Beyond Words: An Exploration of Free-hand Sketches and EEG-based Neurobiological Signatures to Unveil the Underlying Depression among Cancer Patients

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Declaration

It is hereby declared that

1. The thesis report submitted is our own original work while completing degree at Brac University.

2. The thesis report does not contain material previously published or written by a third party, except where this is appropriately cited through full and accurate referencing.

3. The thesis report does not contain material which has been accepted, or submitted, for any other degree or diploma at a university or other institution.

4. We have acknowledged all main sources of help.

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Ethical approval for this study was obtained from the Institutional Review Board (IRB) of Bangladesh University of Engineering and Technology (BUET) (REC reference no. 2684).

Dedication

- Dedicated to the brave souls who are fighting against cancer, honoring their incredible strength and unwavering determination.

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Abstract

Mental well-being is intricately intertwined with physical health and is considered a crucial aspect of an individual's overall well-being. Due to ever-deteriorating health conditions and uncertainty about the future, people who go through life-changing events like cancer diagnosis are more vulnerable to feeling a wide range of emotional distress such as shock, denial, fear, anxiety, depression, etc. However, low patient-to-psychologist-and-psychiatrist ratios, lack of literacy, social stigma, sensitivity regarding seeking professional help, etc. greatly affect the reliability of existing interview or self-reported questionnaire-based depression screening. Moreover, traditional methods are primarily based on verbal communication, which may not be the most effective way to assess, particularly for non-verbal individuals or those with limited communication skills. To address these issues and broaden the scope of depression diagnosis, our research delved into the potential of incorporating free-hand sketching and EEG features into the depression screening process.

In this regard, an in-depth study was conducted among cancer patients of different stages, e.g., stage-1 (n = 25), stage-2 (n = 20), stage-3 (n = 19), and stage-4 (n = 2). Along with demographic data, we collected two free-hand sketches with a theme of 'self-reflection' or how they see themselves before and after diagnosis, from each of them. An affordable, consumer-grade, lightweight EEG headset was also used to collect brainwave signals from the participants during their sketching sessions. We identified several potential neurobiological signatures using the EEG signals. Moreover, we used several computational algorithms and manual processing techniques to identify the presence of indicators (hair density, line boldness, dual stroke, lip line, presence of tears, presence of the lower body, and overall body weight depiction) and also to extract dimensional measurements from the images of the free-hand sketches. We found the after-self-reflection sketches of depressed participants to be significantly smaller than the before-self-reflection ones. We used these extracted features, along with demographic data, to train multiple machine learning models for potentially screening depression among cancer patients. Among them, the Support Vector Machine (SVM) model gave the highest accuracy (85%). We developed a Random Forest model with a better accuracy of 94% by integrating relative EEG power with the previously used data. We validated our findings using the PHQ-9 depression screening scale results that were gathered during the data collection phase. Our approach of utilizing EEG-based neurobiological patterns and free-hand sketches allows for the elicitation of naturalistic expressions through non-verbal communication. As a result, our study can pave the way for large-scale research on this relatively newer depression screening approach focused on the minimization of cultural and linguistic barriers and open up new opportunities for interdisciplinary research in the future.

Keywords: Oncology; Psychiatry; Depression; Free-hand sketches; HCI; EEG; PHQ-9.

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Chapter 1

Introduction

Cancer is a life-changing diagnosis accompanied by significant physical and emotional distress. With an estimated prevalence of 15-27%, depression is considered common psychological distress among cancer patients [74]. It harms both the patient's quality of life and the chance of recovery because it weakens their mental fortitude, which is crucial for overcoming any illness. However, it often remains undetected and untreated as patients themselves and their caregivers often overlook syndromal depression in the process of giving more attention to handling the continuous occurrence of new physical complications. Moreover, cancer patients sometimes choose not to discuss their psychological states, due to the stigma surrounding mental illness, concerns about being perceived as weak, or fear of being judged by others. As these lead to under-reporting of depression and other psychological aspects to the attending physicians, it becomes very easy for busy professional oncologists to miss the signs and misjudge depression, even when it becomes essential and one of the most important factors to consider [31]. The low detection rate of depression and related psychiatric distress is equated with the acute work pressure of oncology specialists [8]. Most oncologists and physicians associated with cancer care don't have access to any standardized and easily accessible screening tool for depression. To diagnose severe depression among oncology patients, existing interviews and self-report-based diagnoses suffer from under-utilization due to various issues with human-human interaction and expectations [16]. The conventional approach to diagnosing depression involves a patient visiting a psychiatric clinic and being observed by a professional practitioner [46]. Thus, limited resources, inadequate distribution of screening tools, obstacles to the present healthcare system, and a scarcity of oncology psychiatrists hamper the mental health of oncology patients to a large extent.

