leaf.

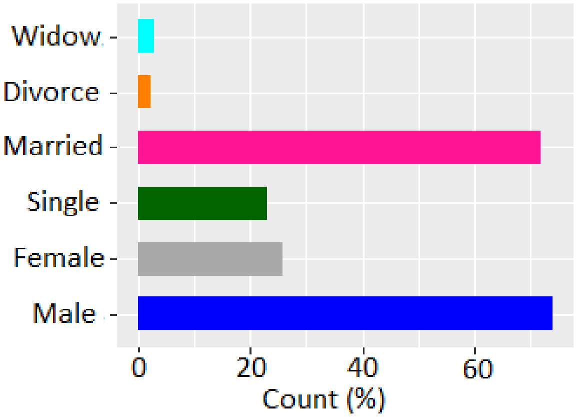
Additionally, in Rohingya people, mostly men are found to be habituated with smoking, and women are very rarely found to be habituated with smoking [147]. We found this scenario over our interviewed participants too. Accordingly, among our 135 participants, 40 (29.6% of total participants) participants reported their habit of smoking. Here, only 1 participant was female and 39 participants were male. Besides, among these participants being habituated with smoking, 13 (32.5%) participants reported negatively having any of the negative feelings. Other than that, 27 (67.5%) participants responded positively to having some of the negative feelings. Among these participants who reported positively about having some negative feelings, 1 (2.5%) participant had the feeling of worthlessness, 5 (12.5%) participants had the feeling like nothing to look forward to, 21 (52.5%) participants had the feeling helplessness, 17 (42.5%) participants had the feeling sadness, 3 (7.5%) participants had the feeling like failure, 12 (30%) participants had the feeling like depression, 11 (27.5%) participants had the feeling unhappiness, and 6 (15%) participants had the feeling hopelessness. Thus, from these numbers, we can infer that the existence of different negative feelings over the participants habituated with smoking substantially vary. Therefore, it is worthy to investigate whether there is an association between the existence of a negative feeling and being habituated with smoking.

It is worth mentioning that, we collected all the data on the existence of negative feelings as well as usages of substance based on the current situation of the participants at the time of our interviews. As recalling historical existences of these aspects can often be difficult for the participants, we did not ask any questions to the participant regarding such existences in the past. Therefore, our study is limited to the current status of the participants. Analyzing further based on the existences in the past could be explored in the future.

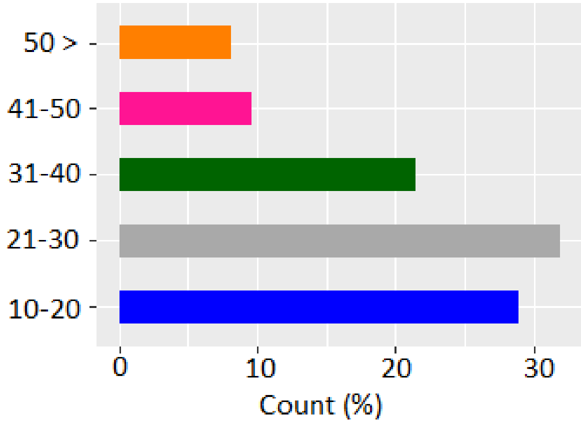
Correlation Network

We have a dataset of 135 Rohingya refugee participants who answered questions about diversified (eight different) negative feelings as well as substance use. Here, we explore the aspect of substance use, as negative feelings are often found to be related to substance use [148]. Accordingly, we investigate different types of associations among the negative feeling while having the aspect of substance use in our consideration.

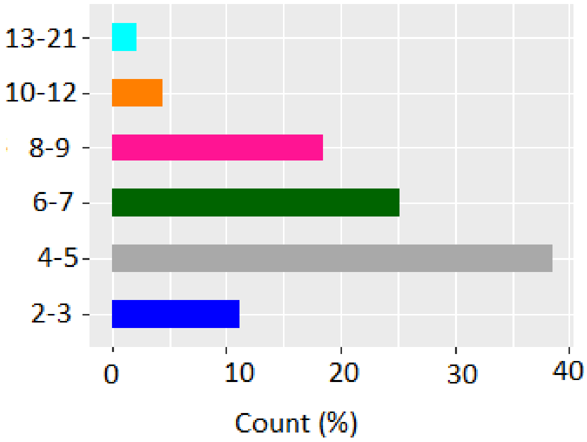
For finding types of associations among our considered eight different negative feelings and substance use, our first approach is to build a correlation network [149, 4] based on significant correlations between the negative feelings as well as with substances called betel leaf (represented as 'pnt' in this study) and smoking. We calculate the correlation matrix [150] (Table 5.1) of our considered eight different negative feelings along with substances, and use it to build a correlation network using the *qgraph* package available in R [151]. This results in an underacted graph as shown in Figure 5.3a. The edges in this graph correspond to Benjamini-Hochberg corrected [152] significant bivariate correlations between two entities, though they ignore the direction of the associations. Here, we use Benjamini-Hochberg correction to adjust the p-value because sometimes small p-values (less than 5%) happen



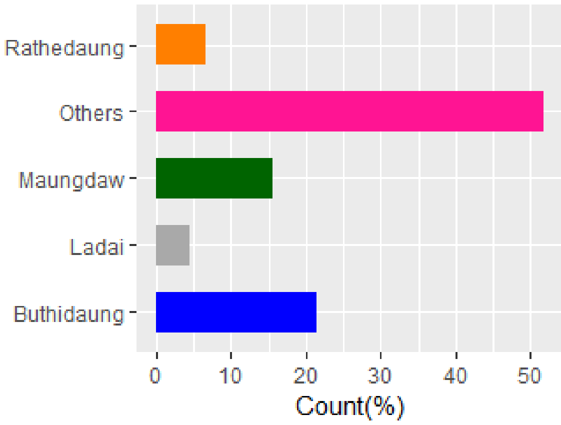
(a) Different group of participants



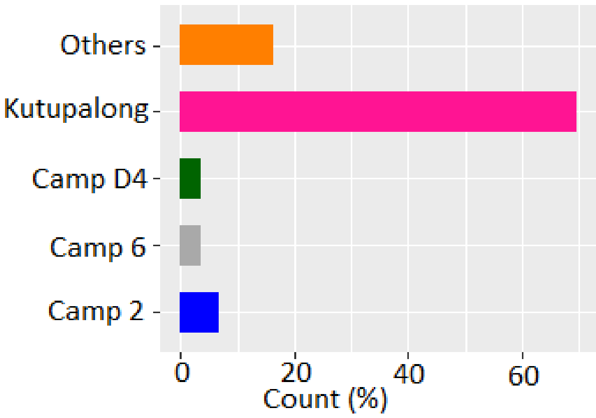
(b) Age (years)



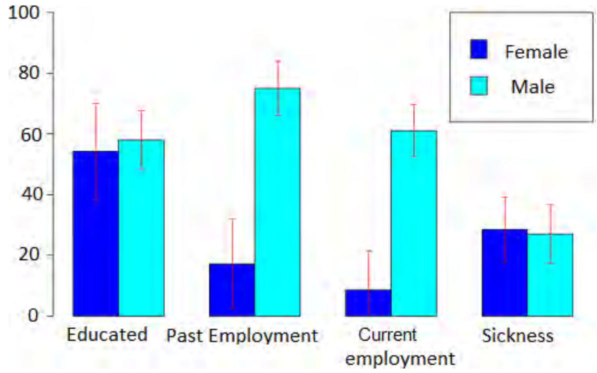
(c) Number of family members



(d) Previous residence



(e) Current residence



(f) Education, employment, and sickness

Figure 5.1: Demographic and socio-economic characteristics of the Rohingya refugee participants in term of their counts in (a)-(c). Bars in (f) show mean percentage of participants under different demographic characteristics

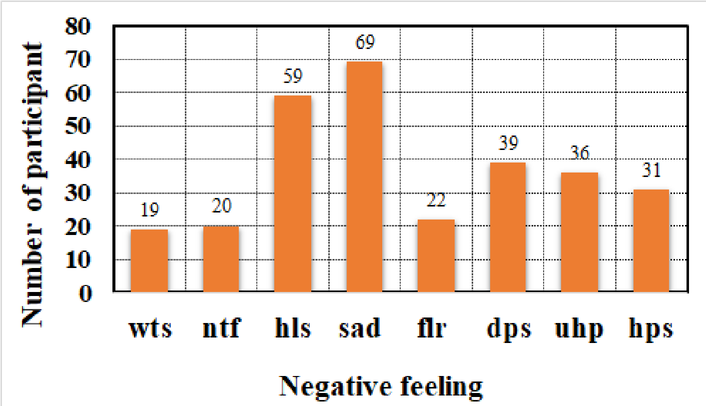


Figure 5.2: Number of participant who said positive about our eight different negative feelings

Table 5.1: Bivariate correlations among eight negative feelings and substance (betel leaf and smoking) (asterisks represent Benjamini-Hochberg corrected [3, 4] statistically significant correlation between two entities; * indicates $P \leq 0.05$, ** indicates $P \leq 0.01$, and *** indicates $P \leq 0.001$)

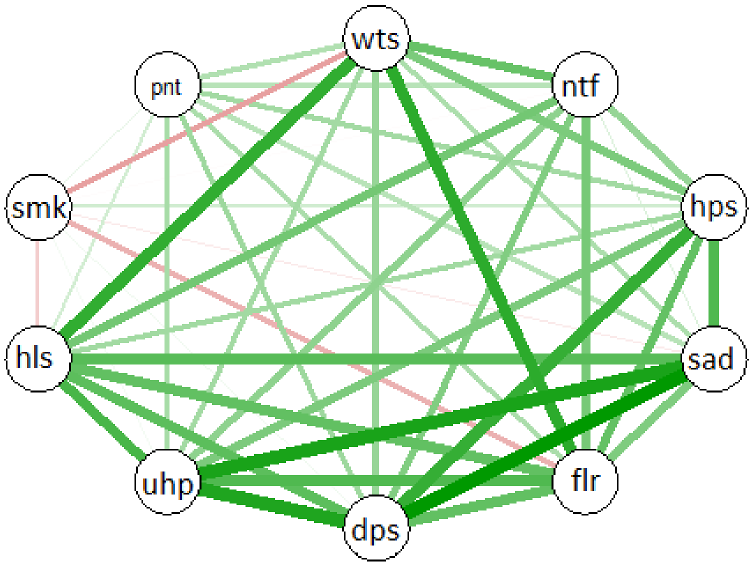
Category	Worthlessness	Nothing to look forward to	Hopelessness	Sadness	Feeling of failure	Depression	Unhappiness	Helplessness	Smoking
Nothing to look forward to (ntf)	0.3832***								
Hopelessness (hps)	0.3297***	0.2643							
Sadness (sad)	0.2091*	0.0832	0.4416***						
Feeling of failure (flr)	0.5314***	0.3424***	0.3898***	0.3221**					
Depression (dps)	0.2618**	0.318**	0.5096***	0.6429***	0.396***				
Unhappiness (uhp)	0.2329*	0.2842**	0.3315***	0.58***	0.4409***	0.5657***			
Helplessness (hls)	0.5187***	0.3538***	0.2339*	0.4202***	0.3955***	0.412***	0.4618***		
Smoking (smk)	-0.2391*	-0.0084	0.1173	-0.0532	-0.1965	0.0365	0.0263	-0.1253	
Betel leaf (pnt)	0.1954	0.1788	0.2314	0.1782	0.2113*	0.2452*	0.2207*	0.1147	0.0546

by chance, which could lead to incorrectly rejecting the true null hypotheses. Benjamini-Hochberg correction helps us to avoid false positive errors.

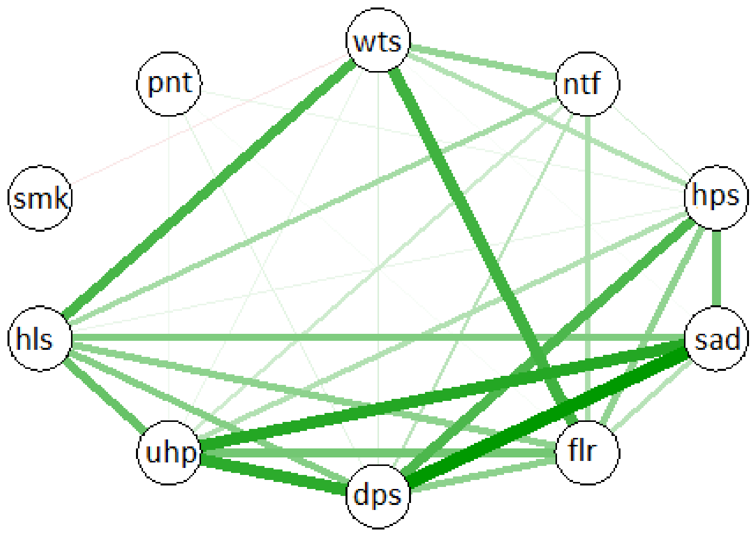
This happens as, in a correlation network, edges indicate the existence of associations (direct or indirect) and the extent of those associations [4]. The widths and shades of edges in this network represent the strengths of the association between connected entities. Here, darker and wider edges represent strong associations between entities than light and thin edges.

We can see from our correlation network (Figure 5.3a) that several negative feelings are strongly interconnected with each other. The strongest association appears between depression and sadness (r = 0.6429). The negative correlations (red edges) in this network appear between worthlessness and smoking, smoking and feeling of failure, and smoking and helplessness. Besides, strong interconnections exist between helplessness and worthlessness, unhappiness and sadness, unhappiness and depression, depression and sadness, depression and hopelessness, and worthlessness and feeling of failure.

Additionally, we develop Bonferroni corrected significant correlation network based on significant



(a) Significant Correlation Network based on Benjamini-Hochberg corrected statistics



(b) Significant Correlation Network based on Bonferroni corrected statistics

Figure 5.3: (a) A Significant Correlation Network based on Benjamini-Hochberg corrected significant bivariate correlations, and (b) A Significant Correction Network based on Bonferroni corrected [2] significance among negative feelings

correlations between the negative feelings as well as with substances betel leaf and smoking as shown in Figure 5.3b. In this significant correlation network, we find that substances such as smoking and betel leaf are not connected with depression or any other negative feelings. We can also find that there exist strong connections between helplessness and worthlessness, unhappiness and sadness, unhappiness and depression, depression and sadness, depression and hopelessness, worthlessness and feeling of failure, which we also find in our Benjamini-Hochberg corrected correlation network.

Partial Correlation Network

As we have mentioned earlier, correlation network do not capture the direction of an association between two negative feelings. Here, in the correlation network, some associations may arise between two entities even if there is no direct interaction between them. This happens when both entities get influenced by another, i.e., a third entity controls their expressions. However, in a partial correlation network [150, 4], edges reflect the only direct association between two entities. Accordingly, we calculate a partial correlation matrix [150] (Table 5.2) for eight different negative feelings and use it to build a partial correlation network as shown in Figure 5.4a. The edges in the partial correlation network reflect the statistically significant partial correlation between different negative feelings. The stronger the partial correlations, the wider and darker the edges.

It becomes evident from Figure 5.4a that the partial correlation network is less dense, i.e., it contains fewer edges than the correlation network. This is because the edges in the partial correlation network reflect only direct associations between entities. For example, we can easily observe from the partial correlation matrix that depression is strongly correlated with sadness, whereas moderately associated with nothing to look forward to. Accordingly, in the partial correlation network, we find a significant positive correlation (green edge) between depression and sadness, and depression and nothing to look forward to. However, if we compare these edges from depression with that in the correlation network, we find that the correlations that appear between depression and other two negative feelings namely unhappiness and hopelessness in the correlation network are most likely caused by indirect associations. For instance, in the case of unhappiness and hopelessness, sadness might work as an intermediary, as sadness is directly correlated with both hopelessness and unhappiness while being correlated with depression.

To measure the importance of the different negative feelings in the partial correlation network, we use centrality measurements of the negative feelings in terms of strength [4, 153] and betweenness [154, 4]. Note that, in a network, strength measures the overall weight of all interactions associated with a particular entity. Now, from a partial correlation network, we get a weighted graph where edges reflect partial correlations among different entities and all the correlations are not of equal strength.

Table 5.2: Partial correlations among eight different negative feelings as well as substances betel leaf and smoking (asterisks represent Benjamini-Hochberg corrected statistically significant correlation between two entities where the effects of other entities are statistically controlled; * indicates $P \leq 0.05$, ** indicates $P \leq 0.01$, and *** indicates $P \leq 0.001$; Note that this table contains less number of significant entries compared to the earlier case due to considering only direct associations here.)

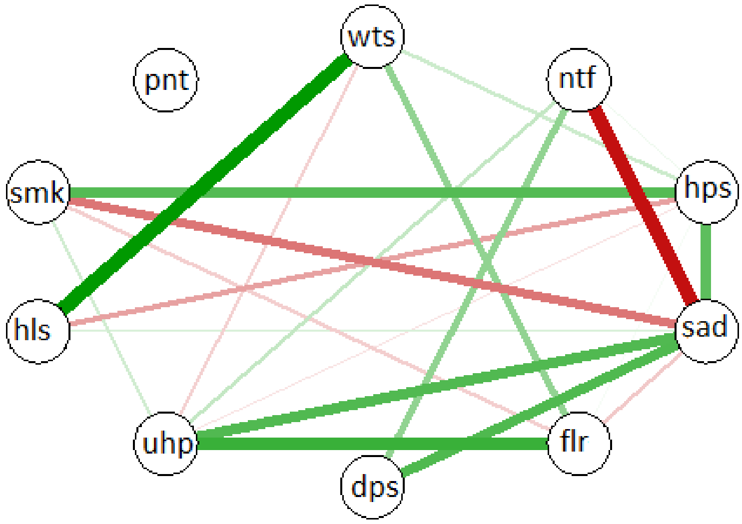
Category	Worthlessness	Nothing to look forward to	Hopelessness	Sadness	Feeling of failure	Depression	Unhappiness	Helplessness	Smoking
Nothing to look forward to (ntf)	0.1614								
Hopelessness (hps)	0.1902	0.0879							
Sadness (sad)	-0.0441	-0.272**	0.2254*						
Feeling of failure (flr)	0.3263**	0.0738	0.1684	0.0406					
Depression (dps)	-0.0593	0.1913	0.2325	0.4013***	0.0705				
Unhappiness (uhp)	-01277	0.1182	-0.0677	0.3178**	0.2545*	0.1753			
Helplessness (hls)	0.392***	0.1585	-0.1348	0.1911	-0.0004	0.07772	0.204		
Smoking (smk)	-0.1898	0.0331	0.2203*	-0.1325	-0.1821	0.0506	0.109	-0.0085	
Betel leaf (pnt)	0.1044	0.0575	0.0583	0.0132	0.0426	0.0731	0.076	-0.0822	0.0696

Therefore, to account for which negative feelings strongly interact with others in the partial correlation network, we take the sum of weights of all interactions associated with a particularly negative feeling. On the other hand, betweenness measures the degree of influence of a particularly negative feeling on the interactions among other entities. In this regard, in our partial correlation network, sadness, unhappiness, and hopelessness emerge as highly central negative feelings. The importance of these negative feelings is also evident from the partial correlation network where strong partial correlations appear among these negative feelings. Besides, sadness has the highest strength score, i.e., the sum of correlations (weights) of all interactions (edges) involving sadness is maximum. Therefore, sadness appears to be the most influential among all the negative feelings. Nonetheless, it is the only negative feeling that is strongly correlated with depression and three other different negative feelings. It also has the highest betweenness score, i.e., it is the most likely one to mediate the interactions among other negative feelings. For example, it connects different negative feelings such as unhappiness, hopelessness, etc.

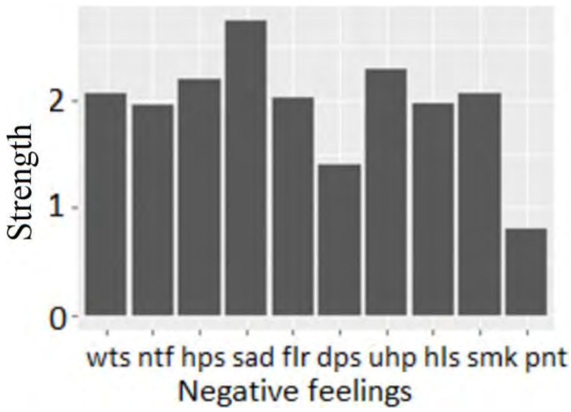
On the other hand, the substance betel leaf (pnt) exhibits the lowest positive strength score. This happens as, among all the partial correlations in a partial correlation network, it shares the weakest interactions with others. Besides, betel leaf, smoking, nothing to look forward to, depression, and feeling of failure in concentrating exhibit zero betweenness score as shown in Figure 5.4c.

Regulatory Network

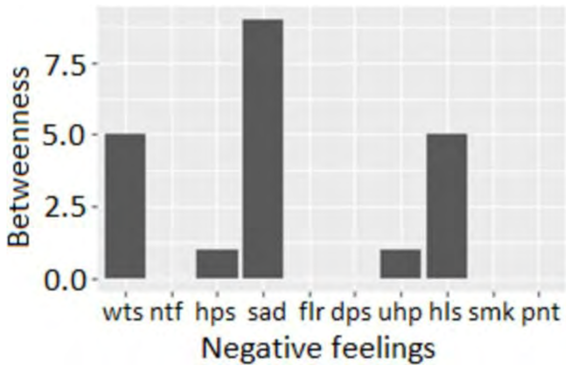
Though the correlation network and partial correlation network provide us the strengths of undirected associations between different negative feelings, they fail to provide any account of the direction of



(a) Partial Correlation Network based on Benjamini-Hochberg correction



(b) Strength of Partial Correlation Network



(c) Betweenness of Partial Correlation Network

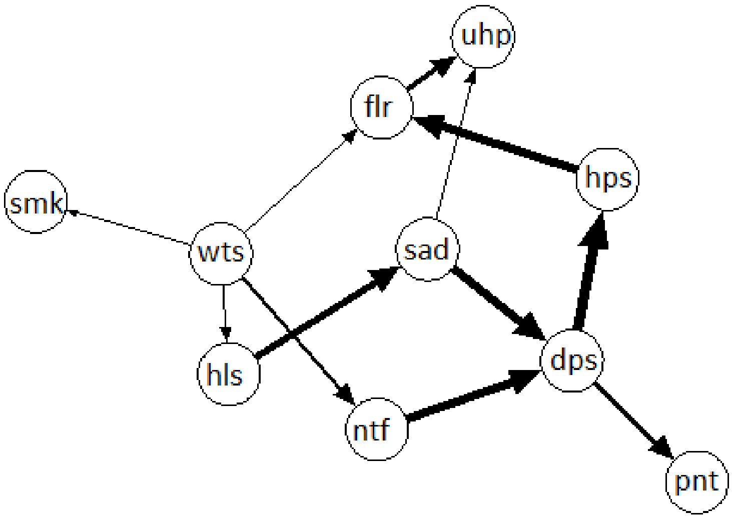
Figure 5.4: (a) A Partial correlation network based on Benjamini-Hochberg corrected significant bivariate correlations, (b) Strength, and (c) Betweenness of the negative feelings and substance usages

these associations. Therefore, we further develop a directed regulatory model of negative feelings from the responses of Rohingya refugees, using bnlearn package [155] available in R. Figure 5.5a shows the regulatory network built from Bayesian inference [156] of the eight different negative feelings along with intake of substances. This model reveals a complex structure of relationship among our considered eight different negative feelings and enables us to infer directions of the associations. Here, the thickness of an edge marks the level of confidence that the prophecy (and potentially causation) flows in the direction as portrayed in the network. Additionally, several significant features get evident from the regulatory network, since it combines aspects from both reflective and formative models of negative feelings.

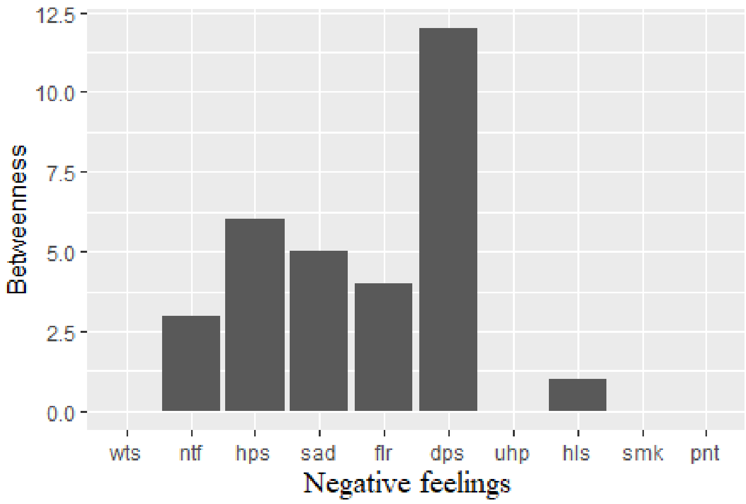
In the directed regulatory model of eight different negative feelings, we investigate the negative feelings that interact with one another. First, the negative feelings that we find to be significant constituents of depression are sadness and the feeling of nothing to look forward to. Besides, we find hopelessness and substance betel leaf to be directly reflective of depression. Worthlessness also functions as a constituent of helplessness, nothing to look forward to, feeling of failure, and smoking. Additionally, helplessness appears as a direct constituent for sadness, hopelessness for feeling of failure, and feeling of failure for unhappiness.

When we measure the centrality of each of these negative feelings in this network in terms of betweenness, feeling of depression emerges as the strongest interacting component within the network, and then come hopelessness, sadness, and feeling of failure. On the other hand worthlessness, unhappiness, smoking, and betel leaf show zero betweenness indicating the weakest interacting component within this regulatory network.

Now, this directed regulatory model of negative feelings differs from the previous other underacted models of negative feelings in a number of ways. First of all, in this regulatory model, depression is associated with three other negative feelings namely sadness, feeling of nothing to look forward to, and helplessness along with substance betel leaf. However, in the previous partial correlation network, we find only feeling of nothing to look forward to and sadness to be associated with depression. Besides, unlike the previous partial correlation network, sadness is strongly connected with both helplessness and unhappiness in the regulatory model. This happens as a Bayesian network connects two entities as cause-effect pairs based on conditional dependency between them, instead of simple correlations. Second, the strength scores of negative feelings in the regulatory network vary from that of negative feelings in the previous partial correlation network. In a partial correlation network, the edge weights present partial correlations (value between 0 to 1) between entities. Therefore, the strength score of each negative feeling is comparatively small. On the other hand, in the regulatory network, the edge weight presents a measure of confidence or strength for the corresponding edge as calculated using Bayesian Information Criterion (BIC) score [145], which is equivalent to the Minimum Description Length (MDL) and is also known as Schwarz Information Criterion.



(a) Regulatory network based on Bayesian Inference of eight different negative feelings along with substance betel leaf and smoking



(b) Betweenness of Regulatory network based on Bayesian Inference of eight different negative feelings along with substance betel leaf and smoking

Figure 5.5: Regulatory network and centrality measures of the negative feelings

EEG Brainwave Data Collection and Analysis over the Collected EEG Data

An electroencephalograph (EEG) [30] presents recorded electrical activity generated by a brain. We collect EEG data during the interview sessions using Neurosky Mindwave [129], which has only one sensor that needs to be placed at FP1 region. The FP1 region constitutes the left side of the frontal lobe and left part of the prefrontal cortex, and is responsible for the execution of cognitive tasks of a human brain. Based on signals collected from this region, the device produces EEG power values for eight different frequency bands. These power values provide useful indications of whether a particular band is increasing or decreasing over time, how strong each band is relative to the other bands, etc.

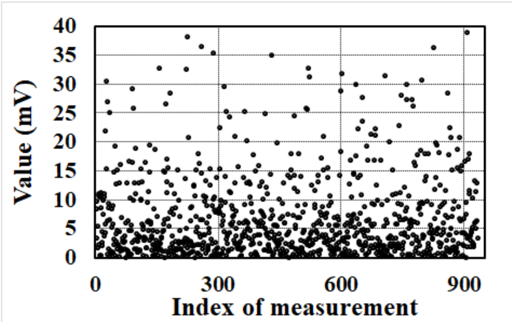
EEG Brainwave Dataset

Our recording time with an EEG device for each participant spans over an average of 15 - 20 minutes. We capture EEG data from all of our 135 Rohingya refugee participants living in Bangladesh. Thus, we have captured around 58000 EEG data points from our participants. Note that, such EEG data consisting of values over different frequency bands are widely used in medical applications for detecting neurological disorders [157]. The different frequency bands of EEG are delta, theta, alpha, beta, and gamma. Over the frequency bands, Neurosky Mindwave [158] device generates different raw-brainwaves as output with a sampling rate of 512 Hz. The brainwaves generate band powers at eight different band frequencies. The band frequencies are delta (0.5 to 2.75 Hz), theta (3.5 to 6.75 Hz), low alpha (7.5 to 9.25 Hz), high alpha (10 to 11.75), low beta (13 to 16.75 Hz), high beta (18 to 29.75 Hz), low gamma (31 to 39.75 Hz), and mid gamma (41 to 49.75 Hz) [130].

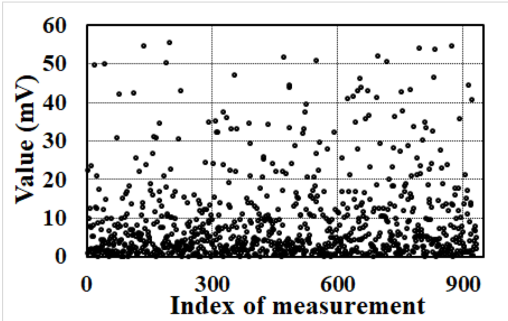
Repetition Analysis over Our Collected EEG Brainwave Dataset

We have conducted a set of analyses over our collected EEG brainwave data to check how far there exists repetition in the collected data. In this regard, first, we have analyzed EEG brainwave data for all of the eight bands collected for one participant. The participant was randomly selected from our 135 participants. We were able to capture 930 EEG signal data points from the participant. Figure shows the values of eight bands (in millivolt) of all the collected EEG signal data points. This figure presents variations in the data points in all of the eight bands.

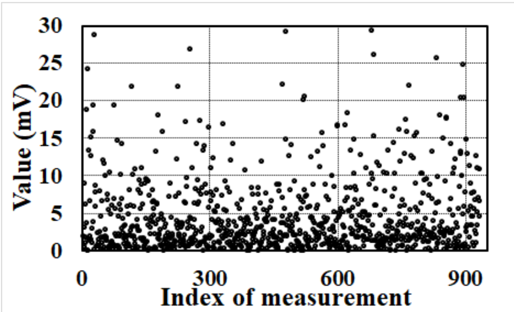
Next, for the same participant, we calculate averages of the EEG signal data points for all of the eight bands. We also calculate averages of the differences between consecutive EEG signal data points for all of the eight bands. We plot these calculated average values along with corresponding standard deviations as error bars in Figure 5.7 to show whether and how far the values vary in consecutive data points. The figure shows that averages of differences in consecutive data points are comparable to that of actual data points in all of the eight bands. This confirms substantial variations in the collected data.



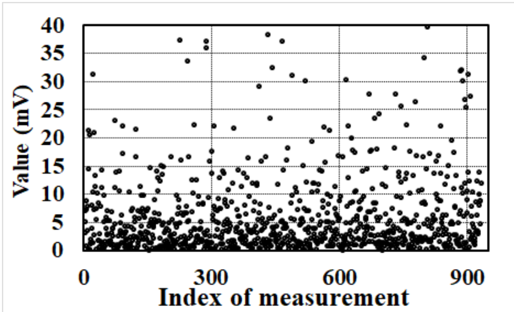
(a) High alpha band values (shown values up to 40 mV, as there are only 16 points having value higher than it)



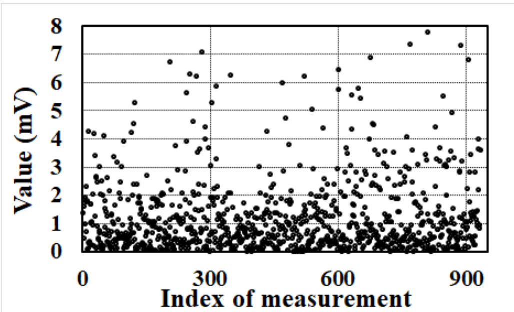
(b) Low alpha band values (shown values up to 60 mV, as there are only 13 points having value higher than it)



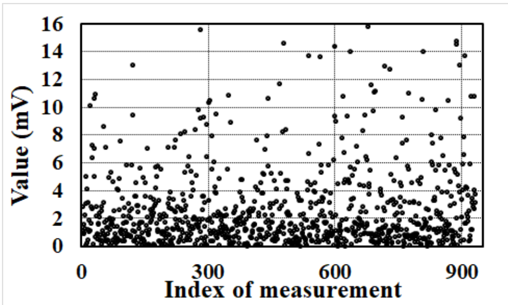
(c) High beta band values (shown values up to 30 mV, as there are only 17 points having value higher than it)



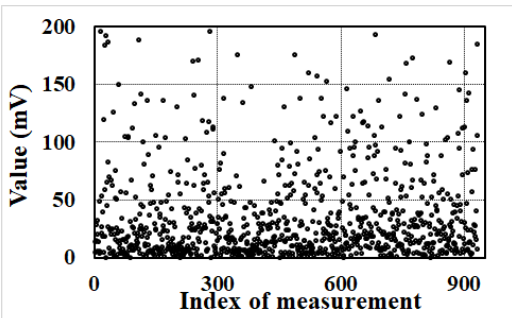
(d) Low beta band values (shown values up to 40 mV, as there are only 12 points having value higher than it)



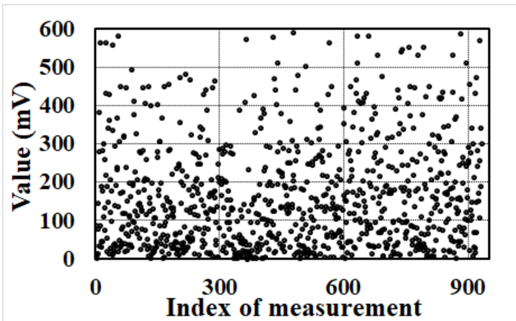
(e) Mid gamma band values (shown values up to 8 mV, as there are only 9 points having value higher than it)



(f) Low gamma band values (shown values up to 16 mV, as there are only 15 points having value higher than it)



(g) Theta band values (shown values up to 200 mV, as there are only 28 points having value higher than it)



(h) Delta band values (shown values up to 600 mV, as there are only 12 points having value higher than it)

Figure 5.6: Values of eight different bands of EEG brainwave data of a random participant

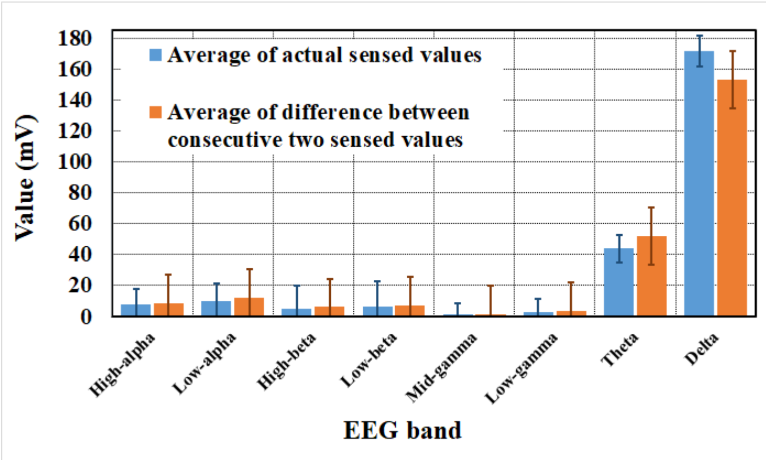
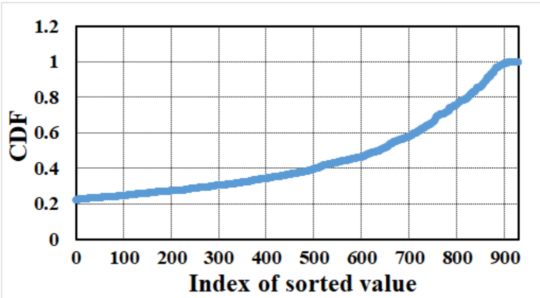


Figure 5.7: Averages of values and differences between consecutive values for all of the eight bands of EEG brainwave data for a random participant (error bars present corresponding standard deviations)

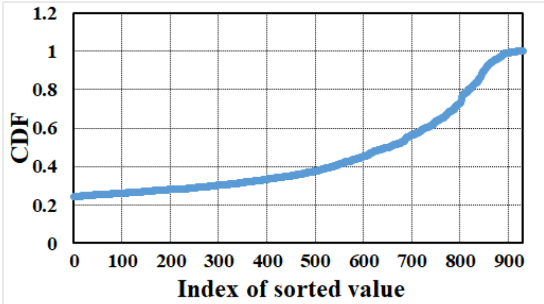
Afterward, we present CDFs of EEG signal data points for all of the eight bands in Figure 5.8 to show how frequently distinct values occur. The figure shows that different ranges of values for EEG signal data points in all of the eight bands exhibit different extents of frequencies.

Additionally, we calculate three different types of distances, namely Euclidean distance, Manhattan distance, and Minkowski distance, between adjacent points of EEG signal data over all of the eight bands. We calculate the distances for three different random participants. We plot the distances in Figure 5.9. The figure shows that consecutive values of EEG signal data points in all of the eight bands exhibit substantial distances. Thus, combining outcomes of Figure 5.6 - 5.9, we can infer that the extent of repetition in the case of EEG signal data should be minimal. Next, we present average values of all eight bands (with corresponding standard deviations) for all of our participants in Figure 5.10. This figure presents substantial variations in the data collected from all the participants.

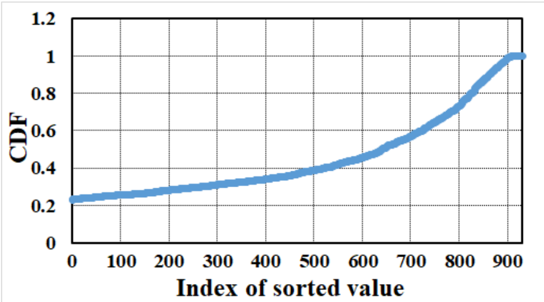
Finally, for further analysis on data repetition, we calculate pairwise cosine similarity [159] of EEG data points over all of the 135 participants. Here, we take the minimum number of 180 EEG data points for each of the participants. Besides, as consideration of all pairs over the participants would need calculation over ${}^{135}C_2$ pairs, we perform our pairwise calculations over consecutive 134 pairs of the participants. This directly or indirectly covers all the participants to be compared with each other in the analysis of cosine similarity. We present the pairwise cosine similarity values found in this way in Figure 5.11. From the figure, we find that pairwise cosine similarity values range over (0.2, 0.6). These values confirm that the repetition of values over EEG data points is limited.