To address the above-mentioned challenges, this study proposes the incorporation of EEG signals and free-hand sketches as non-verbal measures to screen for potential causes of depression among cancer patients. EEG signals can provide valuable insights into a person's mental state, including their level of relaxation, concentration, body-mind integration, alertness, agitation, etc., measured by different band values. Besides, art and sketching have long been relevant in people's lives because they bring out the inner feelings and subtle nuances of emotions that the conscious brain might restrict. By collecting the EEG signals while the patients sketch their self-reflections or how they see themselves before and after their cancer diagnosis, a more comprehensive understanding of a patient's mental state that may otherwise go unnoticed can be gained.

Along with the EEG and sketch data, sociodemographic variables, and a well-accepted depression screening scale were also collected. All the data were collected from cancer patients in a single hospital setting after obtaining their informed consent. The collected data went through various types of analyses, including machine learning and statistical analysis, to explore the potential of non-verbal methods in depression screening among cancer patients, broaden the field of depression screening by presenting a different perspective, and provide oncologists with opportunities to incorporate technologies alongside their expertise. The findings of this study could ultimately help to improve the health care of cancer patients, which aligns with most of the country's goals of ensuring quality health care for its citizens.

1.1 Challenges in the Depression Diagnosis among Cancer Patients

Cancer is a chronic disease with a relatively low recovery rate worldwide. Even though a gradual increase can be seen in recent decades due to science and technology's involvement in the medical sector, whether or not a cancer patient can be cured depends on the type and stage of cancer, the kind of treatment they are receiving, and other factors. In particular, the patient's mental health plays a pivotal role in their journey toward betterment. When patients learn about their cancer diagnosis, it is already a shock for them to comprehend, and they have to go through tremendous emotional distress. Besides, fear of dying, tension about the unsettled future of the family members, and the feeling of being a burden to others break their psychological strength, and they start to question their self-worth. Along with that, the treatment phase is long and both physically and mentally draining. The presence of cancer already damages the patient's immune system, and chemotherapy and radiation therapy, the most commonly used treatment procedures for different types of cancer, have severe side effects like hair loss, tiredness, anaemia, loss of appetite, bruising, bleeding, and more [91]. As a result, people observe striking physical changes within a short period of time. It is at this point that the patient's mental strength and willingness to fight become the driving forces that give them an edge over others.
Existing research has shown that mental and physical health are both uniformly important components of health. However, the situation is a lot different in developing countries like Bangladesh. Due to the low literacy rate and traditional beliefs, especially in rural areas, people are not aware of the importance of mental health, and it remains a taboo topic. The fear of being victimized by social stigma often prevents many cognizant people from seeking professional help. Moreover, the financial crisis is a vital concern for cancer patients and their families. The treatment demands constant cash flow, and patients' conditions deteriorate quickly. As a result, easing their physical distress draws more attention, while their mental distress remains unnoticed.