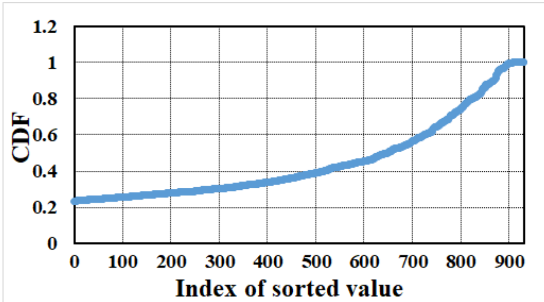
(a) CDF of high alpha band values



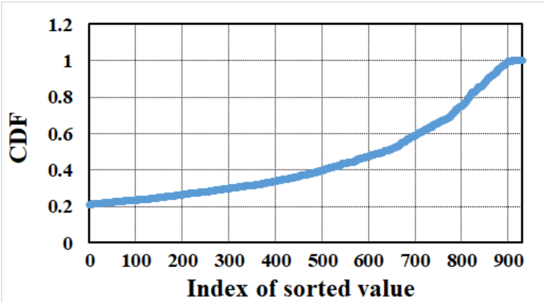
(b) CDF of low alpha band values



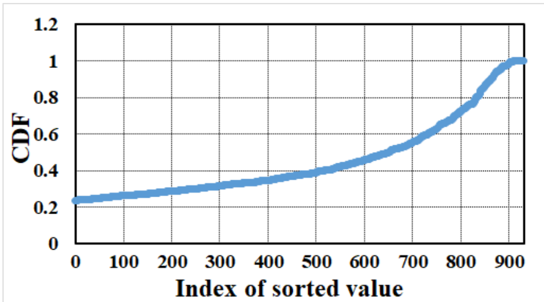
(c) CDF of high beta band values



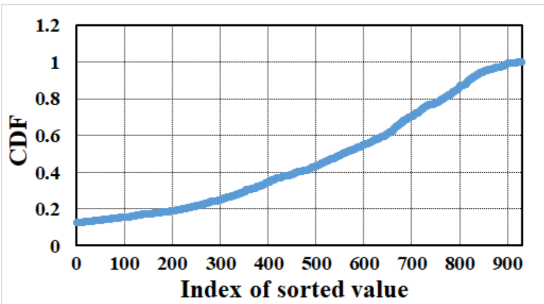
(d) CDF of low beta band values



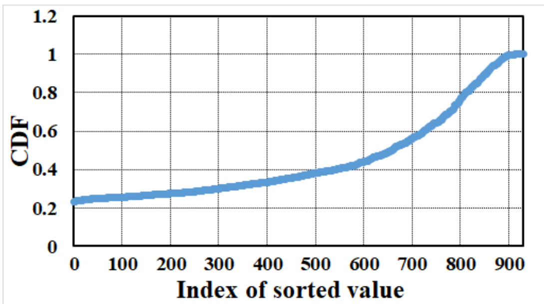
(e) CDF of mid gamma band values



(f) CDF of low gamma band values

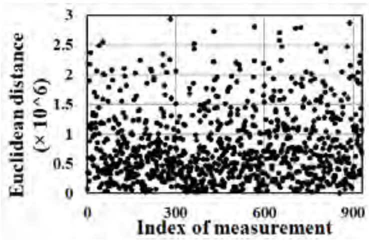


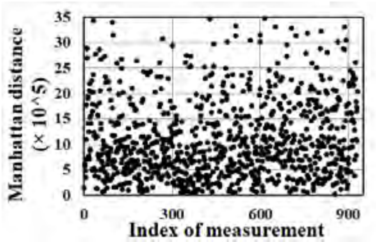
(g) CDF of delta band values

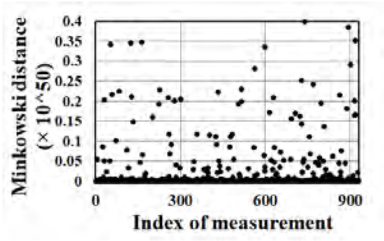


(h) CDF of theta band values

Figure 5.8: CDFs for all of the eight bands of EEG brainwave data of a random participant



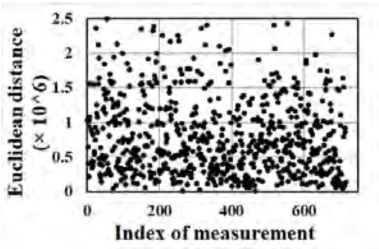


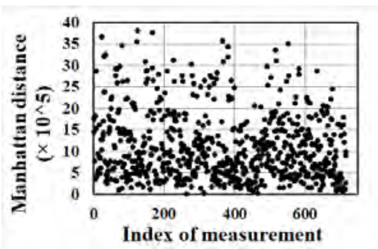


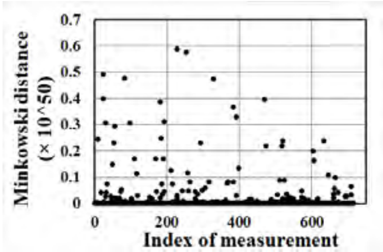
(a) Euclidean distance between consecutive EEG brainwave data points for User 1 (shown up to distance = 3 $\times 10^6$, as there are only 13 distances having values higher than it)

(b) Manhattan distance between consecutive EEG brainwave data points for User 1 (shown up to distance = 35 $\times 10^5$, as there are only 7 distances having values higher than it)

(c) Minkowski distance between consecutive EEG brainwave data points for User 1 (shown up to distance = 0.4 $\times 10^{50}$, as there are only 19 distances having values higher than it)



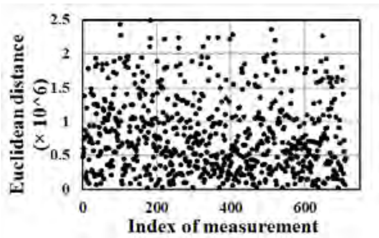


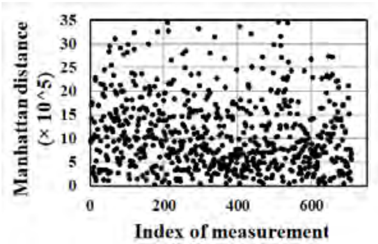


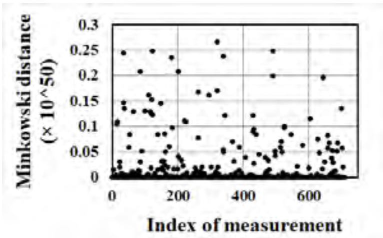
(d) Euclidean distance between consecutive EEG brainwave data points for User 2 (shown up to distance = 2.5 $\times 10^6$, as there are only 19 distances having values higher than it)

(e) Manhattan distance between consecutive EEG brainwave data points for User 2 (shown up to distance = 40 $\times 10^5$, as there are only 13 distances having values higher than it)

(f) Minkowski distance between consecutive EEG brainwave data points for User 2 (shown up to distance = 0.7 $\times 10^{50}$, as there are only 23 distances having values higher than it)







(g) Euclidean distance between consecutive EEG brainwave data points for User 3 (shown up to distance = 2.5 $\times 10^6$, as there are only 6 distances having values higher than it)

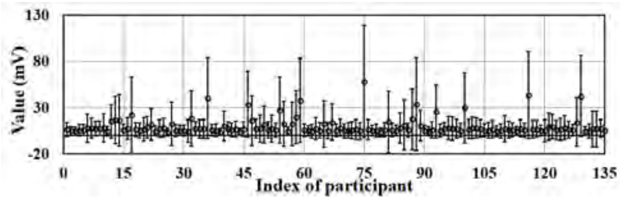
(h) Manhattan distance between consecutive EEG brainwave data points for User 3 (shown up to distance = 35 $\times 10^5$, as there are only 7 distances having values higher than it)

(i) Minkowski distance between consecutive EEG brainwave data points for User 3 (shown up to distance = 0.3 $\times 10^{50}$, as there are only 11 distances having values higher than it)

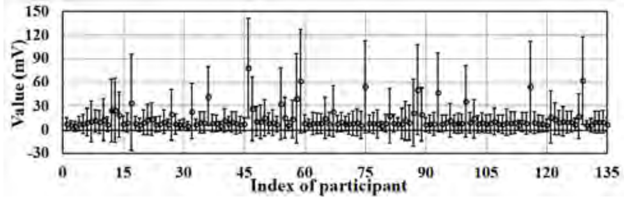
Figure 5.9: Euclidean distance, Manhattan distance, and Minkowski distance between consecutive EEG brainwave data points for three different random participant

Statistical Analysis

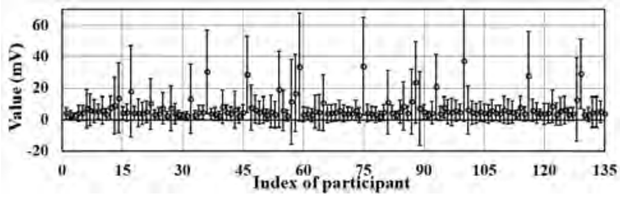
We analyze and find that values of different EEG power bands vary significantly among different groups of participants (e.g., participants who answered positively in response to the questionnaires



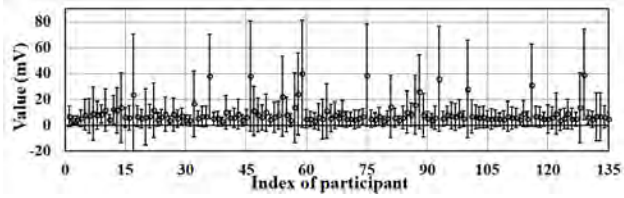
(a) High alpha band values of all participants



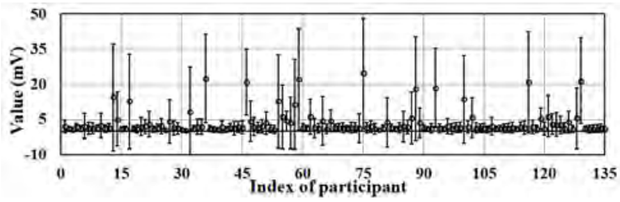
(b) Low alpha band values of all participants



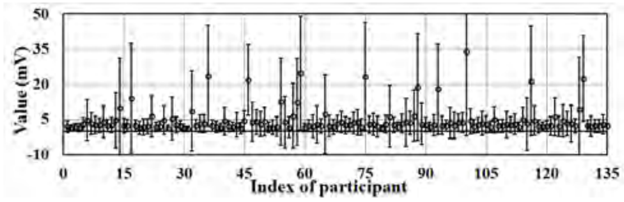
(c) High beta band values of all participants



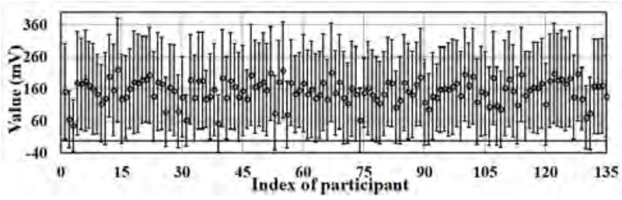
(d) Low beta band values of all participants



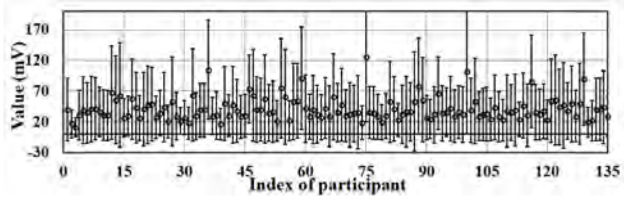
(e) Mid gamma band values of all participants



(f) Low gamma band values of all participants



(g) Delta band values of all participants



(h) Theta band values of all participants

Figure 5.10: Average values with standard deviations for all of the eight bands of EEG brainwave data collected from all participants

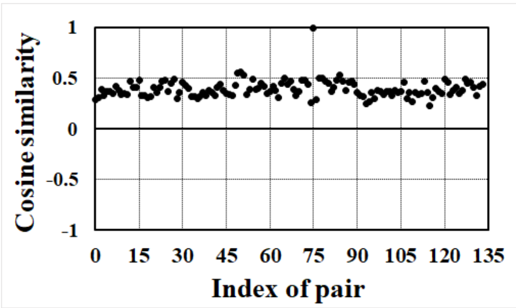


Figure 5.11: Pairwise cosine similarity over the participants for EEG brainwave data (Pair i covers Participant i and i+1)

for various negative feelings and those who did not). For this purpose, we perform F-test and t-test [160] on the relative EEG power measures of the participants. Note that F-test and t-test both work

Table 5.3: Results of F-test and t-test on the relative EEG power of different frequency bands collected while participants were talking (* indicates $P \leq 0.05$, ** indicates $P \leq 0.01$, and *** indicates $P \leq 0.001$; values mentioned within brackets below represent degree of freedom)

Category	Low alpha	High alpha	Low beta	High beta	Low gamma	Mid gamma	Delta	Theta
Worthlessness	F(9962)= 0.49*** t(8449)= -15.37***	F(9962)= 0.51*** t(8512)= -14.68***	F(9962)= 0.53*** t(8546)= -14.58***	F(9962)= 0.42*** t(8295)= -15.67***	F(9962)= 0.34*** t(8108)= -16.03***	F(9962)= 0.52*** t(8519)= -15.99***	F(9962)= 1.07*** t(9865) = -1.14	F(9962)= 0.69*** t(8937)= -13.03***
Depression	F(17663)= 1.43*** t(23231)= 12.45***	F(17663)= 1.59*** t(22403))= 13.04***	F(17663)= 1.39*** t(23493)= 13.19***	F(17663)= 1.21*** t(24744)= 11.15***	F(17663)= 1.29*** t(24142)= 10.28***	F(17663)= 1.72*** t(21814)= 12.68***	F(17663)= 0.99 t(26908)= 5.26***	F(17663)= 1.16*** t(25182)= 8.92***
Feeling of failure	F(10748)= 1.49*** t(10045)= 8.95***	F(10748)= 1.40*** t(10175)= 7.75***	F(10748)= 1.18*** t(10586)= 7.43***	F(10748)= 0.87*** t(11530)= 2.48	F(10748)= 0.95** t(11234)= 2.01	F(10748)= 1.28*** t(10376)= 9.69***	F(10748)= 0.94** t(11244)= -2.99	F(10748)= 1.03 t(10966)= 3.16
Helplessness	F(14540) 1.19*** t(17314)= 7.23***	F(14540) 1.28*** t(17715)= 8.19***	F(14540) 1.24*** t(17486)= 10.56***	F(14540) 1.10*** t(18205)= 8.68***	F(14540) 1.21** t(17606)= 9.77***	F(14540) 1.42*** t(16734)= 10.25***	F(14540) 0.92*** t(19504)= 0.47	F(14540) 1.00 t(18844)= 5.22***
Hopelessness	F(27744)= 1.36*** t(49713)= 8.92***	F(27744)= 1.40*** t(49233)= 10.45***	F(27744)= 1.26*** t(50730)= 10.07***	F(27744)= 1.61*** t(47134)= 12.01***	F(27744)= 2.18*** t(42684)= 16.14***	F(27744)= 1.45*** t(48714)= 10.24***	F(27744)= 0.99 t(53554)= -1.09	F(27744)= 1.24*** t(50984)= 6.96***
Nothing to look forward to	F(10550)= 2.18*** t(91533)= 16.28***	F(10550)= 1.98*** t(92813)= 14.92***	F(10550)= 1.26*** t(91838)= 15.05***	F(10550)= 1.61*** t(92031)= 14.17***	F(10550)= 2.18*** t(92834)= 12.39***	F(10550)= 1.45*** t(91737)= 17***	F(10550)= 0.99 t(110737)= 4.62***	F(10550)= 1.20*** t(10133)= 9.95***
Sadness	F(27199)= 0.69*** t(55230)= -6.34***	F(27199)= 0.84*** t(54269)= -3.00***	F(27199)= 0.76*** t(54869)= -2.82	F(27199)= 1.06*** t(51955)= -1.00	F(27199)= 1.30*** t(49099)= 2.78	F(27199)= 0.78*** t(54762)= -5.21***	F(27199)= 1.05*** t(52029)= 5.74***	F(27199)= 1.12*** t(51222)= 3.84**
Unhappiness	F(16447)= 0.41*** t(36804)= -18.97***	F(16447)= 0.35*** t(39974)= -17.26***	F(16447)= 0.38*** t(38344)= -16.76***	F(16447)= 0.44*** t(35640)= -18.41***	F(16447)= 0.41*** t(36747)= -18.47***	F(16447)= 0.27*** t(45084)= -22.34***	F(16447)= 1.05*** t(23144)= 7.31***	F(16447)= 0.84*** t(25443)= -5.88***

for different sets of distributions. As the distribution to which our collected data belong is unknown to us, we explored both types of hypothesis tests. Here, F-test reveals whether values of EEG activity show similar variance (change) over the different groups of people or not. On the other hand, the t-test measures whether the levels of EEG activity are similar or different (greater or less) over different groups of people. We present the outcomes of both types of tests in Table 5.3.

From F-test, we find significant variance in all the eight bands for people who answered positively for three different negative feelings namely worthlessness, sadness, and unhappiness. Besides, low alpha, high alpha, low beta, high beta, and mid gamma bands show significant variances for all people who answered positively for all our considered negative feelings. Table 5.4 provides a brief summary of the analysis over the relative EEG power of different groups of participants. From the table, we can see that most of the relative power band data show significant variances for different

Table 5.4: An overview of relative EEG power analysis for different groups of people (Check mark in a cell indicates that statistically significant variance exists in the power of that particular EEG signal between the participants who positively reported about a particular negative feeling and those who reported negatively about that particular feeling)

Category	Low alpha	High alpha	Low beta	High beta	Low gamma	Mid gamma	Delta	Theta
Worthlessness	C	C	C	C	C	C	C	C
Depression	C	C	C	C	C	C		C
Feeling of failure	C	C	C	C	C	C	C	
Helplessness	C	C	C	C	C	C	C	
Hopelessness	C	C	C	C	C	C		C
Nothing to look forward to	C	C	C	C	C	C		C
Sadness	C	C	C	C	C	C	C	C
Unhappiness	C	C	C	C	C	C	C	C

Table 5.5: An overview of relative EEG power analysis for different groups of people (Check mark in a cell indicates that statistically significant level exists in the power of that particular EEG signal between the participants who positively reported about a particular negative feeling and those who reported negatively about that particular feeling)

Category	Low alpha	High alpha	Low beta	High beta	Low gamma	Mid gamma	Delta	Theta
Worthlessness	C	C	C	C	C	C		C
Depression	C	C	C	C	C	C	C	C
Feeling of failure	C	C	C			C		
Helplessness	C	C	C	C	C	C		C
Hopelessness	C	C	C	C	C	C		C
Nothing to look forward to	C	C	C	C	C	C	C	C
Sadness	C	C				C	C	C
Unhappiness	C	C	C	C	C	C	C	C

groups of people.

Besides, the t-test reveals significant levels in different EEG power bands over different groups of people. We find significant levels in all eight bands for people who answered positively for three different negative feelings, namely depression, nothing to look forward to, and unhappiness. Besides, low alpha, high alpha, and mid gamma bands show significant levels for all people who answered positively for all our considered negative feelings. Table 5.5 provides a brief summary of the relative EEG power analysis over different groups of participants. From the Table 5.5, we can see that most of the relative power band data exhibit significant levels for different groups of people.

Note that, F-test and t-test both follow different calculations and measurements. For example, F-test adopts standard deviations and t-test adopts averages as the bases of determining statistical significance. As the bases are different for the two tests, it is natural to find different statistical significance based on the two test.

Machine Learning based Analysis

Our data set contains 58000 EEG signal data points for all eight power bands labeled by corresponding negative feelings. From this dataset, we develop eight different datasets for each of the negative feelings. Here, each dataset contains positively responded participants for specific negative feeling data as well as negatively responded participants for the specific negative feeling data. Over each of these datasets, we explore a total of 45 different machine learning-based classification algorithms implemented in the WEKA toolkit [42]. Table 5.6 shows outcomes of the exploration based on only the best-found machine learning algorithms.

In our analysis, we use 10-fold cross-validation [161]. Cross-validation refers to a resampling procedure used to evaluate machine learning models. 10-fold cross-validation divides the dataset randomly into 10 parts, from where randomly selected 9 parts are used as training datasets and the remaining one part is used as validation dataset. This procedure is repeated for 10 times. The benefit of 10-fold cross-validation is that each of the parts works as a training dataset as well as a validation dataset. Besides, in the case of evaluating classification models using the WEKA toolkit, we get micro averages of precision, recall, and F-measure for each class, and then weighted average [162, 163, 164] for each of the metrics considering all the classes. In our study, WEKA considers the classes having existence and non-existence of a negative feeling (‘Y’ and ‘N’) for calculating precision, recall, and F-measure in this manner. The advantage of using the notion of weighted average statistics is that we can check the performance considering all the classes individually [165]. Additionally, we also calculate accuracy, which refers to the proportion of total number of correct predictions considering all classes.

Table 5.6 shows outcomes from all these perspectives. From the table, we can find that Random Sub Space [166] algorithm provides the highest accuracies for nothing to look forward to (85.72%), depression (72.9%), unhappiness (75.07%), and helplessness (78.8%). Besides, Random Forest [167, 168] algorithm provides the highest accuracies for worthlessness (86.80%) and felling of failure (85.4%). Classification using the Regression algorithm also provides the highest accuracies for sadness (56.42%) and hopelessness (55.8%). Other than that, SGD [169], Simple Logistic [170], and Attribute Selected Classifier [171] algorithms also provide good accuracies for classifying several different negative feelings based on EEG brainwave signals.

Additionally, for conducting further machine-learning based analysis over frames of data, we cal-

Table 5.6: Performance of the best machine learning algorithms for different negative feelings while predicting existence of negative feelings based on EEG signal. Here, Y column shows the number of points associated with existence of the corresponding negative feeling and N column shows the number of points associated with not existence of the corresponding negative feeling. Besides, Precision, Recall, and F-Measure columns show weighted averages of precision, recall, and F-measure accordingly.

Negative Feeling	Y	N	Precision	Recall	F-Measure	Accuracy	ML Algorithm
Worthlessness	9963	48037	0.82	0.87	0.81	86.80%	RandomForest
Nothing to look forward to	10551	47449	0.84	0.86	0.79	85.72%	RandomSubSpace
Hopelessness	27745	30255	0.54	0.55	0.49	55.3%	ClassificationViaRegression
Sadness	27200	30800	0.54	0.56	0.47	55.68%	ClassificationViaRegression
Feeling of failure	10749	47251	0.81	0.85	0.79	85.4%	RandomForest
Depression	17664	40336	0.68	0.73	0.62	72.9%	RandomSubSpace
Unhappiness	16448	41552	0.72	0.75	0.64	75.07%	RandomSubSpace
Helplessness	14541	43459	0.75	0.78	0.69	78.5%	RandomSubSpace

Table 5.7: Performance of the best machine learning algorithms for different negative feelings while predicting existence of negative feelings based on EEG signals mean values (5 points average). Here, Y column shows the number of points associated with existence of the corresponding negative feeling and N column shows the number of points associated with not existence of the corresponding negative feeling. Besides, Precision, Recall, and F-Measure columns show weighted averages of precision, recall, and F-measure accordingly.

Negative Feeling	Y	N	Precision	Recall	F-Measure	Accuracy	ML Algorithm
Worthlessness	1453	9532	0.84	0.87	0.82	87.04%	RandomForest
Nothing to look forward to	1570	9415	0.82	0.86	0.79	85.74%	RandomSubSpace
Hopelessness	4981	6004	0.55	0.56	0.53	55.48%	ClassificationViaRegression
Sadness	4871	6114	0.54	0.55	0.51	55.41%	ClassificationViaRegression
Feeling of failure	2081	8904	0.81	0.86	0.80	85.51%	RandomForest
Depression	2978	8007	0.68	0.73	0.63	72.99%	RandomSubSpace
Unhappiness	2737	8248	0.71	0.75	0.65	75.09%	RandomSubSpace
Helplessness	2359	8626	0.73	0.79	0.69	78.53%	RandomSubSpace

culate mean values of every consecutive 5 data points and consecutive 10 data points for each of the eight bands in our EEG brainwave. While doing so, we had to exclude a few data when we did not have an expected number (5 or 10) of consecutive data. Thus, we get two datasets consisting of 10985 and 5467 data points considering consecutive 5 and 10 data respectively, where each data point contains mean values of EEG signals for all of the eight bands separately. Over these datasets, we conduct machine-learning based analysis using Weka toolkit [42]. Table 5.7 and 5.8 show the outcomes of classifications over these frames of data. From the results of these tables, we find similar accuracies in predicting the negative feelings compared to that we have already found in our previous machine-learning based analysis considering no framing over data points.

Table 5.8: Performance of the best machine learning algorithms for different negative feelings while predicting existence of negative feelings based on EEG signals mean values (10 points average). Here, Y column shows the number of points associated with existence of the corresponding negative feeling and N column shows the number of points associated with not existence of the corresponding negative feeling. Besides, Precision, Recall, and F-Measure columns show weighted averages of precision, recall, and F-measure accordingly.

Negative Feeling	Y	N	Precision	Recall	F-Measure	Accuracy	ML Algorithm
Worthlessness	723	4744	0.85	0.87	0.83	87.42%	RandomForest
Nothing to look forward to	782	4685	0.82	0.86	0.79	85.73%	RandomSubSpace
Hopelessness	2481	2986	0.54	0.55	0.52	54.86%	ClassificationViaRegression
Sadness	2424	3043	0.54	0.56	0.53	55.61%	ClassificationViaRegression
Feeling of failure	1015	4452	0.81	0.86	0.80	85.51%	RandomForest
Depression	1482	3985	0.69	0.73	0.63	73.09%	RandomSubSpace
Unhappiness	1362	4105	0.74	0.75	0.65	75.18%	RandomSubSpace
Helplessness	1173	4294	0.73	0.79	0.69	78.54%	RandomSubSpace

Head Movement Data Collection and Analysis over the Col-lected Head Movement Data

In addition to EEG brainwave, we also explore head movement data of our participants for the purpose of predicting negative feelings. In doing so, we follow similar processes as already described above for EEG brainwave data. We explain each of the processes pertinent to head movement data in the following subsections.

Head Movement Dataset

During our interview sessions with Rohingya refugees, in parallel to collecting EEG brainwave data, we also collected head movements data (data collected by accelerometer and gyroscope) using eSense BLE (earable device) [172, 92]. The eSense device comes with an invensense MPU 6500 six-axis inertial measurement unit (IMU) including a 3-axis accelerometer and a 3-axis gyroscope [172]. We record the output of the 3-axis accelerometer, which consists of accelerometer-X, accelerometer-Y, and accelerometer-Z. We also record the output of the 3-axis gyroscope, which consists of gyroscope-X, gyroscope-Y, gyroscope-Z. In this regard, we capture 98000 data points and label them with our considered eight different negative feelings as found during our interview session.

Repetition Analysis over the Collected Head Movement Dataset

We have conducted a set of analyses over our collected head movement data points to check how far there exists repetition in the collected data. In this regard, firstly from our 135 participants, we select one random participant's head movement data points for all of the 3-axis accelerometer and 3-axis gyroscope. We were able to capture 1288 points of head movement data from that participant. In Figure 5.12, we plot the values of the 3-axis accelerometer and 3-axis gyroscope of head movement data points and show the variations. Here, values of accelerometer data point are in meter/second^2, and values of gyroscope data point are in degree/second.

Next, for the same participant as already adopted for EEG brainwave data, we calculate averages of the head movement data points for all of the axes of 3-axis accelerometer and 3-axis gyroscope. We also calculate averages of the differences between consecutive head movement data points for all of the axes of 3-axis accelerometer and 3-axis gyroscope. We plot these calculated average values along with corresponding standard deviations as error bars in Figure 5.13 to show whether and how far the values vary in consecutive data points. The figure shows that averages of differences in consecutive data points are comparable to that of actual data points in all of the axes of 3-axis accelerometer and 3-axis gyroscope. This confirms substantial variations in the collected data.

Afterward, we present CDFs of head movement data points for all of the axes of 3-axis accelerometer and 3-axis gyroscope in Figure 5.14 to show how frequently distinct values occur. The figure shows that different ranges of values for head movement data points in all of the axes of 3-axis accelerometer and 3-axis gyroscope exhibit different extents of frequencies.

Additionally, we calculate three different types of distances, namely Euclidean distance, Manhattan distance, and Minkowski distance, between adjacent points of head movement data over all of the axes of 3-axis accelerometer and 3-axis gyroscope. We calculate the distances for three different random participants. We plot the distances in Figure 5.15. The figure shows that consecutive values of head movement data points in all of the axes of 3-axis accelerometer and 3-axis gyroscope exhibit substantial distances. Thus, combining outcomes of Figure 5.12 - 5.15, we can infer that the head movement data exhibit variations in all of the axes of 3-axis accelerometer and 3-axis gyroscope. However, we can observe a potentially higher extent of repetition in the case of head movement data (especially for gyroscope data in all the three axes) compared to that of EEG signal data. Next, we present average values of all of the axes of 3-axis accelerometer and 3-axis gyroscope (with corresponding standard deviations) for all of our participants in Figure 5.16. This figure presents substantial variations in the data collected from all the participants.

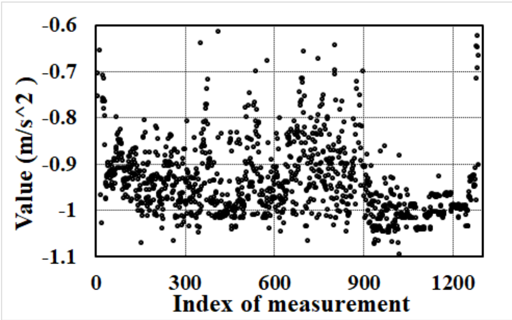
Finally, for further analysis on data repetition, we calculate pairwise cosine similarity [159] over head movement data points. Here, similar to the earlier case of cosine similarity analysis over EEG data points, we take a minimum number of 180 head movement data points for a participant. Note that, for some technical issues during our data collection, we get a total number of 116 participants having a minimum number of 180 head movement data points. As consideration of all pairs over the participants would need calculation over ${}^{116}C_2$ pairs, we perform our pairwise calculations over consecutive 115 pairs of the participants. This directly or indirectly covers the 116 participants in the analysis of cosine similarity. We present the pairwise cosine similarity values found in this way in Figure 5.17. From the figure, we find that pairwise cosine similarity values range over (-0.2, 0.5). These values confirm that the repetition of values over head movement data points is limited.

Statistical Analysis

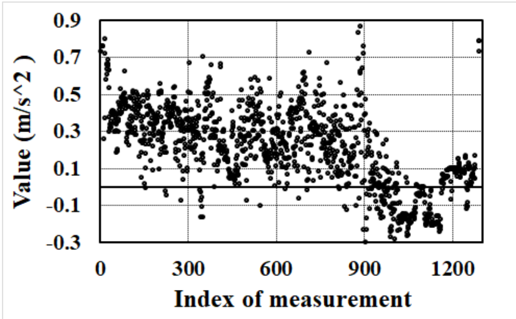
We analyze the collected values of different head movements, which consist of outcomes of the three-axis accelerometer and the three-axis gyroscope. We observe that the values vary significantly among different groups of participants (e.g., participants who answered positively in response to the questionnaires for various negative feelings and those who did not). For this purpose, similar to the previous case with EEG data, we perform F-test and t-test [173] on the head movement data collected from the participants. Here, as we have already mentioned, F-test and t-test both work for different sets of distributions. In our case, as the distribution to which our collected data belong is unknown to us, we explored both types of hypothesis tests.

F-test reveals whether values of accelerometer and gyroscope show similar variance (change) among different groups of people or not. On the other hand, the t-test measures whether the levels of accelerometer and gyroscope activity are similar or different (greater or less) among different groups of people. We present the outcomes of both types of tests in Table 5.9.

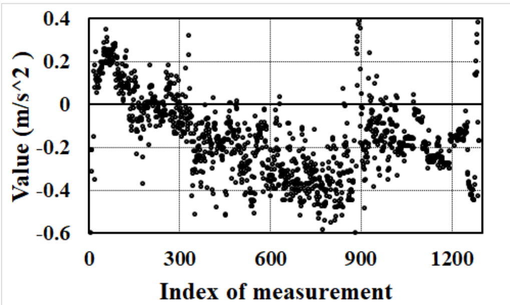
The results from F-test reveal significant variances over data collected by accelerometer and gyroscope among different groups of people. We observe significant variances in all the six axes for people who answered positively for four different negative feelings. These negative feelings are worthlessness, helplessness, hopelessness, and nothing to look forward to. Besides, accelerometer-Y and gyroscope-Z axes show significant variances over all the different groups of people. Table 5.10 provides a summary



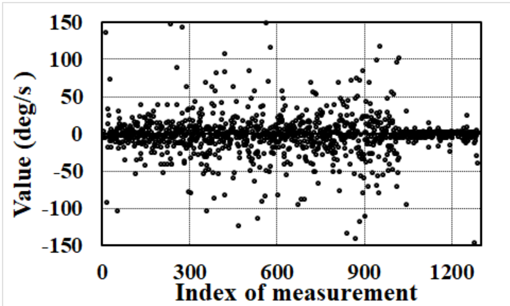
(a) Values of accelerometer along the X axis (shown values within the range between -1.1 m/s^2 to -0.6 m/s^2, as there are only 28 points having values, beyond this range)



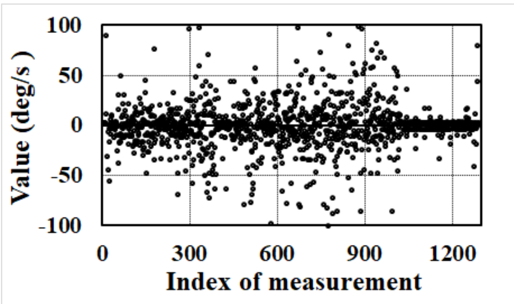
(b) Values of accelerometer along the Y axis (shown values within the range between -0.3 m/s^2 to 0.9 m/s^2, as there are only 19 points having values, beyond this range)



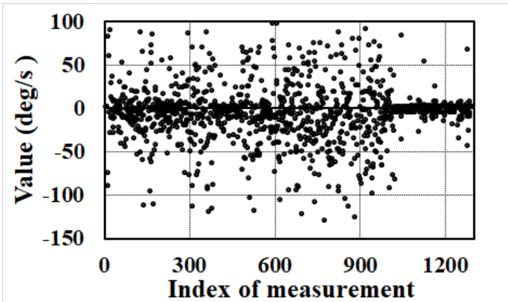
(c) Values of accelerometer along the Z axis (shown values within the range between -0.6 m/s^2 to 0.4 m/s^2, as there are only 18 points having values, beyond this range)



(d) Values of gyroscope along the X axis (shown values within the range between -150 deg/s to 150 deg/s, as there are only 36 points having values, beyond this range)



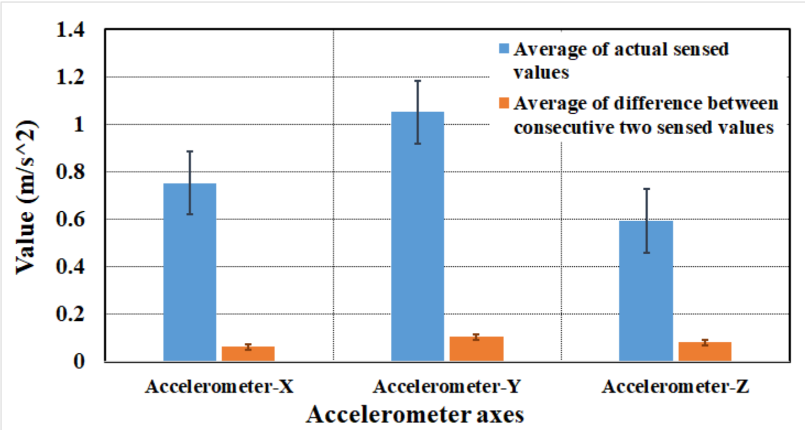
(e) Values of gyroscope along the Y axis (shown values within the range between -100 deg/s to 100 deg/s, as there are only 23 points having values, beyond this range)



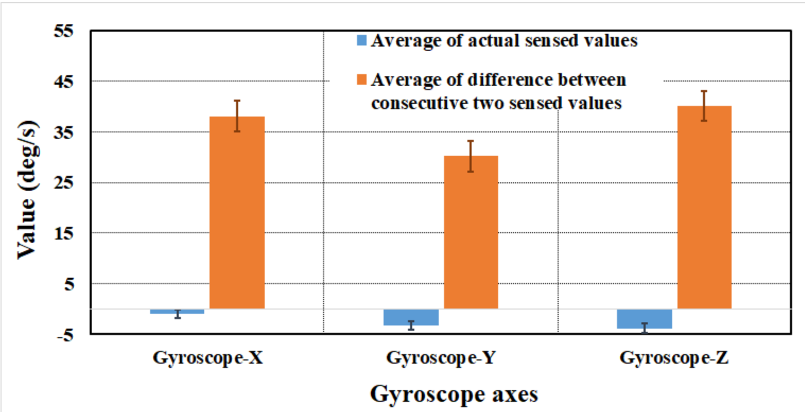
(f) Values of gyroscope along the Z axis (shown values within the range between -150 deg/s to 100 deg/s, as there are only 32 points having values, beyond this range)

Figure 5.12: Values of accelerometer and gyroscope along all of the 3-axis for head movement data of a random participant

of the relative head movements (accelerometer and gyroscope) among different groups of participants. From the table, we can see that most of the relative accelerometer and gyroscope data exhibit significant variances for different groups of people.



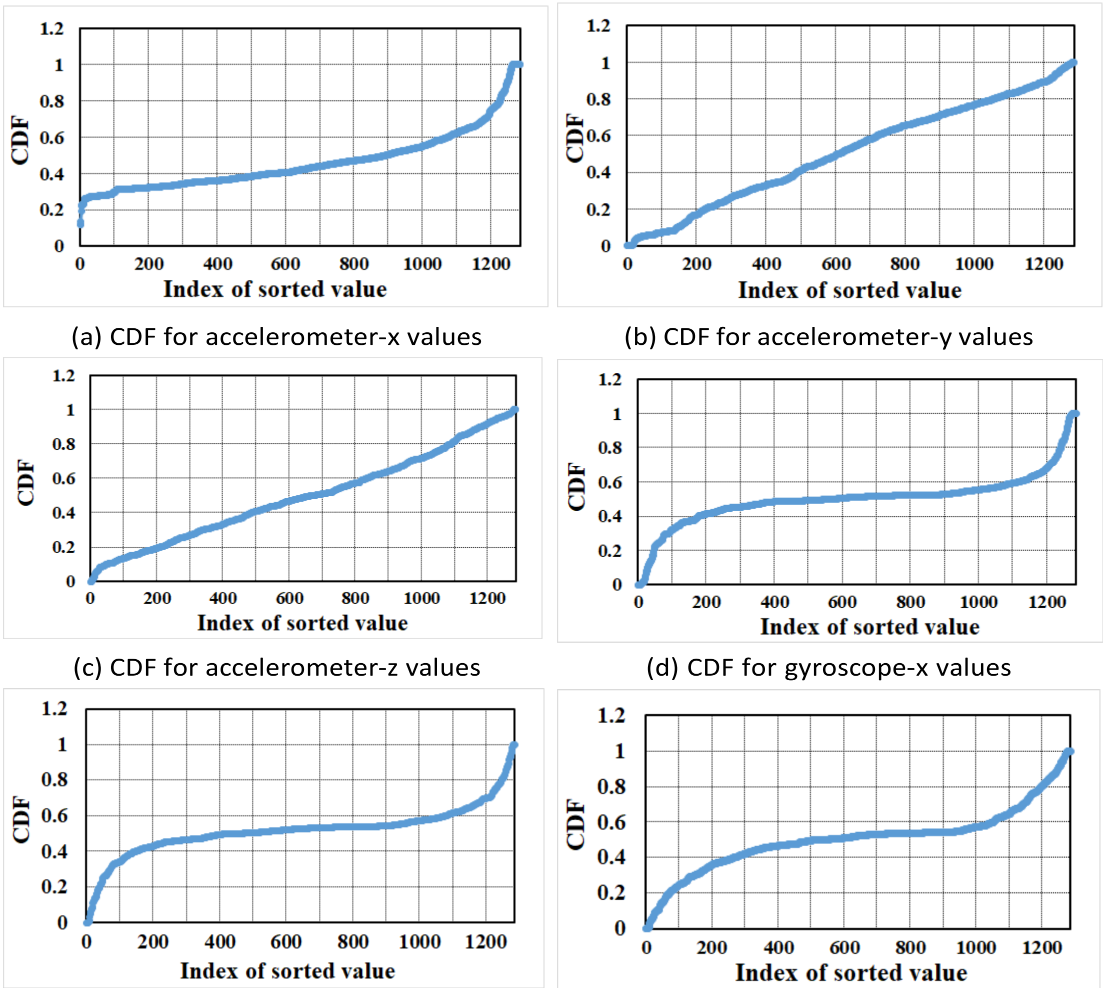
(a) Accelerometer values



(b) Gyroscope values

Figure 5.13: Averages of values and differences between consecutive values for all of the three axes of accelerometer and gyroscope for a random participant (error bars present corresponding standard deviations)

The results from the t-test reveal significant levels over data collected by accelerometer and gyroscope over different groups of people. We observe accelerometer-Y show significant levels over all the different groups of people. Table 5.11 provides a summary of the analysis over relative head movements (accelerometer and gyroscope) for different groups of participants. As mentioned earlier, F-test and t-test both follow different calculations and measurements. For example, F-test adopts standard deviations and the t-test adopts averages as the basis of determining statistical significance. As the bases are different for the two tests, it is natural to find different statistical significance based on the two tests.