In Bangladesh, there is a severe imbalance in the population to mental health professional ratio. In accordance with the World Health Organization report of 2021,

Figure 1.1: Bangladesh Cancer Society Hospital and Welfare Home

there were 565 psychologists (0.34 per 100,000), 260 psychiatrists (0.16 per 100,000 population), as well as 700 nurses (0.4 per 100,000) who provided mental health speciality care [90]. However, almost all the specialists are concentrated in major urban areas, making it difficult for the rural population to access them even when they feel the need to. Despite these challenges, oncologists and other professionals working in cancer palliative care units recognize the need to incorporate mental health specialists into the treatment plan with the hope of uplifting the patient's psychological strength and speeding up physical recovery simultaneously. To tackle the existing shortage, doctors can work as a temporary bridge between patients and mental health professionals. To elucidate, they can prescribe medications, therapies, etc., from their prior knowledge to patients who do not need extensive support, and after a certain level, they can refer the patients to mental health professionals. To aid the process, a screening tool can work as a support system for doctors to determine whether they will handle the patients' mental health themselves or if a referral will be needed. If the method of screening could be non-verbal or minimally interactive, it could eliminate communication barriers and allow for better detection of patients' mental states, reducing the fear factors and biases associated with sharing sensitive and personal experiences with strangers.
To minimize the challenges associated with cancer patients' psychological aspects, proper support systems should be implemented. These support systems should address the need for mental health services and incorporate screening tools that allow doctors to identify patients in need of mental health services. It is crucial to raise awareness about the importance of mental health and destigmatize mental health-related issues in society to ensure that cancer patients receive holistic care.

Figure 1.2: Cancer patients in Bangladesh [70]

1.2 EEG and Free-hand Sketches as Non-verbal Measures

Depression is traditionally defined by the presence of some severe depressive symptoms, which, if untreated, can linger for a long period of time. These symptoms of distress and sadness can reflect the emergence of an abnormal underlying neurobiological measure in response to sudden stress or memories. Recent discoveries in neuroscience have shown neurobiological irregularities in depressed individuals and identified several unusual neurobiological signatures of depression [71]. EEG is a physiological method of measuring brain signal activity. Our interest in EEG stems from the fact that it provides great spatiotemporal resolutions for analyzing brain processes that assist describe the anomalies related to various depressive disorders [18]. Instead of conventional questionnaire-based diagnosis methods, EEG offers clearer and less conflicting responses connected with a specific phenomenon. Additionally, using EEG may help to avoid problems with human-to-human interaction and involvement, like language barriers and the inability to read self-help surveys. As a result, we examine in this work whether EEG may be used to detect neurobiological indicators of depression in cancer patients while they engage in various activities.

In addition to investigating the neurobiological indicators for depression screening in cancer patients, we have started using non-verbal expression (free-hand sketching) to pinpoint the underlying cognitive impairment. Due to their availability, originality, portability, ease of creation, and intricate visual depiction of their cancer experience, we have picked free-hand sketches. This method is appropriate for the uneducated and underprivileged community, who may lack literacy and technical skills, due to its inexpensive overhead (needs only a pencil and paper) [65], [119].

Previously, the psychiatric community has investigated the benefits and therapeutic potential of artistic endeavors, creative expression, and nonverbal communication among various populations with diagnoses of various cognitive dysfunctions. Studies estimate that non-verbal communication contributes to a significant portion of interpersonal communication, ranging from 70% to 93% of the total context [85]. Sketch, as a non-verbal communication medium, can aid in the screening of depression by allowing individuals to visually express their emotions, thoughts, and experiences. Sketching provides an alternative outlet for self-expression, enabling individuals to communicate complex feelings that may be difficult to articulate verbally. It can help uncover underlying emotions and provide visual cues that assist in assessing the severity and nature of depressive symptoms. Furthermore, sketches can serve as a valuable tool for therapists to gain insights into a person's inner world, identify patterns, and tailor appropriate interventions for their emotional well-being. Self-portraits or basic sketches of one's own body image may offer an invaluable glimpse into the patient's viewpoint. It provides an alternative form of communication that can help the drawers explore the significance of their circumstances by accessing information that the conscious mind may have repressed or denied [10]. Consequently, in this study, we provide a preliminary demonstration of the concept for an innovative, inexpensive, and inventive way to identify prospective depression cases among cancer patients using free-hand sketching. We illustrate how free-hand sketching in particular might be incorporated with ubiquitous computing methods to enhance depression detection among disadvantaged cancer patients in economically challenged developing nations.