(a) CDF for accelerometer-x values

(b) CDF for accelerometer-y values

(c) CDF for accelerometer-z values

(d) CDF for gyroscope-x values

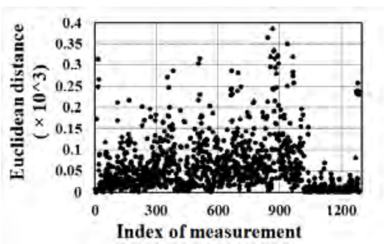
(e) CDF for gyroscope-y values

(f) CDF for gyroscope-z values

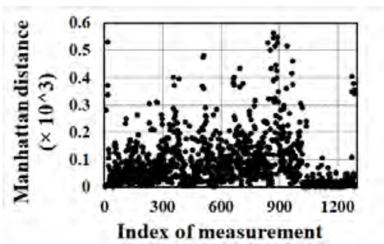
Figure 5.14: CDF for three-axis accelerometer and three-axis gyroscope values of head movement data of a random participant

Machine Learning based Analysis

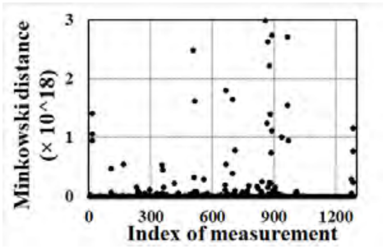
Our dataset contains 98000 head movement data for all the six axes labeled by associated negative feelings. From this dataset, we develop different datasets for each of the negative feelings resulting in eight different datasets. Here, each dataset contains positively responded participants as well as negatively responded participants for the specific negative feeling. Over each of these datasets, we explore a total of 38 different machine learning-based classification algorithms implemented in the WEKA toolkit [42]. Table 5.12 shows outcomes of the exploration based on only the best-found machine learning algorithms. Similar to EEG, here we again perform 10-fold cross-validation and



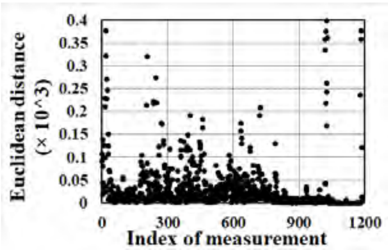
(a) Euclidean distance between adjacent head movement data points for User 1 (shown up to distance = 0.4×10^3, as there are only 11 distances having values higher than it)



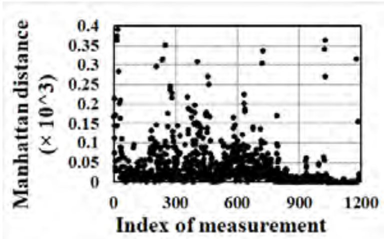
(b) Manhattan distance between adjacent head movement data points for User 1 (shown up to distance = 0.6×10^3, as there are only 19 distances having values higher than it)



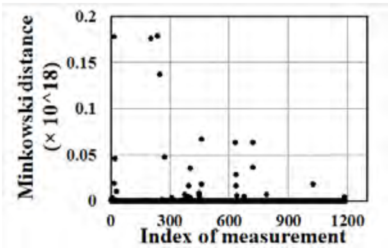
(c) Minkowski distance between adjacent head movement data points for User 1 (shown up to distance = 3×10^{18}, as there are only 23 distances having values higher than it)



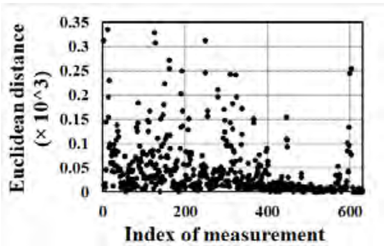
(d) Euclidean distance between adjacent head movement data points for User 2 (shown up to distance = 0.4×10^3, as there are only 15 distances having values higher than it)



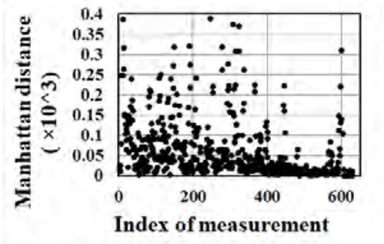
(e) Manhattan distance between adjacent head movement data points for User 2 (shown up to distance = 0.4×10^3, as there are only 24 distances having values higher than it)



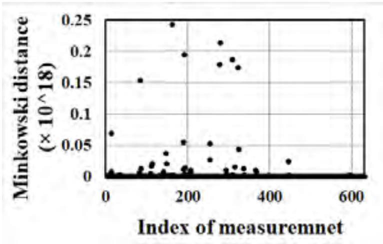
(f) Minkowskidistance between adjacent head movement data points for User 2 (shown up to distance = 0.2×10^{18}, as there are only 26 distances having values higher than it)



(g) Euclidean distance between adjacent head movement data points for User 3 (shown up to distance = 0.35×10^3, as there are only 11 distances having values higher than it)



(h) Manhattan distance between adjacent head movement data points for User 3 (shown up to distance = 0.4×10^3, as there are only 20 distances having values higher than it)

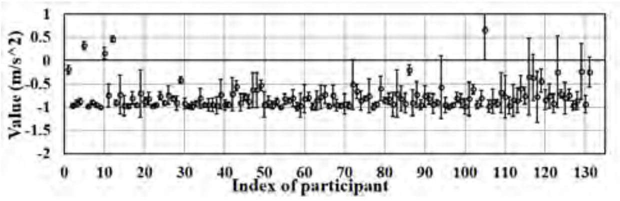


(i) Minkowski distance between adjacent head movement data points for User 3 (shown up to distance = 0.25×10^{18}, as there are only 24 distances having values higher than it)

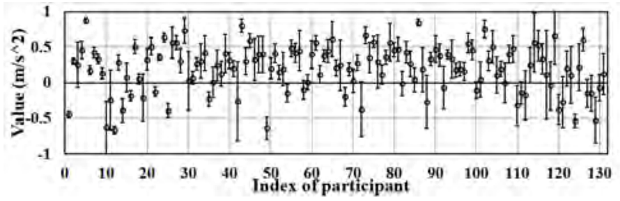
Figure 5.15: Euclidean distance, Manhattan distance, and Minkowski distance between adjacent points of head movement data of three different random participants

show its results in the table. Besides, as mentioned before in the case of EEG, we calculate accuracy as well as weighted averages of precision, recall, and F-measure.

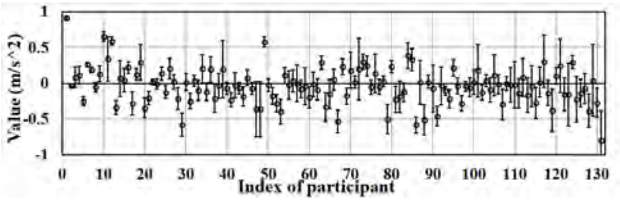
From the table, we can find that we can achieve the highest accuracy of 92.05% in classifying



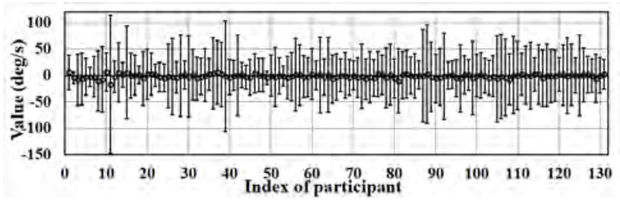
(a) Accelerometer-x values of all participants



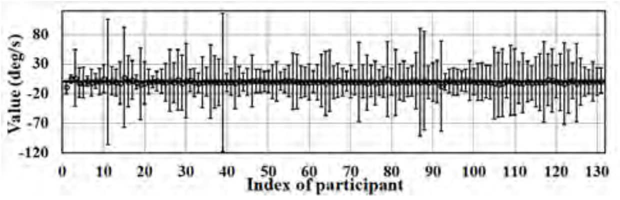
(b) Accelerometer-y values of all participants



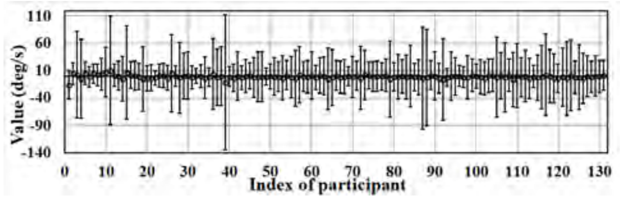
(c) Accelerometer-z values of all participants



(d) Gyroscope-x values of all participants



(e) Gyroscope-y values of all participants



(f) Gyroscope-z values of all participants

Figure 5.16: Average values with standard deviations for all of the 3-axis accelerometer and 3-axis gyroscope values of head movement data collected from all participants

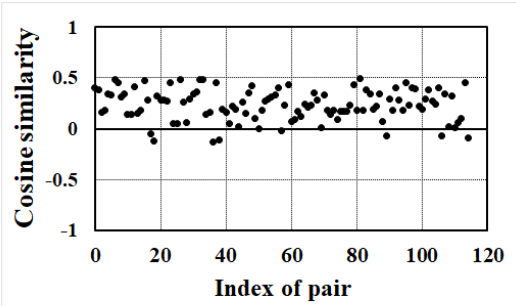


Figure 5.17: Pairwise cosine similarity over the participants for head movement data (Pair i covers Participant i and i+1)

the negative feeling worthlessness. Besides, as found from Table 5.12, Random Forest algorithm [174, 175] achieves the highest accuracies for six of the negative feelings. These negative feelings are worthlessness (92.05%), nothing to look forward to (88.30%), sadness (74.30%), feeling of failure (87.50%), unhappiness (80.06%), and helplessness (86.52%). Besides, the Bagging algorithm [176, 177, 178] also exhibits good accuracy on our considered eight different negative feelings while classifying them based on head movements data (accelerometer and gyroscope). Moreover, the Bagging algorithm

Table 5.9: Results of F-test and t-test on head movement data covering data collected by accelerometer and gyroscope (* indicates $P \leq 0.05$, ** indicates $P \leq 0.01$, and *** indicates $P \leq 0.001$; values mentioned within brackets below represent degree of freedom)

Category	Accelerometer-X	Accelerometer-Y	Accelerometer-Z	Gyroscope-X	Gyroscope-Y	Gyroscope-Z
Worthlessness	F(24262)= 0.43*** t(16871)= -25.96***	F(24262)= 1.2*** t(12144)= -39.53***	F(24262)= 0.63*** t(14435)= 47.13***	F(24262)= 0.88*** t(13058)= 1.89**	F(24262)= 0.64*** t(14341)= -1.33	F(24262)= 0.54*** t(15242)= -2.19**
Depression	F(42910)= 1.43*** t(54590)= 27.22***	F(42910)= 1.03*** t(56864)= 6.64***	F(42910)= 1.50*** t(48541)= -59.48***	F(42910)= 0.99 t(57878)= 2.71**	F(42910)= 1.05 t(56472)= -0.05	F(42910)= 0.92*** t(59635)= -2.53
Feeling of failure	F(30071)= 1.85*** t(24928)= -1.33	F(30071)= 1.60*** t(20432)= -52.97***	F(30071)= 0.98 t(23644)= 33.24***	F(30071)= 0.83*** t(25134)= 3.45***	F(30071)= 0.90*** t(24334)= -0.59	F(30071)= 1.87*** t(24663)= 0.85
Helplessness	F(32537)= 0.45*** t(42480)= -40.66***	F(32537)= 1.04*** t(28530)= -56.58***	F(32537)= 0.61*** t(36145)= -1.334	F(32537)= 0.84*** t(31031)= 3.041**	F(32537)= 0.77*** t(32331)= -0.016	F(32537)= 0.78*** t(32187)= -2.78***
Hopelessness	F(51574)= 1.92*** t(81251)= 5.89***	F(51574)= 1.44*** t(77183)= -25.679***	F(51574)= 1.30*** t(74459)= 4.3894***	F(51574)= 1.91*** t(81077)= 0.0146	F(51574)= 0.77*** t(82857)= 0.83	F(51574)= 0.77*** t(82863)= -1.66
Nothing to look forward to	F(25873)= 0.28*** t(26695)= -58.19***	F(25873)= 0.71*** t(17042)= -3.04***	F(25873)= 0.35*** t(23535)= 19.78***	F(25873)= 0.90*** t(15799)= -0.312	F(25873)= 0.71*** t(17090)= -2.98***	F(25873)= 0.63*** t(17794)= -1.28
Sadness	F(52087)= 1.02 t(80174)= 9.45***	F(52087)= 0.89*** t(81923)= 0.95***	F(52087)= 1.43*** t(73455)= -28.99***	F(52087)= 1.09*** t(79014)= 2.21	F(52087)= 1.16*** t(77840)= 0.059	F(52087)= 1.08*** t(79176)= -1.27
Unhappiness	F(38952)= 1.05*** t(44813)= 9.69***	F(38952)= 0.93*** t(47509)= -13.27***	F(38952)= 1.37*** t(40140)= -48.87***	F(38952)= 0.97 t(46475)= 3.39***	F(38952)= 1.02 t(45421)= 0.004	F(38952)= 1.03*** t(45324)= -0.55

Table 5.10: An overview of relative head movements (accelerometer and gyroscope) data analysis for different groups of people (check mark in a cell indicates that statistically significant variance exists in the axis of that particular accelerometer and gyroscope signals between the participants who positively reported about a particular negative feelings and those who reported negatively about that effect)

Category	Accelerometer-X	Accelerometer-Y	Accelerometer-Z	Gyroscope-X	Gyroscope-Y	Gyroscope-Z
Worthlessness	C	C	C	C	C	C
Depression	C	C	C			C
Feeling of failure	C	C		C	C	C
Helplessness	C	C	C	C	C	C
Hopelessness	C	C	C	C	C	C
Nothing to look forward to	C	C	C	C	C	C
Sadness		C	C	C	C	C
Unhappiness	C	C			C	C

Table 5.11: An overview of relative head movements (accelerometer and gyroscope) data analysis for different groups of people (check mark in a cell indicates that statistically significant level exists in the axis of that particular accelerometer and gyroscope signal between the participants who positively reported about a particular negative feelings and those who reported negatively about that effect)

Category	Accelerometer-X	Accelerometer-Y	Accelerometer-Z	Gyroscope-X	Gyroscope-Y	Gyroscope-Z
Worthlessness	C	C	C	C		C
Depression	C	C	C	C		
Feeling of failure		C	C	C		
Helplessness	C	C		C		C
Hopelessness	C	C	C			
Nothing to look forward to	C	C	C		C	
Sadness	C	C	C			
Unhappiness	C	C	C	C		

Table 5.12: Performance of the best machine learning algorithms for different negative feelings while predicting existence of negative feelings based on head movement data. Here, Y column shows the number of points associated with existence of the corresponding negative feeling and N column shows the number of points associated with not existence of the corresponding negative feeling. Besides, Precision, Recall, and F-Measure columns show weighted averages of precision, recall, and F-measure accordingly.

Negative Feeling	Y	N	Precision	Recall	F-Measure	Accuracy	ML Algorithm
Worthlessness	24263	73737	0.91	0.92	0.91	92.05%	Random Forest
Nothing to look forward to	25874	72126	0.87	0.88	0.86	88.3%	Random Forest
Hopelessness	51575	46425	0.71	0.72	0.71	71.46%	Bagging
Sadness	52088	45912	0.74	0.74	0.74	74.30%	Random Forest
Feeling of failure	30072	67926	0.87	0.88	0.86	87.50%	Random Forest
Depression	42911	55089	0.77	0.78	0.77	77.96%	Bagging
Unhappiness	38953	59047	0.79	0.80	0.79	80.06%	Random Forest
Helplessness	32538	65462	0.86	0.87	0.85	86.52%	RandomForest

provides the highest accuracies for hopelessness (71.46%) and depression (77.96%).

Additionally, for conducting further machine-learning based analysis over frames of data, we calculate mean values of every consecutive 5 data points and 10 data points for each axis of the 3-axis accelerometer and 3-axis gyroscope. Here, we also had to exclude a few data when we did not have an expected number (5 or 10) of consecutive data. Accordingly, we get two datasets consisting of 18655 and 9299 data points, where each data point contains mean values of head movement data for all the axes of accelerometer and gyroscope. Over these datasets, we conduct machine learning-based analysis using Weka toolkit. Tables 5.13 and 5.14 show the outcomes of classifications over these frames of data. From the results of these tables, we find similar accuracies in predicting the negative feelings compared to that we have already found in our previous machine-learning based analysis considering no framing over data points.

Table 5.13: Performance of the best machine learning algorithms for different negative feelings while predicting existence of negative feelings based on mean values of head movement data (5 points average). Here, Y column shows the number of points associated with existence of the corresponding negative feeling and N column shows the number of points associated with not existence of the corresponding negative feeling. Besides, Precision, Recall, and F-Measure columns show weighted averages of precision, recall, and F-measure accordingly.

Negative Feeling	Y	N	Precision	Recall	F-Measure	Accuracy	ML Algorithm
Worthlessness	4000	14655	0.91	0.92	0.90	91.56%	Random Forest
Nothing to look forward to	4450	14205	0.86	0.88	0.85	87.76%	Random Forest
Hopelessness	8896	9759	0.77	0.78	0.76	77.72%	Bagging
Sadness	8910	9745	0.73	0.73	0.73	73.11%	Random Forest
Feeling of failure	5125	13530	0.86	0.87	0.86	86.91%	Random Forest
Depression	7683	10972	0.76	0.76	0.76	76.42%	Bagging
Unhappiness	7596	11059	0.78	0.79	0.78	79.09%	Random Forest
Helplessness	5616	13039	0.85	0.87	0.85	85.99%	Random Forest

Table 5.14: Performance of the best machine learning algorithms for different negative feelings while predicting existence of negative feelings based on mean values of head movement data (10 points average). Here, Y column shows the number of points associated with existence of the corresponding negative feeling and N column shows the number of points associated with not existence of the corresponding negative feeling. Besides, Precision, Recall, and F-Measure columns show weighted averages of precision, recall, and F-measure accordingly.

Negative Feeling	Y	N	Precision	Recall	F-Measure	Accuracy	ML Algorithm
Worthlessness	1978	7321	0.90	0.91	0.89	91.12%	Random Forest
Nothing to look forward to	2557	6742	0.86	0.87	0.86	86.91%	Random Forest
Hopelessness	4688	4611	0.69	0.69	0.68	68.75%	Bagging
Sadness	4557	4742	0.72	0.72	0.72	72.27%	Random Forest
Feeling of failure	2557	6742	0.92	0.86	0.87	86.91%	Random Forest
Depression	3831	5468	0.75	0.76	0.75	76.12%	Bagging
Unhappiness	3439	5860	0.78	0.79	0.77	78.97%	Random Forest
Helplessness	2802	6497	0.85	0.86	0.84	85.49%	Random Forest

Now, up to this point, we have investigated analysis over the EEG and head movement data in isolation. Next, to dig in further, we explore EEG and head movement data in combination, i.e., through blending the both types of data.

Blending of EEG and Head Movement Data

As mentioned before, we have 58000 EEG data points and 98000 head movement data points in our two different datasets. We have eight bands of data in the EEG dataset, and we have 3-axis accelerometer and 3-axis gyroscope data in our head movement dataset. For conducting further analysis, we blend

EEG data points with head movement data points and conduct machine learning-based analysis over this blended dataset.

Blended Dataset: Combination of both EEG and Head Movement Data

In our analysis over blended data, first, we prepare a blended dataset. In doing so, we consider sampling rates of our data collection for EEG and head movement data. In both the cases of data collection, our sampling rate was 1 Hz. Even though the sampling rate matches in both the cases, the time intervals of data collection in the two cases differed during our data collection. This happened as we collected our head movement data throughout the full interview sessions without any break, whereas we collected our EEG data separately during three different activities (interviewing, showing videos, and sketching) having breaks in EEG data collection between two successive activities. We had to keep the breaks in EEG data collection owing to the data collection system process featured by the system we availed. The data collection process featured by the EEG system gave us no explicit timestamp, and therefore, we restarted the data collection during a new activity resulting in breakages in the EEG data collection. The presence of breakages in EEG data collection and absence of any such breakage in head movement data collection resulted in non-synchronized data.

Considering this aspect, we first attempt to prepare a blended dataset having synchronized data points. To do so, we take data points collected only during the first activity, i.e., interviewing. As per our experience, the oral interview sessions lasted longer than five minutes. Accordingly, we filter out data collected during the first five minute (or 300 seconds) to get a blended synchronized dataset. Here, we omit data of those participants who had less data collected due to technical issues. Following this process, we get a total of 18300 data points resulting in a synchronized blended dataset consisting of both EEG and head movement data.

Additionally, as per our on-field experiences, collecting synchronized EEG and head movement data can become difficult owing to different modalities of data collection of the two different devices used for sensing EEG and head movement. Therefore, we also explore how our proposed method will perform in the case of the non-synchronized blended dataset, i.e., a blended dataset consisting of both EEG and head movement data out of synchronization. Accordingly, we prepare two datasets based on non-synchronized EEG and head movement data. To do so, we sort both EEG and head movement data according to their data collection indices. Afterward, we follow two different approaches for preparing two different non-synchronized blended datasets.

In our first approach, we take the minimum number of data points from both of EEG and head movement data, and merge them based on their index of appearance. In this process, some data points from EEG or head movement data get omitted. Besides, after the omissions from EEG or head movement data, we get a total of 37000 data points resulting in a blended dataset consisting of non-synchronized EEG and head movement data.