1.3 Our Research Objectives

Cancer patients face numerous challenges, including serious mental health issues like depression. Unfortunately, existing systems for screening depression among cancer patients are often inadequate, and there is a severe shortage of oncology psychiatrists in developing and underdeveloped countries. To address these issues, we propose a plan to leverage the advancements in Human-Computer Interaction (HCI) to minimize Human-Human interactions and screen for depression among cancer patients more accurately.

Our research aims to investigate the potential of Electroencephalogram (EEG) and free-hand sketches as alternative screening methods for depression among cancer patients. We plan to conduct mixed research among different groups of cancer patients to achieve the following objectives:

1. Gain a deep understanding of the various psychological aspects of cancer patients, particularly those related to depression.

2. Overcome the challenges associated with screening for depression among cancer patients.

3. Utilize EEG signal data to extract neurobiological signatures of depression among cancer patients.

4. Explore the potential of non-verbal measures, such as free-hand sketching and EEG, for depression screening among cancer patients.

5. Develop a low-cost and innovative screening method for depression to deal with resource constraints.

By achieving these objectives, we aim to contribute to the development of more effective and efficient screening methods for depression among cancer patients. This research has the potential to address the mental health challenges faced by cancer patients worldwide, particularly those in resource-constrained settings.

1.4 Key Research Questions

The key research questions of our study are as follows:

RQ1. Can Graph-based Analysis be utilized to identify correlations between depression and its symptoms?

RQ2. Does the EEG data of cancer patients reveal any neurobiological signatures associated with depression?

RQ3. Can non-invasively collected data uncover potential connections between sketch features and the mental states of cancer patients?

1.5 Our contributions

In this study, we investigated an alternative method for screening depression in cancer patients by utilizing non-verbal communication measures. We examined the features extracted from free-hand sketches and EEG signals to identify potential cases of depression. Our research involved a mixed-method analysis of patients at different stages of cancer, including Stage 01 (n = 25), Stage 02 (n = 20), Stage 03 (n = 19), and Stage 04 (n = 2). This diverse population allowed us to explore the relationship between socio-economic backgrounds, depression severity, and the identified features.

- To screen for depression, we collaborated with an expert psychiatrist and implemented a validated questionnaire. By analyzing the questionnaire responses, we investigated the association between different depressive symptoms and depression levels. We developed three models- Correlation Network, Partial Correlation Network, and Regulatory Network, to better understand the underlying structure of depression and its associated symptoms.

- We proposed a unique and affordable method for identifying potential cases of depression in cancer patients. By utilizing EEG signals and free-hand sketches, we developed a novel approach to screen for depression. Our initial findings, which focused on neurobiological abnormalities and the underlying structure of depression, offer valuable insights that can contribute to the diagnosis and treatment of depression in this particular group of patients.

- Our study represents one of the first attempts to explore non-verbal measures for assessing depression in cancer patients. By relieving patients of the burden and stigma associated with sharing personal feelings, our approach aims to enhance individual privacy and improve the overall well-being of cancer patients.

- This research contributes to the field by presenting a creative and innovative method for depression screening, offering valuable insights into the underlying structure of depression, and providing a direction for the diagnosis and treatment of depression among cancer patients.

1.6 Thesis Organization

Chapter 1 of this report serves as the introduction, where we described our motivation behind choosing this topic, highlighted the challenges faced by doctors in diagnosing depression among cancer patients, provided an overview of our research questions, and outlined our objectives and contributions. Moreover, Chapter 2 delves into a comprehensive review of previous works related to our research topic. Next, Chapter 3 presents an overview of the important concepts we have used throughout our study, such as Clique, Centrality, Directed Acyclic Graph, and Statistical Significance Test. Furthermore, Chapter 4 describes our research methodology and the procedure we followed for data collection and analysis. Then, Chapter 5 and Chapter 6 present the findings we obtained from the analyses and their implications and significance, respectively. Chapter 7 reflects future research directions and a comprehensive conclusion summarizing our key findings. Lastly, the Appendix includes additional materials for further references, such as demographic questions and the consent form.

Chapter 2

Literature Review

We cite research papers in the body of related works to examine the importance of screening for depression among cancer patients. Papers related to present systems for screening depression in cancer patients, the use of free-hand sketching, and digital snapshots of the sketches in other cognitive dysfunctions, and how the computer is being used in mental healthcare for cancer patients are also reviewed below.