In our second approach, we consider the fact that we collected more data points for head movement than EEG due to having more time of data collection for head movement compared to EEG. Accordingly, we blend EEG data with head movement data by skipping one index of data from head movement dataset. Following this process, we get a total of 26256 data points resulting in a blended dataset consisting of non-synchronized EEG and head movement data. Now, over these three blended datasets, we conduct machine learning based analysis for classify negative feelings.

Machine Learning based Analysis

We conduct machine learning based analyses over all the blended datasets. Similar to other cases, here we also perform 10-fold cross-validation in our analyses. Here, we apply only the Random Forest algorithm over the datasets, as we have found this algorithm to be the best one in most of our earlier cases. Table 5.15 presents our findings over the blended synchronized dataset. The classification accuracies in the case of blended synchronized data mostly present better performance compared to the earlier cases.

The results reported so far are based on weighted averages for both (Y and N) classes. Now, as the blended synchronized dataset mostly provides better results compared to the previous cases, we also explore precision, recall, and F-measure values for each of the classes (Y and N). Table 5.16 presents outcomes for positively responded (Y) class over the blended synchronized dataset. Besides, Table 5.17 presents outcomes for negatively responded (N) class over the blended synchronized dataset. From both these tables, it becomes evident that we get worse performance in the case of having a lower number of data points. Examples include Y classes for worthlessness, nothing to look forward to, and helplessness. On the other hand, we get better performance in the case of a having higher number of data points. Examples include N classes for all the negative feelings. Besides, we find that we get balanced performance when we have a nearly equal number of data points for both the Y and N classes of the same negative feeling. Outcomes for sadness demonstrate this finding.

Additionally, Table 5.18 presents accuracies achieved over the first blended non-synchronized

Table 5.15: Performance of Random Forest algorithm in classifying different negative feelings based on blended (having both EEG and head movement) synchronized dataset. Here, Y column shows the number of points associated with existence of the corresponding negative feeling and N column shows the number of points associated with not existence of the corresponding negative feeling. Besides, Precision, Recall, and F-Measure columns show weighted averages of precision, recall, and F-measure accordingly.

Negative Feeling	Y	N	Precision	Recall	F-Measure	Accuracy
Worthlessness	1500	16800	0.96	0.96	0.95	95.60%
Nothing to look forward to	2700	15600	0.88	0.88	0.85	88.28%
Hopelessness	8100	10200	0.78	0.78	0.78	78%
Sadness	8400	9900	0.81	0.81	0.80	80.52%
Feeling of failure	2700	15600	0.94	0.94	0.93	93.71%
Depression	5100	13200	0.86	0.87	0.86	86.45%
Unhappiness	4500	13800	0.86	0.86	0.84	85.63%
Helplessness	3000	15300	0.89	0.89	0.87	88.87%

Table 5.16: Performance of Random Forest algorithm in classifying different negative feelings based on blended (having both EEG and head movement) synchronized dataset. Here, Y column shows the number of points associated with existence of the corresponding negative feeling and N column shows the number of points associated with not existence of the corresponding negative feeling. Besides, Precision, Recall, and F-Measure columns show precision, recall, and F-measure of Y class accordingly.

Negative Feeling	Y	N	Precision	Recall	F-Measure	Accuracy
Worthlessness	1500	16800	0.93	0.50	0.65	95.60%
Nothing to look forward to	2700	15600	0.86	0.25	0.38	88.28%
Hopelessness	8100	10200	0.80	0.66	0.73	78%
Sadness	8400	9900	0.81	0.75	0.78	80.52%
Feeling of failure	2700	15600	0.89	0.65	0.75	93.71%
Depression	5100	13200	0.85	0.62	0.72	86.45%
Unhappiness	4500	13800	0.86	0.50	0.63	85.63%
Helplessness	3000	15300	0.91	0.35	0.51	88.87%

dataset consisting the minimum number of available EEG and head movement data points. This table shows that the accuracies achieved in this case are bit lower than the accuracies found over the synchronized dataset.

Finally, Table 5.19 presents accuracies achieved over the second blended non-synchronized dataset consisting of EEG and head movement data, where we skip one index of data from head movement dataset. Similar to the last case, this table again shows that the accuracies achieved with this non-synchronized are bit lower than the accuracies found over the synchronized dataset. From these results, we can conclude that the loss of synchronization could result in marginal degradation in the

Table 5.17: Performance of Random Forest algorithm in classifying different negative feelings based on blended (having both EEG and head movement) synchronized dataset. Here, Y column shows the number of points associated with existence of the corresponding negative feeling and N column shows the number of points associated with not existence of the corresponding negative feeling. Besides, Precision, Recall, and F-Measure columns show precision, recall, and F-measure of N class accordingly.

Negative Feeling	Y	N	Precision	Recall	F-Measure	Accuracy
Worthlessness	1500	16800	0.96	0.99	0.98	95.60%
Nothing to look forward to	2700	15600	0.88	0.99	0.93	88.28%
Hopelessness	8100	10200	0.77	0.87	0.82	78%
Sadness	8400	9900	0.80	0.85	0.83	80.52%
Feeling of failure	2700	15600	0.94	0.99	0.96	93.71%
Depression	5100	13200	0.87	0.96	0.91	86.45%
Unhappiness	4500	13800	0.86	0.97	0.91	85.63%
Helplessness	3000	15300	0.89	0.99	0.94	88.87%

Table 5.18: Performance of Random Forest algorithm in classifying different negative feelings based on blended (having both EEG and head movement) non-synchronized dataset consisting minimum number of EEG and head movement data points. Here, Y column shows the number of points associated with existence of the corresponding negative feeling and N column shows the number of points associated with not existence of the corresponding negative feeling. Besides, Precision, Recall, and F-Measure columns show weighted averages of precision, recall, and F-measure accordingly.

Negative Feeling	Y	N	Precision	Recall	F-Measure	Accuracy
Worthlessness	8800	28200	0.91	0.92	0.91	92.6%
Nothing to look forward to	6186	30814	0.85	0.85	0.83	85.56%
Hopelessness	16697	20303	0.73	0.75	0.72	74.61%
Sadness	16668	20332	0.74	0.75	0.73	75.20%
Feeling of failure	6789	30211	0.90	0.90	0.90	90.64%
Depression	11362	25638	0.81	0.80	0.80	81.39%
Unhappiness	11021	25979	0.79	0.79	0.78	79.71%
Helplessness	7470	29530	0.86	0.87	0.85	86.65%

accuracy of classifying the negative feelings.

5.8 Achieving the Best Performances

We find different performances in performing the task of classification based on EEG data, head movement data, and blended data comprising both EEG and head movement data for our considered eight different negative feelings. Comparing all these performance in classifying the different negative feelings, we distinguish the best performing classifiers and corresponding bases of classification, i.e., whether the basis for the best case is EEG data, head movement data, or blended data comprising

Table 5.19: Performance of Random Forest algorithm in classifying different negative feelings based on blended (having both EEG and head movement) non-synchronized dataset achieved through skipping adjacent index from head movement data points. Here, Y column shows the number of points associated with existence of the corresponding negative feeling and N column shows the number of points associated with not existence of the corresponding negative feeling. Besides, Precision, Recall, and F-Measure columns show weighted averages of precision, recall, and F-measure accordingly.

Negative Feeling	Y	N	Precision	Recall	F-Measure	Accuracy
Worthlessness	4079	22176	0.91	0.90	0.87	90.2%
Nothing to look forward to	4724	21531	0.85	0.85	0.81	85.03%
Hopelessness	11826	14429	0.76	0.75	0.75	75.1%
Sadness	12318	13937	0.73	0.73	0.73	72.96%
Feeling of failure	5946	20309	0.87	0.87	0.86	86.88%
Depression	8053	18202	0.79	0.80	0.79	80.1%
Unhappiness	9015	17240	0.76	0.76	0.74	76.18%
Helplessness	5507	20748	0.86	0.86	0.83	85.5%

both EEG and head movement data.

Table 5.20 shows the outcomes of the comparison from the perspective of accuracy. Here, we can find the highest accuracies based on the blended synchronized data for seven of our negative feelings, which are worthlessness (95.60%), hopelessness (78%), sadness (80.52%), feeling of failure (93.71%), depression (86.45%), unhappiness (85.63%), and helplessness (88.87%). Besides, we find the highest accuracy based on head movement data for the rest one of our considered negative feelings, which is nothing to look forward to (88.3%). Nonetheless, even in this case, the accuracy obtained through blended synchronized data (88.28%) is very close to the best accuracy achieved using head movement data. Additionally, in all the cases, Random Forest appears to be the best performing machine learning algorithm.

In addition to identifying the best performing classifiers with corresponding bases (or datasets) from the perspective of accuracy, we also identify the same from the perspective of F-Measure. In this case, we find the same best-performing classifiers and bases compared to what we have already identified from the perspective of accuracy. As such, we find the highest F-Measure based on the blended synchronized data for seven of our negative feelings, which are worthlessness (0.95), hopelessness (0.78), sadness (0.80), feeling of failure (0.93), depression (0.86), unhappiness (0.86), and helplessness (0.87). We find the highest F-Measure based on head movement data for the rest one of our negative feelings, which is nothing to look forward to (0.86). Similar to the earlier case, for this feeling of nothing to look forward to, the blended synchronized data provides a very close F-Measure

Table 5.20: Best performances of machine learning classifiers based on different datasets for predicting existence of different negative feelings

Negative Feeling	F-Measure	Accuracy	Dataset	Machine Learning Algorithm
Worthlessness	0.95	95.60%	EEG and Head Movement data	Random Forest
Nothing to look forward to	0.86	88.3%	Head Movement data	Random Forest
Hopelessness	0.78	78%	EEG and Head Movement data	Random Forest
Sadness	0.80	80.52%	EEG and Head Movement data	Random Forest
Feeling of failure	0.93	93.71%	EEG and Head Movement data	Random Forest
Depression	0.86	86.45%	EEG and Head Movement data	Random Forest
Unhappiness	0.86	85.63%	EEG and Head Movement data	Random Forest
Helplessness	0.87	88.87%	EEG and Head Movement data	Random Forest

(0.85) compared to the F-Measure achieved using head movement data.

It is worth mentioning that existing research studies tried to classify emotions and mental states with different levels of accuracy. For example, using two autonomic nervous signals such as SKT and PPG in combination, classifying sadness and happiness achieved an accuracy of 92.41% [179]. Besides, classifying depression levels achieved an accuracy of 77% [180]. Nonetheless, classifying mental illness achieved an accuracy of 77% [181]. Thus, the results achieved in our study are comparable to those already reported in the literature.

Chapter 6

Discussion

This study examines different associations over eight different negative feelings, particularly focusing on the context of Rohingya refugees. In our study, we interviewed 135 Rohingya refugees who lived in Kutupalong [131], the largest refugee camp in Bangladesh. Our interview sessions occurred in the camp office with official permission from the authority. We conducted our interview sessions with Rohingya refugees in a warm and friendly manner through which we can get actual information from them. Our participants cover diversified demography. Using our dataset collected from these participants, we conduct several analyses and reveal different associations between our considered eight different negative feelings. Here, we conduct statistical and machine learning-based analyses on EEG brainwave signals, head movement data, and blended data comprising both EEG signals and head movement data collected from Rohingya refugees to find significant changes in variances and levels pertinent to different groups of Rohingya refugees.

Association Models

This study investigates diversified associations between different negative feelings based on our collected data. We investigate various association models such as correlation network, partial correlation network, and regulatory network. In the correlation network, we find the strongest association between depression and sadness. Other strong associations exist between helplessness and worthlessness, unhappiness and sadness, unhappiness and depression, depression and sadness, depression and hopelessness, and worthlessness and feeling of failure. Here, to control the false discovery rate, we use Benjamini-Hochberg correction [3, 4] in our analysis.

Next, we generate another correlation network based on Bonferroni corrected statistics and display the significant edges between entities. In this network, we find strong connections between helplessness and worthlessness, unhappiness and depression, unhappiness and sadness, depression and sadness, depression and hopelessness, and worthlessness and feeling of failure, which exhibits commonalities with the findings observed from the previous correlation network.

The correlation network fails to capture the direction of association between two negative feelings. Moreover, in a correlation network, some associations may arise between two components even if there is no direct interaction between them. Therefore, getting only direct associations, we generate the partial correlation network, where edges reflect only direct associations between entities. A partial correlation network is less dense, i.e., contains fewer edges than the correlation network, as edges only reflect direct associations. From the partial correlation network, we find similar outcomes as found from the correlation network. In our partial correlation network, depression is strongly correlated with sadness and moderately associated with nothing to look forward to. If we compare this structure to that of the correlation network, we find that the correlations that appear between depression and the other two negative feelings, i.e., unhappiness and hopelessness in the correlation network, are most likely caused by indirect associations. To further measure the importance of negative feelings in the partial correlation network, we use centrality measurements such as strength and betweenness of the negative feelings. Sadness, unhappiness, and hopelessness emerge as highly central negative feelings in these measurements. Among them, sadness has the highest strength score. Therefore, sadness appears to be more influential than other negative feelings. Besides, sadness is the only negative feeling that is strongly correlated with depression and two other different negative feelings. It also has the highest betweenness score, i.e., it is most likely to mediate the interactions among other negative feelings. For example, it connects different negative feelings such as unhappiness, hopelessness, depression, etc.

The correlation network and partial correlation network both fail to provide any account of the directions of associations among our considered negative feelings. To overcome this, we generate a regulatory network using a directed acrylic graph to check the directions of the associations among our considered eight different negative feelings. Here, we find that the negative feelings that appear to be significant constituents of depression are sadness and feeling of nothing to look forward to. Besides, among the negative feelings, we find hopelessness (and substance betel leaf) to be directly reflected by depression. Additionally, worthlessness functions as a constituent of helplessness, feeling of failure and smoking. In addition, this network directly predicts that unhappiness, substance betel leaf, and smoking are likely to be caused by interactions among others negative feelings such as sadness and feeling of failure. Furthermore, worthlessness has a direct association with smoking, feeling of nothing to look forward to, feeling of failure, and helplessness. Additionally, helplessness is directly associated with sadness. When we measure the centrality of each negative feeling in this network, depression emerges as the strongest interacting component within the network and then comes hopelessness and sadness.

Note that, in our study, we develop three different association models through three different networks for three different purposes. First, we develop the correlation network from the interview data regarding eight different negative feelings along with intake of substance betel leaf and smoking. We do so, as the correlation network presents direct and indirect associations between different entities in the network. Thus, from such a network, we can find many different (direct and indirect) associations that can provide valuable comprehensive information about associations between the different negative feelings. Next, for getting only direct associations between the entities, we develop the partial correlation network. Thus, from such a network, we find only filtered-out associations among the negative feelings that can provide information about direct associations leaving the indirect ones. However, note that both these networks are unable to give any direction of the associations. To dig out the directions of associations, we develop the regulatory network. From the regulatory network, we get information about influential negative feelings that work behind the formation of other negative feelings. Now, as all these three different networks present different kinds of information about associations over the negative feelings, we have developed all these networks in a chronological manner.

It is worth mentioning that all the correlations between several negative feelings, as revealed through our study, have several different applications. One of the most prominent applications in this regard is to utilize the outcomes in psychological therapies, which usually adopt similar findings over emotions [182, 183]. This is of particular importance in the case of special groups of people such as the population with autism [184, 185, 186]. Nonetheless, our findings can also be utilized in the emerging applications of robotics [187, 188]. In such types of populations, exploring negative feelings could be valuable to detect their mental health conditions and to prevent them from major damages that might cause due to different physiological disorders.

Analysis over EEG Brainwave Signals

In our study, in terms of neurological aspects, we collect EEG brainwave signal data during the interview sessions and conduct statistical and machine learning-based analyses for classifying our considered eight different negative feelings. Our data set contains 58000 EEG signal data points labeled by associated negative feelings. Over this dataset, we conduct a set of analyses to check how far there exists repetition in the collected data. In this regard, firstly from our 135 participants, we select one random participant's EEG signal data points for eight bands. We were able to capture 930 points of EEG signal data from that participant. We plot the values of eight bands of EEG signal data and show the variations in the data points in all of the eight bands. Next, for the same participant, we calculate averages of the EEG signal data points for all of the eight bands. We also calculate averages of the differences between consecutive EEG signal data points for all of the eight bands. We plot these calculated average values along with corresponding standard deviations as error bars in the figure to show whether and how far the values repeat in consecutive data points. The figure shows that averages of differences in consecutive data points are comparable to that of actual data points in all of the eight bands.

Afterward, we present CDFs of EEG signal data points for all of the eight bands to show how frequently distinct values occur. Finally, we calculate three different types of distances, namely Euclidean distance, Manhattan distance, and Minkowaski distance, between adjacent points of EEG signal data over all of the eight bands. We calculate the distances for three different random participants and find that consecutive values of EEG signal data points in all of the eight bands exhibit substantial distances. Thus, we can infer that the extent of repetition in the case of EEG signal data should be minimal. Next, we present average values of all eight bands (with corresponding standard deviations) for all of our participants and find substantial variations over the data collected from all the participants. Finally, we calculate pairwise cosine similarity of EEG data points for our 135 participants and find that pairwise cosine similarity values range over (0.2, 0.6). These values confirm that the repetition of values over EEG data points is limited.

Additionally, we perform F-test and t-test over the EEG data points dataset. F-test reveals significant variances in different EEG power bands among the different groups of people under consideration. We observe the significant variance in all eight bands of EEG signal for people pertinent to three different negative feelings namely worthlessness, sadness, and unhappiness. Besides, low alpha, high alpha, low beta, high beta, and mid gamma bands exhibit significant variance for all the groups of people pertinent to all our considered negative feelings. On the other hand, the t-test reveals significant levels in different EEG power bands over different groups of people. We find significant levels in all eight bands for people who answered positively for three different negative feelings, namely depression, nothing to look forward to, and unhappiness. Besides, low alpha, high alpha, and mid gamma bands show significant levels for all people who answered positively for all our considered negative feelings.

Next, in the machine learning-based analyses, we use a total of 45 different classification algorithms. Here, we find that Random Sub Space [166] algorithm provides the highest accuracies of classification for nothing to look forward to (85.72%), depression (72.9%), unhappiness (75.07%), and helplessness (78.8%). Random Forest [167, 168] algorithm provides the highest accuracies in classifying worthlessness (86.80%) and feeling of failure (85.04%). Besides, classification via Regression algorithm provides the highest accuracies for sadness (56.42%) and hopelessness (55.8%).

Additionally, for conducting further machine-learning based analysis over frames of data, we calculate mean values of every consecutive 5 data points and consecutive 10 data points for each of the eight bands in our EEG brainwave. Thus, we get two datasets consisting of 10985 and 5467 data points, where each data point contains EEG signals mean values for all of the eight bands. Over these datasets, we conduct machine learning-based analysis using the Weka toolkit [42]. From the results, we find similar accuracies in predicting the negative feelings compared to that we have already found in our previous machine learning-based analysis considering no framing over data points.

Analysis over Head Movement Data

For associating general human activity as a non-verbal biomarker, we also collected head movement data using a 3-axis accelerometer and 3-axis gyroscope during interview sessions. We conduct statistical and machine learning-based analyses over the collected data set for associating them with our considered eight different negative feelings. Our data set contains 98000 head movement data labeled by associated negative feelings. Over this dataset, we conduct a set of analyses to check how far there exists repetition in the collected data. In this regard, firstly from our 135 participants, we select one random participant's head movement data points for all of the 3-axis accelerometer and 3-axis gyroscope. We were able to capture 1288 points of head movement data points from that participant.

We plot the values of the 3-axis accelerometer and 3-axis gyroscope of head movement data points and show the variations.

Next, for the same participant, we calculate averages of the head movement data points for all of the 3-axis accelerometer and 3-axis gyroscope. We also calculate averages of the differences between consecutive head movement data points for all of the 3-axis accelerometer and 3-axis gyroscope. We plot these calculated average values along with corresponding standard deviations as error bars to show whether and how far the values repeat in consecutive data points and find that, averages of differences in consecutive data points are comparable to that of actual data points in all of the 3-axis accelerometer and 3-axis gyroscope.