2.1 Importance of Depression Screening among Cancer Patients

Major depression or depressive syndromes are common among cancer patients. Although depressive symptoms can emerge at any moment during an oncological disease, particular times, such as the following diagnosis, are associated with a higher risk. The prevalence rates reported varied widely (up to 60%), highlighting diagnostic challenges. Only 15 to 50 percent of oncologists recognize depression in their patients, and even fewer patients receive appropriate treatment. As a result, the quality of life suffers greatly [54]. Another study used the Hospital Anxiety and Depression Scale (HADS) [49] to compare the prevalence of anxiety and depression in cancer patients compared to the normal people [7]. They discovered that the risk of psychological distress in malignant patients is approximately twice than that of the healthy general individuals. We also found out from another literature that depression among cancer patients is more severe than in the general population. They used the PHQ-9 scale on an oversized sample of cancer patients. The study shows the importance of using standardized and simply applicable tools to detect depression [31].

Figure 2.1: Our data collection moments

Three large-scale investigations have found that cancer patients experience discomfort at a rate that is more than 30% overall. Quality of life is impacted by stress, anxiety, and depression, as well as by treatment satisfaction and involvement [11], [12], [15], [17], [20], [22]. However, busy cancer doctors frequently ignore symptoms of syndromal anxiety and despair [12]. The insignificant identification rate of distress and accompanying psychological problems seem to be linked to cancer professionals' working strain. The majority of cancer-care doctors don't employ screening tools regularly. In one survey of palliative medicine doctors, most of the doctors said that they had never utilized a screening tool [8]. However, depression screening tools might be limited to the patients and physicians associated with cancer. Therefore, in this work, we have proposed an innovative method to potentially screen for depression that will be easily accessible and will help in tackling the scarcity of oncology psychiatrists for the diagnosis of depression to a large extent.

2.2 Present Systems to Screen Depression among Cancer Patients

Many technological interventions are present for screening for depression among cancer patients. For example, in a study, we learned about the strategy of screening for depression among cancer patients from a smartphone application. A mobile mental health tracker's propensity was examined in a study. As markers of depression, the app employs three daily psychological state assessments (satisfaction with sleep, mood, and anxiety). Three processing strategies are covered (ratio, average, and frequency) for producing indicator variables. The study also demonstrated the effect of reporting adherence while using a mobile mental state tracker and the accuracy of depression screening [79]. In another research pre-proof, we observed mobile applications in oncology. The study leveraged the advancement of mobile technology to look at the health conditions of oncology patients. The study outcomes show that using this app can help detect various severe syndromes of cancer [79].

The technological interventions for screening depression among cancer patients are extremely limited among patients and oncologists. We hope to help people that are struck by severe depression while undergoing the agony of cancer treatment.

2.3 Uses of Digitalized Free-hand Sketches in Cognitive Dysfunctions

We prefer to pursue the use of the distinct characteristics of freehand sketching since they can reflect the visual representation of inner feelings and experiences. Free-hand sketches are very simple to make, inexpensive, and unique. It will also provide the advantage of non-verbal measures of depression among cancer patients. Also, free-hand sketches are further deployed in clinical trials for the evaluation of a variety of cognitive dysfunctions, including amnesia, Alzheimer's disease, dementia, and post-traumatic stress disorder. In a study, a basic scoring system was developed to identify people with cognitive dysfunction who could have Alzheimer's disease. The research showed CDT (Clock Drawing Test) [38] as a good alternative screening tool to the MINI scale [35]. However, they necessitate human interaction in evaluating the sketches and are frequently susceptible to human interpretation [68]. Another study found that using computer vision to diagnose Parkinson's disease can help. This research presents an automated machine-learning method for distinguishing Parkinson's disease patients from control groups based on the spirals and meanders drawn by the patients [59].

A paper focused on PTSD patients demonstrated the feasibility of free-hand sketching as a screening tool for probable PTSD in underrepresented communities, hoping to enhance future research into affordable and accessible PTSD clinical evaluation methods [84]. The authors involved three groups in Bangladesh (Rohingya refugees, slum-dwellers, and engineering students) in the sketching process with the theme 'Home'. They assessed the photographs, merged the findings with the sketch subject and the participants' gender and group, and integrated EEG data for better accuracy. The authors noticed significant group, gender, and PTSD impacts within the sketching features and supported the interactions between the variables during the research. They developed a logistic regression model with reasonable accuracy for potentially screening PTSD.

In a study, researchers reported human figure sketching as a complementary method for diagnosing depression in university students [93]. Traditional screening approaches used in psychological treatment for depression, such as questionnaires or surveys, are not always successful. The authors added that students might feel forced to portray themselves well. Because of this, it might be hard to tell who is depressed and who isn't. In this study, the authors proposed that practicing human figure sketching could help with this issue. They described its operation and its use as an auxiliary depression screening instrument. They also discussed research that used human figure painting as a diagnostic tool for depression in various groups. The authors discussed the advantages of employing human figure sketching as an additional tool for depression screening, such as its potential to overcome social desirability bias and its simplicity. However, they noted some caveats to this method, including that experts were required to interpret the drawings and that there might be some cultural disparities in how the illustrations were understood. This research shed light on the present status of depression screening procedures. It also suggested that human figure sketching might be a helpful adjunct tool for spotting depressive symptoms among college students. This finding showed that this technique might help detect people whose emotions and ideas were concealed during standard screening procedures.

Another research explored body image perceptions in head and neck cancer patients, and they used a drawing analysis method for eliciting conversations during patients' clinical visits [73]. Researchers found drawing analysis a valuable tool for exploring body image perception. The use of drawing as a method for exploring body image perception is still rare among cancer patients. However, the study highlights the importance of addressing negative body image perceptions to improve the quality of life for cancer patients. Researchers used interventions such as Cognitive-Behavioural Therapy (CBT) and Mindfulness-based Stress Reduction (MBSR), which have been shown to improve body image perceptions and quality of life for cancer patients. However, they did not mention the most effective interventions for addressing negative body image perceptions in this patient population. Overall, their study provided valuable insights into drawing analysis to explore body image perceptions in head and neck cancer patients, which may inform future research on interventions to improve the quality of life for this patient population.

Researchers investigated distinguishing changes in self-perception among breast cancer survivors who underwent different treatments to cure the disease [50]. Researchers used the Machover Draw-A-Person test as a projective tool to conduct the study. Three judges analyzed the drawings based on predetermined criteria for selected features. Results showed that those who underwent different treatments had different self-perceptions. Mastectomy-treated patients had lower self-esteem and body image scores than those who underwent breast-conserving surgery or radiotherapy. Moreover, those who received chemotherapy had lower scores on body image than those who did not. The study suggests that the Machover Draw-A-Person test could be used to identify changes in self-perception among breast cancer survivors. This method could also be applied to planning interventions to alleviate distress. However, this study has limitations, such as small sample size and the need for a control group.

Therefore, our goal is to ascertain whether the development of machine learning and image processing, independent of human interaction, can recognize a visual pattern from pictures of freehand sketches drawn by individuals with severe depression among cancer patients.

2.4 Machine Learning Usage on Oncology Patients

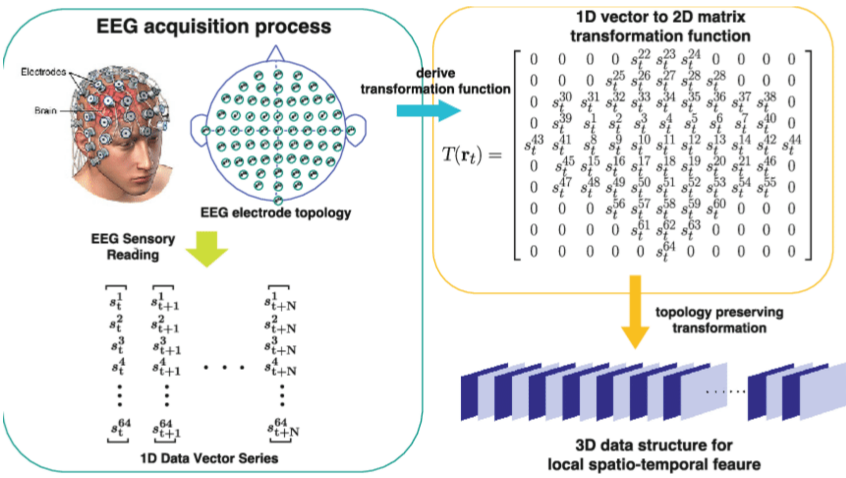


Figure 2.2: EEG signal to transformation matrix [40]