Afterward, we present CDFs of head movement data points for all of the 3-axis accelerometer and 3-axis gyroscope to show how frequently distinct values occur and find that different ranges of values for head movement data points in all of the 3-axis accelerometer and 3-axis gyroscope exhibit different extents of frequencies. Additionally, we calculate three different types of distances, namely Euclidean distance, Manhattan distance, and Minkowaski distance, between adjacent points of head movement data points over all of the 3-axis accelerometer and 3-axis gyroscope. We calculate the distances for three different random participants and find that consecutive values of head movement data points in all of the 3-axis accelerometer and 3-axis gyroscope exhibit substantial distances. Thus, combining outcomes of all these experiments, we can infer a potentially higher extent of repetition in the case of head movement data (specially for gyroscope data in all the three axes) compared to that of EEG signal data. Next, we present average values of all of the axes of the 3-axis accelerometer and 3-axis gyroscope (with corresponding standard deviations) for all of our participants and find substantial variations over the data collected from all the participants. Finally, we calculate pairwise cosine similarity of head movement data points for our 116 participants and find that pairwise cosine similarity values cover in a range between -0.2 to 0.5, which specifies the extent of repetition in the case of head movement data points is limited.

In our statistical analyses over the data set, we perform F-test and t-test [173] on the values of head movement data. Here, F-test reveals similarity over the variance of values collected by accelerometer and gyroscope pertinent to the different groups of people. On the other hand, the t-test measures similarity over the levels of values called by accelerometer and gyroscope pertinent to different groups of people. We find significant variances in all six axes of head movement data for four different negative feelings, namely worthlessness, helplessness, hopelessness, and nothing to look forward to. Besides, accelerometer-Y and gyroscope-Z show significant variances for all the groups of people who answer positively for all of our considered negative feelings. Additionally, we also observe accelerometer-Y show significant levels over all the different groups of people.

In our machine learning-based analysis, we use a total of 38 different classification algorithms. Here, we find that, the Random Forest algorithm [174, 175] exhibits the highest accuracies for six different negative feelings. These are worthlessness (92.05%), nothing to look forward to (88.30%), sadness (74.30%), feeling failure (87.50%), unhappiness (80.06%), and helplessness (86.52%). It is evident from these results that the head movement data exhibit better classification accuracies for all the negative feelings compared to that of the EEG brainwave signal.

Additionally, for conducting further machine learning-based analysis over frames of data, we calculate mean values of every consecutive 5 data points and 10 data points for each axis of the 3-axis accelerometer and 3-axis gyroscope. Accordingly, we get two datasets consisting of 18655 and 9299 data points, where each data point contains mean values of head movement data for all the axes of the accelerometer and gyroscope. Over these datasets, we conduct machine learning-based analysis using the Weka toolkit. From the results, we find similar accuracies in predicting the negative feelings compared to that we have already found in our previous machine learning-based analysis considering no framing over data points.

Analysis over Blending of EEG Signals and Head Movement Data

After analyzing the EEG signals and head movement data in isolation, we combine EEG brainwave signal data points and head movement data points of our interviewees and conduct machine learning-based analysis over these datasets. Here, we prepare three different datasets - one with synchronized data points and another two with non-synchronized data points.

We find that the blended synchronized dataset provides improved accuracies in most of the cases. Besides, the non-synchronized datasets provide accuracies close (however, marginally degraded) to that found with the synchronized dataset. Accordingly, we can conclude that we can focus on blended data even if synchronization is not confirmed.

Best Performances from All Different Analyses

We find different performances in performing the task of classification based on EEG data, head movement data, and blended data comprising both EEG and head movement data for our considered eight different negative feelings. Comparing all these performances in classifying the different negative feelings, we distinguish the best performing classifiers and corresponding bases of classification, i.e., whether the basis for the best case is EEG data, head movement data, or blended data comprising both EEG and head movement data.

Outcomes of the comparison from the perspective of accuracy, we can find that the highest accuracies based on the blended synchronized data for seven of our negative feelings. We find the highest accuracy based on head movement data for only one of our considered negative feelings, which is nothing to look forward to. However, even in this case, the blended synchronized data provides an accuracy that is very close to the best case. In all the cases, Random Forest appears to be the best performing machine learning algorithm.

In addition to identifying the best performing classifiers with corresponding bases (or datasets) from the perspective of accuracy, we also identify the same from the perspective of F-Measure. In this case, we find the same best-performing classifiers and bases compared to what we have already identified from the perspective of accuracy.

Therefore, we can say that, from machine learning-based analyses, we can achieve good classification accuracies and F-Measure for classifying our eight different negative feelings. This presents the possibility of using EEG brainwave signal and head movement data as non-verbal biomarkers in isolation as well as in combination.

Chapter 7

Avenues for Future Work

Now, from the outcomes of our study, we report some scopes of future work. For example, better representation of the association hierarchy of our considered eight different negative feelings directed association model development is necessary and we use directed acyclic graph (DAG) for this purpose. As DAG is an acyclic graph, it does not allow any cycle. However, negative feelings might affect other negative feelings, which in turn could affect others. Thus, the feedback might often loop back to the first negative feeling. Because of the limitation of DAG, we cannot be able to get such cyclic relationships among our considered eight negative feelings. Therefore, exploring cyclic graphical models could be a future work of our study.

Additionally, in the future, it will be valuable to use Association Rule Mining (ARM) and other advanced data mining approaches for further analyzing associations among the negative feelings. Other than that, as we have already described about difficulties in wearing necessary devices during our interview sessions, it will be valuable to explore conducting interviews with and without devices to compare their performances.

Besides, for collecting head movement data, we use one eSense earbud due to cover more participants' data collection with limited devices. We had only three eSense earbud devices. Each earbud can support only a couple of interviews. After that, it need time to get recharged and for avoiding this time suspension, we only used one earbud for collecting data of head movement from participants whereas other devices got charged. However, leveraging two different streams (one earbud per ear) could be more precise than one stream data. Therefore, in the future, we plan to collect data using two earbuds (one earbud per ear) for an interviewee for tracking head movement data more precisely and conduct analysis on the more precise head movement data.

Other than that, in our study, we use a consumer-grade, single-electrode, and portable EEG headset. Though Neurosky Mindwave devices are inexpensive and easier to use, the quality of their produced data is not as accurate as that of the devices with large numbers of electrodes. Therefore, in the future, it will be valuable to collect EEG brainwave signal data using devices having large numbers of electrodes and do the analysis accordingly. Nonetheless, collecting synchronized data consisting of both EEG and head movement presents yet another aspect of future research.

Besides, from EEG and head movement data, there exists a good scope to measure the attention level of interviewees, which may lead to a new direction in our study context. Therefore, in the future, it will be worthy to explore the attention level of the interviewees.

Additionally, our datasets of EEG brainwave signal data and head movement data contain fewer numbers of data labeled by positively responded for particular negative feelings compared with data labeled by negatively responded for particular negative feelings. Among our considered eight different negative feelings, worthlessness, feeling of nothing to look forward to, and feeling of failure shows maximum imbalance data. Therefore, in our future work, we would like to add analysis to balance all these datasets in terms of numbers of the positively responded dataset and negatively responded dataset for particular negative feelings and conduct machine learning-based analysis over them.

Besides, we also get lower classification accuracies for a few of the negative feelings compared to other negative feelings. Examples in this regard cover hopelessness (78%) and sadness (80.52%). Therefore, in future, we would like to explore more on why we have got the lower accuracies and how we can enhance them. Other than that, according to Plutchik's Wheel of Emotions [189], there exist eight different fundamental emotions that build the foundation for all other emotions. Analyzing commonality and differences between the emotion wheel and our revealed correlations over negative feelings present a potential future work of this study.

On the other hand, our study focuses on marginalized communities, from which we choose the Rohingya refugee population and explore their negative feelings. There also exist other marginalized communities such as slum dwellers, street children, beggars, etc. Therefore, our study could also be valuable to explore these communities in the future.

Besides, due to resource limitations, we were unable to onboard a psychiatrist during our interview sessions. However, during our study and analysis, we onboarded a local psychiatrist. Therefore, in future, we would like to onboard a local psychiatrist during our interview sessions to ensure more robust data collection. Finally, for all the findings in our study, we based on a questionnaire on negation feelings that maintains similarities with LEVEL 2—Depression—Adult (PROMIS Emotional Distress—Depression—Short Form) [133]. In the future, we can choose a more elaborated and recent standard to get more comprehensive information from the interviewees.

Chapter 8

Conclusion

Computationally analyzing associations among different negative feelings and revealing relevant neurobiological biomarkers are yet to be explored in the literature to the best of our knowledge. Therefore, in this study, we explore associations among eight different important negative feelings along with investigating EEG signals and head movement data as potential non-verbal biomarkers for the negative feelings. Here, we particularly focus on the case of Rohingya refugees in Bangladesh.

We collect interviews from the Rohingya refugees on their negative feelings based on a set of questionnaires. We also collect their EEG signals and head movement data while participating in our interview session. Later, we analyze associations and other aspects of the negative feelings based on the collected interview data. We also investigate classification of the negative feelings based on the collected EEG signals. Further, we explore head movement data (collected using a 3-axis accelerometer and 3-axis gyroscope) for the same purpose of classifying the negative feelings.

We perform in-depth analysis over eight different negative feelings based on our collected data using graph theoretic approaches as well as statistical methods. We correlate the different negative feelings based on the analysis. We also perform machine learning-based analysis to classify the negative feelings based on EEG signals and head movement data to enable going beyond the interview-only diagnosis approach. Our analysis confirms that we can classify most of the negative feelings with significant accuracy. The outcomes of our study can help in diversified real cases covering diagnosis of psychological disorders, identifying potential cases of intention to criminal activities, and so on, as they all get influenced by the negative feelings.

Chapter 9

Performance of different Machine Learning Algorithms in Classifying Negative Feelings

Table 9.1: Classification precision of machine learning based algorithms while using EEG brainwave signals

Algorithm	wts	ntf	hps	sad	flr	dps	uhp	hls
SGD	0	0	0.586	0.31	0	0	0	0
SMO	0	0	0.596	0.31	0	0	0	0
J48	0.811	0.804	0.55	0.539	0.803	0.652	0.7	0.632
IBk	0.78	0.767	0.521	0.497	0.757	0.607	0.644	0.669
JRip	0.809	0.803	0.549	0.537	0.8	0.646	0.669	0.711
OneR	0.785	0.774	0.512	0.502	0.754	0.607	0.631	0.663
PART	0.833	0.791	0.549	0.539	0.8	0.637	0.698	0.616
ZeroR	0	0	0	0.31	0	0	0	0
SGD Text	0	0	0	0.31	0	0	0	0
REP Tree	0.799	0.788	0.529	0.525	0.783	0.632	0.648	0.689
LogitBoos	0	0	0.557	0.31	0	0	0	0.724
Stacking	0	0	0	0.31	0	0	0	0
Vote	0	0	0	0.31	0	0	0	0
Hoeffding Tree	0.787	0.748	0.539	0.528	0.753	0.606	0.621	0.662
Bagging	0.817	0.803	0.536	0.518	0.806	0.641	0.66	0.703
AdaBoostM1	0	0	0.56	0.31	0	0	0	0
Multi Scheme	0	0	0	0.31	0	0	0	0
Decision Stump	0	0	0.56	0.31	0	0	0	0
Random Tree	0.783	0.769	0.524	0.5	0.761	0.61	0.646	0.672
BayesNet	0.798	0.784	0.536	0.526	0.765	0.637	0	0.687
Naive Bayes	0.798	0.786	0.548	0.513	0.767	0.641	0.68	0.688
Naive Bayes Multinomial	0.783	0.765	0.528	0.511	0.761	0.641	0.651	0.67
Naive Bayes Multinomial Text	0	0	0	0.31	0	0	0	0
Naive Bayes Multinomial Updateable	0.783	0.765	0.528	0.511	0.761	0.616	0.651	0.67
Naive Bayes Updateable	0.798	0.786	0.548	0.513	0.767	0.641	0.68	0.688
Logistic Regression	0.786	0.776	0.568	0.55	0.758	0.639	0	0.669
Multilayer Perceptron	0.813	0.794	0.529	0.514	0.796	0.641	0	0.703
Simple Logistic	0	0	0.571	0.31	0	0	0	0
Voted Perceptron	0.774	0.75	0.543	0.535	0.772	0.625	0	0.637
Random Forest	0.824	0.808	0.542	0.52	0.812	0.649	0.681	0.688
Decision Table	0.832	0	0.556	0.518	0	0	0	0
Attribute Selected Classifier	0.791	0.809	0.55	0	0.805	0.672	0	0
Classification Via Regression	0.803	0.797	0.542	0.536	0.795	0.698	0.676	0.695
CV Parameter Selection	0	0	0	0.31	0	0	0	0
Iterative Classifier Optimizer	0	0	0.558	0.31	0	0	0	0
Randomizable Filtered Classifier	0.78	0.765	0.519	0.498	0.756	0.604	0.641	0.668
Random SubSpace	0.819	0.839	0.534	0.511	0.875	0.679	0.717	0.749
Weighted Instances HandlerWrapper	0	0	0	0.31	0	0	0	0
Input Mapped Classifier	0	0	0	0.31	0	0	0	0

Table 9.2: Classification recall of machine learning based algorithms while using EEG brainwave signals

Algorithm	wts	ntf	hps	sad	flr	dps	uhp	hls
SGD	0.868	0.857	0.552	0.556	0.854	0.729	0.751	0.785
SMO	0.868	0.857	0.551	0.556	0.854	0.729	0.751	0.785
J48	0.868	0.857	0.557	0.557	0.854	0.728	0.751	0.785
IBk	0.783	0.769	0.522	0.498	0.763	0.609	0.648	0.67
JRip	0.867	0.857	0.558	0.557	0.853	0.728	0.75	0.784
OneR	0.863	0.852	0.517	0.509	0.849	0.607	0.719	0.765
PART	0.868	0.857	0.556	0.558	0.854	0.728	0.751	0.785
ZeroR	0.868	0.857	0.547	0.556	0.854	0.729	0.751	0.785
SGD Text	0.868	0.857	0.547	0.556	0.854	0.729	0.751	0.785
REP Tree	0.865	0.854	0.537	0.539	0.85	0.718	0.741	0.778
LogitBoos	0.868	0.857	0.558	0.556	0.854	0.729	0.751	0.785
Stacking	0.868	0.857	0.547	0.556	0.854	0.729	0.751	0.785
Vote	0.868	0.857	0.547	0.556	0.854	0.729	0.751	0.785
Hoeffding Tree	0.868	0.856	0.552	0.552	0.853	0.725	0.75	0.779
Bagging	0.867	0.856	0.543	0.529	0.854	0.719	0.744	0.781
AdaBoostM1	0.868	0.857	0.557	0.556	0.854	0.729	0.751	0.785
Multi Scheme	0.868	0.857	0.547	0.556	0.854	0.729	0.751	0.785
Decision Stump	0.868	0.857	0.557	0.556	0.854	0.729	0.751	0.785
Random Tree	0.779	0.764	0.525	0.501	0.758	0.607	0.645	0.671
BayesNet	0.827	0.817	0.55	0.55	0.837	0.697	0.751	0.751
Naive Bayes	0.83	0.823	0.554	0.481	0.831	0.708	0.339	0.76
Naive Bayes Multinomial	0.604	0.606	0.531	0.49	0.592	0.708	0.495	0.568
Naive Bayes Multinomial Text	0.868	0.857	0.547	0.556	0.854	0.729	0.751	0.785
Naive Bayes Multinomial Updateable	0.604	0.606	0.531	0.49	0.592	0.559	0.495	0.568
Naive Bayes Updateable	0.83	0.823	0.554	0.481	0.831	0.708	0.339	0.76
Logistic Regression	0.867	0.856	0.556	0.559	0.853	0.728	0.751	0.784
Multilayer Perceptron	0.868	0.857	0.545	0.539	0.854	0.728	0.751	0.784
Simple Logistic	0.868	0.857	0.557	0.556	0.854	0.729	0.751	0.785
Voted Perceptron	0.866	0.854	0.554	0.557	0.852	0.725	0.751	0.782
Random Forest	0.868	0.857	0.552	0.535	0.854	0.721	0.749	0.78
Decision Table	0.868	0.857	0.556	0.555	0.854	0.729	0.751	0.785
Attribute Selected Classifier	0.868	0.857	0.557	0.556	0.854	0.729	0.751	0.785
Classification Via Regression	0.867	0.857	0.553	0.557	0.853	0.729	0.751	0.785
CV Parameter Selection	0.868	0.857	0.547	0.556	0.854	0.729	0.751	0.785
Iterative Classifier Optimizer	0.868	0.857	0.557	0.556	0.854	0.729	0.751	0.785
Randomizable Filtered Classifier	0.785	0.769	0.52	0.5	0.764	0.607	0.646	0.673
Random SubSpace	0.868	0.857	0.546	0.534	0.854	0.729	0.751	0.785
Weighted Instances HandlerWrapper	0.868	0.857	0.547	0.556	0.854	0.729	0.751	0.785
Input Mapped Classifier	0.868	0.857	0.547	0.556	0.854	0.729	0.751	0.785

Table 9.3: Classification F-Measure of machine learning based algorithms while using EEG brainwave signals

Algorithm	wts	ntf	hps	sad	flr	dps	uhp	hls
SGD	0	0	0.41	0.398	0	0	0	0
SMO	0	0	0.403	0.398	0	0	0	0
J48	0.807	0.794	0.486	0.433	0.791	0.616	0.644	0.69
IBk	0.782	0.768	0.522	0.497	0.76	0.608	0.646	0.669
JRip	0.808	0.796	0.506	0.479	0.79	0.618	0.646	0.695
OneR	0.808	0.794	0.513	0.503	0.786	0.628	0.654	0.693
PART	0.807	0.793	0.488	0.454	0.787	0.616	0.644	0.69
ZeroR	0	0	0	0.398	0	0	0	0
SGD Text	0	0	0	0.398	0	0	0	0
REP Tree	0.81	0.797	0.526	0.52	0.792	0.631	0.655	0.698
LogitBoos	0	0	0.471	0.398	0	0	0	0.691
Stacking	0	0	0	0.398	0	0	0	0
Vote	0	0	0	0.398	0	0	0	0
Hoeffding Tree	0.806	0.791	0.491	0.485	0.786	0.617	0.644	0.692
Bagging	0.813	0.8	0.535	0.517	0.794	0.637	0.657	0.7
AdaBoostM1	0	0	0.46	0.398	0	0	0	0
Multi Scheme	0	0	0	0.398	0	0	0	0
Decision Stump	0	0	0.457	0.398	0	0	0	0
Random Tree	0.781	0.766	0.525	0.5	0.759	0.609	0.646	0.671
BayesNet	0.811	0.798	0.49	0.488	0.789	0.65	0	0.706
Naive Bayes	0.811	0.801	0.468	0.457	0.79	0.649	0.294	0.707
Naive Bayes Multinomial	0.667	0.663	0.529	0.483	0.651	0.649	0.527	0.604
Naive Bayes Multinomial Text	0	0	0	0.398	0	0	0	0
Naive Bayes Multinomial Updateable	0.667	0.663	0.529	0.483	0.651	0.58	0.527	0.604
Naive Bayes Updateable	0.811	0.801	0.468	0.457	0.79	0.649	0.294	0.707
Logistic Regression	0.807	0.792	0.442	0.426	0.786	0.617	0	0.691
Multilayer Perceptron	0.808	0.793	0.496	0.493	0.7	0.616	0	0.692
Simple Logistic	0	0	0.444	0.398	0	0	0	0
Voted Perceptron	0.806	0.79	0.494	0.439	0.787	0.62	0	0.69
Random Forest	0.813	0.801	0.535	0.515	0.794	0.64	0.656	0.696
Decision Table	0.806	0	0.462	0.41	0	0	0	0
Attribute Selected Classifier	0.806	0.792	0.489	0	0.787	0.615	0	0
Classification Via Regression	0.808	0.794	0.485	0.474	0.788	0.615	0.644	0.691
CV Parameter Selection	0	0	0	0.398	0	0	0	0
Iterative Classifier Optimizer	0	0	0.467	0.398	0	0	0	0
Randomizable Filtered Classifier	0.782	0.767	0.519	0.499	0.76	0.605	0.644	0.67
Random SubSpace	0.806	0.792	0.522	0.497	0.786	0.619	0.644	0.691
Weighted Instances HandlerWrapper	0	0	0	0.398	0	0	0	0
Input Mapped Classifier	0	0	0	0.398	0	0	0	0

Table 9.4: Classification accuracy of machine learning based algorithms while using EEG brainwave signals

Algorithm	wts	ntf	hps	sad	flr	dps	uhp	hls
KNN [190] [191]	86.7%	85.7%	52.5%	53.4%	85.3%	72%	74.8%	78.7%
M5P[192]	86.8%	85.6%	56.6%	57.7%	85.4%	72.9%	75.1%	78.4%
SGD [169]	86.8%	85.7%	55.2%	55.6%	85.4%	72.9%	75.1%	78.5%
SMO [193]	86.8%	85.7%	55.1%	55.6%	85.3%	72.9%	75.1%	78.5%
J48	86.6%	85.7%	55.7%	55.7%	85.4%	72.8%	75.1%	78.4%
IBk [194]	78.3%	76.9%	52.2%	49.8%	76.3%	60.9%	64.8%	67.0%
JRip [195]	86.7%	85.6%	55.7%	55.6%	85.4%	72.8%	75.1%	78.4%
OneR [196]	86.3%	85.2%	51.7%	50.9%	84.8%	68.8%	71.8%	76.5%
PART	86.7%	85.6%	55.7%	55.6%	85.4%	72.8%	75.1%	78.4%
ZeroR [197]	86.3%	85.2%	51.7%	50.9%	84.8%	68.8%	71.8%	76.5%
SGD Text [198]	86.8%	85.7%	54.7%	55.7%	85.3%	72.9%	75.1%	78.5%
REP Tree [199]	86.5%	85.4%	53.7%	53.9%	85.0%	71.8%	74.1%	77.8%
LogitBoos [200]	86.8%	85.7%	55.7%	55.6%	85.4%	72.8%	75.1%	78.5%
Stacking	86.8%	85.7%	54.7%	55.6%	85.4%	72.8%	75.1%	78.5%
Vote [201]	86.8%	85.7%	55.7%	55.6%	85.4%	72.8%	75.1%	78.5%
Hoeffding Tree [202]	86.8%	85.6%	55.2%	55.2%	85.3%	72.5%	74.9%	77.9%
Bagging [203]	86.71%	85.6%	54.3%	52.8%	85.4%	71.9%	74.4%	78.1%
AdaBoostM1 [204]	86.8%	85.7%	55.7%	55.6%	85.4%	72.9%	75.1%	75.5%
Multi Scheme	86.8%	85.7%	54.6%	55.6%	85.4%	72.8%	75.1%	78.5%
Decision Stump [205]	86.8%	85.7%	55.7%	55.6%	85.4%	72.9%	75.1%	78.5%
Random Tree	77.9%	76.4%	52.5%	50.1%	75.8%	60.7%	64.5%	67.1%
BayesNet [206]	82.7%	81.7%	54.9%	55.0%	83.7%	69.7%	75.1%	75.1%
Naive Bayes [193]	82.9%	82.3%	55.4%	48.1%	83.1%	70.8%	33.9%	75.9%
Naive Bayes Multinomial [207]	60.4%	60.6%	53.1%	49.0%	59.2%	55.9%	49.5%	56.7%
Naive Bayes Multinomial Text	86.8%	85.7%	54.7%	55.6%	85.4%	71.8%	75.1%	77.5%
Naive Bayes Multinomial Updateable	86.4%	60.6%	53.1%	49.0%	59.2%	55.9%	49.5%	56.8%
Naive Bayes Updateable	82.9%	82.3%	55.4%	48.1%	83.1%	70.7%	33.8%	75.9%
Logistic Regression [208]	86.7%	85.6%	55.6%	55.9%	85.2%	72.8%	75.1%	78.4%
Multilayer Perceptron [209]	86.8%	85.7%	54.5%	53.9%	85.3%	72.8%	75.1%	78.4%
Simple Logistic [210]	86.8%	85.7%	55.7%	55.9%	85.3%	72.9%	75.1%	78.5%
Voted Perceptron	86.6%	85.4%	55.4%	55.7%	85.2%	72.5%	75.1%	78.2%
Random Forest [167]	86.8%	85.7%	55.2%	55.5%	85.4%	72.1%	74.9%	78.0%
Filtered Classifier	86.8%	85.7%	55.6%	55.6%	85.4%	72.8%	75.1%	78.5%
Decision Table [167]	86.7%	85.6%	55.7%	55.6%	85.4%	72.8%	75.1%	78.5%
Attribute Selected Classifier [211]	86.8%	85.7%	55.7%	55.7%	85.4%	72.8%	75.1%	78.5%
Classification Via Regression	86.8%	85.6%	55.9%	56.2%	85.4%	72.8%	74.9%	78.4%
CV Parameter Selection	86.8%	85.7%	54.7%	55.6%	85.4%	72.8%	75.1%	78.5%
Iterative Classifier Optimizer	86.8%	85.7%	55.7%	55.6%	85.4%	72.8%	75.1%	78.5%
Multi Class Classifier	86.7%	85.6%	55.7%	55.6%	85.4%	72.8%	75.1%	78.4%
Multi Class Classifier Updateable	86.8%	85.6%	55.2%	55.6%	85.4%	72.9%	75.1%	78.5%
Random Committee	86.2%	83.8%	54.2%	52.1%	84.8%	69.8%	69.8%	76.5%
Randomizable Filtered Classifier	78.5%	76.8%	51.9%	49.9%	76.4%	60.6%	64.6%	67.3%
Random SubSpace	86.8%	85.7%	54.6%	53.6%	85.4%	72.9%	75.1%	78.5%
Weighted Instances HandlerWrapper	86.7%	85.6%	55.7%	55.6%	85.4%	72.8%	75.1%	78.5%
Input Mapped Classifier	86.7%	85.6%	55.7%	55.6%	85.4%	72.8%	75.1%	78.5%

Table 9.5: Classification precision of machine learning based algorithms while using head movement data

Algorithm	wts	ntf	hps	sad	flr	dps	uhp	hls
SGD	0	0	0.537	0.554	0	0.519	0	0
SMO	0	0	0.44	0	0	0	0	0
J48	0.908	0.855	0.706	0.715	0.848	0.759	0.765	0.834
Ibk	0.877	0.838	0.667	0.693	0.829	0.724	0.756	0.819
OneR	0.843	0.803	0.567	0.582	0.765	0.646	0.684	0.731
ZeroR	0	0	0	0	0	0	0	0
SGDText	0	0	0	0	0	0	0	0
REPTree	0.905	0.847	0.704	0.714	0.846	0.758	0.76	0
LogitBoos	0	0	0.617	0.586	0.778	0.671	0.746	0.762
Stacking	0	0	0	0	0	0	0	0
Vote	0	0	0	0	0	0	0	0
HoeffdingTree	0.866	0.772		0.618	0.745	0.677	0.694	0.778
Bagging	0.912	0.866	0.714	0.734	0.86	0.774	0.785	0.851
AdaBoostM1	0	0	0.469	0.572	0.748	0.646	0.747	0
MultiScheme	0	0	0	0	0	0	0	0
DecisionStump	0	0	0.679	0.683	0	0	0.747	0
RandomTree	0.874	0.83	0.652	0.677	0.816	0.709	0.742	0.808
BayesNet	0.865	0.798	0.627	0.617	0.784	0.688	0.701	0.764
NaiveBayes	0.836	0.769	0.552	0.548	0.764	0.611	0.676	0.718
NaiveBayesMultinomialText	0	0	0	0	0	0	0	0
NaiveBayesUpdateable	0	0.769	0.552	0.548	0.764	0.611	0.676	0.718
Logistic Regression Analysis	0.811	0.759	0.598	0.569	0.745	0.634	0.715	0.647
SimpleLogistic	0	0	0.615	0.569	0	0.657	0.728	0
VotedPerceptron	0.785	0.753	0.524	0.54	0.707	0.645	0.576	0.669
RandomForest	0.913	0.868	0.71	0.913	0.913	0.773	0.793	0.859
FilteredClassifier	0.885	0.842	0.683	0.692	0.831	0.74	0.745	0.814
DecisionTable	0.889	0.833	0.674	0.675	0.827	0.731	0.741	0.818
AttributeSelectedClassifier	0.889	0.837	0.707	0.716	0.792	0.76	0.763	0.832
ClassificationViaRegression	0.847	0.796	0.608	0.614	0.779	0.649	0.669	0.752
CVParameterSelection	0	0	0	0	0	0	0	0
IterativeClassifierOptimizer	0	0	0.617	0.586	0.778	0.671	0.746	0.762
MultiClassClassifier	0.811	0.759	0.598	0.569	0.745	0.634	0.715	0.647
MultiClassClassifierUpdateable	0	0	0.537	0.554	0	0.519	0	0
RandomCommittee	0.901	0.862	0.693	0.716	0	0.753	0	0.849
RandomizableFilteredClassifier	0.837	0.795	0.616	0.618	0.767	0.67	0.714	0.768
RandomSubSpace	0.898	0.879	0.683	0.69	0.837	0.756	0.783	0.834
WeightedInstancesHandlerWrapper	0	0	0	0	0	0	0	0
InputMappedClassifier	0	0	0	0	0	0	0	0

Table 9.6: Classification recall of machine learning based algorithms while using head movement data

Algorithm	wts	ntf	hps	sad	flr	dps	uhp	hls
SGD	0.882	0.863	0.556	0.556	0.812	0.659	0.706	0.783
SMO	0.882	0.863	0.552	0.549	0.812	0.659	0.706	0.783
J48	0.916	0.877	0.708	0.715	0.86	0.765	0.777	0.845
Ibk	0.88	0.843	0.666	0.693	0.831	0.727	0.759	0.82
OneR	0.882	0.862	0.571	0.584	0.81	0.674	0.718	0.78
ZeroR	0.882	0.863	0.555	0.549	0.812	0.659	0.706	0.783
SGDText	0.882	0.863	0.555	0.549	0.812	0.659	0.706	0.783
REPTree	0.914	0.872	0.705	0.714	0.858	0.764	0.773	0.842
LogitBoos	0.882	0.863	0.604	0.591	0.817	0.681	0.725	0.793
Stacking	0.882	0.863	0.555	0.549	0.812	0.659	0.706	0.783
Vote	0.882	0.863	0.555	0.549	0.812	0.659	0.706	0.783
HoeffdingTree	0.889	0.856	0.639	0.621	0.809	0.695	0.723	0.804
Bagging	0.92	0.882	0.714	0.735	0.87	0.78	0.793	0.859
AdaBoostM1	0.882	0.863	0.602	0.577	0.81	0.671	0.725	0.783
MultiScheme	0.882	0.863	0.555	0.549	0.812	0.659	0.706	0.783
DecisionStump	0.882	0.863	0.574	0.569	0.812	0.659	0.725	0.783
RandomTree	0.876	0.833	0.651	0.676	0.818	0.712	0.746	0.809
BayesNet	0.889	0.86	0.629	0.62	0.818	0.704	0.728	0.795
NaiveBayes	0.877	0.847	0.557	0.558	0.81	0.654	0.676	0.759
NaiveBayesMultinomialText	0.882	0.863	0.555	0.549	0.812	0.659	0.706	0.783
NaiveBayesUpdateable	0.882	0.847	0.557	0.558	0.81	0.654	0.713	0.759
Logistic Regression Analysis	0.882	0.862	0.583	0.566	0.81	0.666	0.721	0.782
SimpleLogistic	0.882	0.863	0.594	0.566	0.812	0.672	0.723	0.783
VotedPerceptron	0.879	0.86	0.549	0.554	0.808	0.67	0.693	0.777
RandomForest	0.921	0.883	0.711	0.921	0.921	0.778	0.801	0.865
FilteredClassifier	0.898	0.868	0.683	0.693	0.847	0.748	0.758	0.827
DecisionTable	0.903	0.866	0.675	0.676	0.844	0.74	0.755	0.829
AttributeSelectedClassifier	0.903	0.865	0.707	0.717	0.82	0.766	0.775	0.843
ClassificationViaRegression	0.826	0.781	0.603	0.6	0.756	0.599	0.647	0.724
CVParameterSelection	0.882	0.863	0.555	0.549	0.812	0.659	0.706	0.783
IterativeClassifierOptimizer	0.882	0.863	0.604	0.591	0.817	0.681	0.725	0.793
MultiClassClassifier	0.882	0.862	0.583	0.566	0.81	0.666	0.721	0.782
MultiClassClassifierUpdateable	0.882	0.863	0.556	0.556	0.812	0.659	0.706	0.783
RandomCommittee	0.911	0.881	0.693	0.717	0.812	0.76	0.706	0.857
RandomizableFilteredClassifier	0.84	0.8	0.615	0.621	0.772	0.673	0.718	0.77
RandomSubSpace	0.894	0.867	0.679	0.689	0.833	0.746	0.76	0.816
WeightedInstancesHandlerWrapper	0.882	0.863	0.555	0.549	0.812	0.659	0.706	0.783
InputMappedClassifier	0.882	0.863	0.555	0.549	0.812	0.659	0.706	0.783

Table 9.7: Classification F-Measure of machine learning based algorithms while using head movement data

Algorithm	wts	ntf	hps	sad	flr	dps	uhp	hls
SGD	0	0	0.444	0.451	0	0.523	0	0
SMO	0	0	0.399	0	0	0	0	0
J48	0.908	0.849	0.705	0.715	0.848	0.759	0.761	0.831
Ibk	0.878	0.84	0.666	0.693	0.83	0.725	0.758	0.82
OneR	0.841	0.802	0.568	0.583	0.768	0.635	0.674	0.731
ZeroR	0	0	0	0	0	0	0	0
SGDText	0	0	0	0	0	0	0	0
REPTree	0.906	0.846	0.703	0.714	0.847	0.758	0.758	0
LogitBoos	0	0	0.554	0.583	0.769	0.607	0.634	0.73
Stacking	0	0	0	0	0	0	0	0
Vote	0	0	0	0	0	0	0	0
HoeffdingTree	0.856	0.799	0	0.615	0.744	0.671	0.67	0.766
Bagging	0.911	0.856	0.712	0.735	0.858	0.774	0.779	0.846
AdaBoostM1	0	0	0.553	0.551	0.742	0.593	0.634	0
MultiScheme	0	0	0	0	0	0	0	0
DecisionStump	0	0	0.446	0.439	0	0	0.634	0
RandomTree	0.875	0.831	0.651	0.676	0.817	0.71	0.744	0.809
BayesNet	0.858	0.805	0.616	0.609	0.787	0.675	0.69	0.761
NaiveBayes	0.844	0.798	0.552	0.49	0.765	0.597	0.634	0.73
NaiveBayesMultinomialText	0	0	0	0	0	0	0	0
NaiveBayesUpdateable		0.798	0.552	0.49	0.765	0.597	0.634	0.73
Logistic Regression Analysis	0.826	0.799	0.507	0.49	0.74	0.583	0.636	0.687
SimpleLogistic	0	0	0.526	0.49	0	0.582	0.636	0
VotedPerceptron	0.826	0.798	0.478	0.494	0.73	0.586	0.59	0.69
RandomForest	0.911	0.858	0.709	0.722	0.869	0.772	0.787	0.853
FilteredClassifier	0.872	0.821	0.677	0.692	0.824	0.732	0.729	0.8
DecisionTable	0.885	0.819	0.671	0.676	0.821	0.724	0.722	0.802
AttributeSelectedClassifier	0.885	0.808	0.703	0.716	0.762	0.76	0.76	0.828
ClassificationViaRegression	0.835	0.788	0.604	0.6	0.766	0.609	0.655	0.735
CVParameterSelection	0	0	0	0	0	0	0	0
IterativeClassifierOptimizer	0	0	0.554	0.583	0.769	0.607	0.634	0.73
MultiClassClassifier	0.826	0.799	0.507	0.49	0.74	0.583	0.636	0.687
MultiClassClassifierUpdateable	0	0	0.444	0.451	0	0.523	0	0
RandomCommittee	0.9	0.859	0.693	0.716	0	0.753	0	0.846
RandomizableFilteredClassifier	0.838	0.798	0.615	0.615	0.769	0.671	0.716	0.769
RandomSubSpace	0.854	0.809	0.668	0.683	0.779	0.713	0.706	0.762
WeightedInstancesHandlerWrapper	0	0	0	0	0	0	0	0
InputMappedClassifier	0	0	0	0	0	0	0	0

Table 9.8: Classification accuracy of machine learning based algorithms while using head movement data

Algorithm	wts	ntf	hps	sad	flr	dps	uhp	hls
SGD	88.2%	81.2%	55.6%	88.2%	88.2%	65.9%	70.6%	78.3%
SMO	88.2%	81.2%	55.2%	88.2%	88.2%	65.9%	70.6%	78.3%
J48	91.6%	86.0%	70.8%	91.4%	91.6%	76.5%	77.7%	84.5%
IBk	87.9%	83.1%	66.6%	87.9%	87.9%	72.7%	75.9%	82.3%
OneR	88.2%	80.9%	57.1%	88.2%	88.2%	67.3%	71.8%	77.9%
ZeroR	88.2%	81.2%	55.5%	88.2%	88.2%	65.3%	70.6%	78.3%
SGDText	88.2%	81.2%	55.6%	88.2%	88.2%	65.9%	70.6%	78.3%
REPTree	91.4%	85.4%	70.5%	91.4%	91.4%	76.5%	77.3%	84.2%
LogitBoos	88.2%	81.7%	60.4%	88.2%	88.2%	68.1%	72.5%	79.3%
Stacking	88.2%	81.2%	55.5%	88.2%	88.2%	65.9%	70.6%	78.3%
Vote	88.2%	81.2%	55.5%	88.2%	88.2%	65.9%	70.6%	78.3%
HoeffdingTree	88.9%	80.8%	63.6%	91.3%	88.9%	69.5%	72.3%	80.4%
Bagging	92.0%	87.0%	71.5%	92.0%	92.0%	77.9%	79.3%	85.8%
AdaBoostM1	88.2%	81.0%	60.2%	88.2%	88.2%	67.1%	72.5%	78.3%
MultiScheme	88.2%	81.2%	55.5%	88.2%	88.2%	65.9%	70.6%	78.3%
DecisionStump	88.2%	81.2%	57.4%	88.9%	88.2%	65.8%	72.4%	78.3%
RandomTree	87.6%	81.3%	65.1%	88.2%	87.6%	71.2%	74.6%	86.5%
BayesNet	88.9%	81.7%	62.9%	88.9%	88.9%	76.5%	72.7%	79.5%
NaiveBayes	87.7%	81.0%	55.7%	87.7%	87.7%	65.4%	71.3%	75.9%
NaiveBayesMultinomialText	88.2%	81.2%	55.5%	88.2%	88.2%	65.4%	70.6%	78.3%
NaiveBayesUpdateable	87.7%	81.0%	55.7%	87.7%	87.7%	65.4%	71.3%	75.9%
Logistic Regression Analysis	88.2%	81.2%	58.6%	88.2%	81.2%	66.9%	72.6%	78.3%
SimpleLogistic	88.2%	81.2%	59.6%	88.2%	88.2%	67.9%	72.6%	78.3%
VotedPerceptron	87.9%	80.7%	54.9%	87.9%	87.9%	66.9%	63.3%	77.7%
RandomForest	92.1%	87.5%	71.1%	74.30%	87.5%	77.8%	80.1%	86.5%
FilteredClassifier	89.8%	84.7%	68.6%	89.6%	89.4%	74.8%	75.1%	82.5%
DecisionTable	90.2%	84.6%	67.7%	90.6%	90.4%	74.8%	75.1%	82.5%
AttributeSelectedClassifier	91.8%	82.7%	70.7%	91.7%	91.4%	76.8%	77.1%	84.5%
ClassificationViaRegression	86.8%	85.6%	55.9%	56.2%	85.4%	72.8%	74.9%	78.4%
CVParameterSelection	88.5%	81.2%	55.5%	88.2%	88.2%	65.8%	70.6%	78.3%
IterativeClassifierOptimizer	88.2%	81.7%	60.4%	88.2%	88.2%	68.1%	72.5%	79.3%
MultiClassClassifier	88.2%	81.7%	60.4%	88.2%	88.2%	68.1%	72.5%	79.3%
MultiClassClassifierUpdateable	88.2%	81.7%	60.4%	88.2%	88.2%	68.1%	72.5%	79.3%
RandomCommittee	91.3%	86.3%	69.3%	91.1%	91.1%	76.0%	79.2%	85.7%
RandomizableFilteredClassifier	83.9%	86.3%	61.4%	83.9%	83.9%	67.3%	71.6%	77.3%
RandomSubSpace	89.4%	83.3%	67.9%	89.4%	89.4%	74.6%	76.0%	81.5%
WeightedInstancesHandlerWrapper	88.2%	81.2%	55.5%	88.2%	88.2%	65.9%	70.6%	78.3%
InputMappedClassifier	88.2%	81.2%	55.5%	88.2%	88.2%	65.9%	70.6%	78.3%

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