A research paper based on Machine Learning over Oncology patients presents an outline of a study on the psychological distress of cancer patients and a machine learning approach that uses three algorithms - CHART, Boosting, and Bagging - to make classification models for determining a patient's level of distress-supported disease classification [87]. For evaluation of a medical institution's rating and forecast of the quantity of suffering in cancer patients, classification models were constructed utilizing machine learning approaches like decision trees and ensemble algorithms.

Research-based on Machine Learning used EEG signals as a system was demonstrated which can recognize emotions based on EEG signals. They use valence and arousal models over a dataset for the research [63]. Furthermore, EEG signals were decomposed into three different frequency bands, and to define this frequency band, multiple algorithms were used. Comparing the accuracy between the models, SVM shows better accuracy than the other models. According to their research, other models may perform better based on the scenarios, but they needed more research to get a higher validated accuracy measure.

Chapter 3

Preludes

In this Chapter, various theoretical and experimental concepts are described which have been used in this research analysis. We first start with the graph theory concepts that we used for the statistical analysis in this study i.e. Depression Correlation Network among Cancer Patients, Depression Partial Correlation Network.

3.1 Clique

In statistics, a clique refers to a subset of individuals or units within a larger population or network that are mutually connected or linked to each other. More specifically, it is a group of individuals where each member has a direct connection or relationship with every other member of the group [92]. More specifically, a clique is a subset of nodes of an undirected graph, where every edge or vertices are adjacent. Thus, its induced subgraph is the complete graph of the entire network.

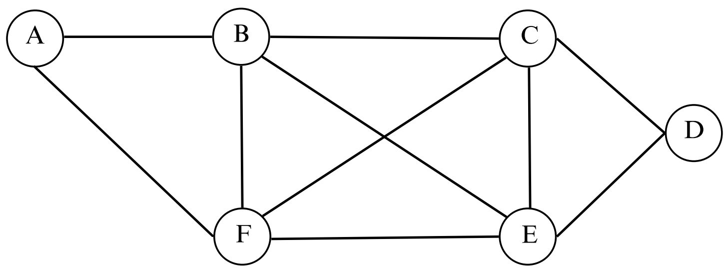


Figure 3.1: An undirected graph to explain Clique, Maximum Clique, and Maximal Clique

For example, in the undirected graph (Figure 3.1), there are three cliques. One clique contains the nodes A, B, F as, there are connections between (A-B), (B-F), and (A-F), and these networks make a complete subgraph of 3 nodes. The second clique consists of the nodes B, C, E, F where every two nodes are connected, creating a complete subgraph of 4 nodes. Another clique has the nodes C, D, E, here (C-D), (D-E), and (E-C) are interconnected, and this completes a subgraph of 3 nodes.

A clique, in the context of the depression correlation network among cancer patients, is a subset of entities where each entity correlates with every other entity in the subset, creating a full subnetwork of connections. Such subnetworks will assist us in locating the PHQ-9 questionnaire's group of depressed symptoms that interact and have an impact on how the patients' depression emerges. Because psychiatric symptoms are so important in the development of depression in cancer patients, these subnetworks may be of special importance in identifying potential psychiatric symptoms. Additionally, the maximum clique in a network is the one with the most nodes — there cannot be another clique with more nodes [77]. For instance, in the undirected network depicted in Figure 3.1, there are three cliques: one with four nodes B, C, E, F, and two with three nodes each A, B, F, C, E, D. Because another clique has more nodes than the three-node clique, the three-node clique is not the maximum clique. As a result, the clique with four nodes B, C, E, F is the largest clique in the graph because no other clique has more than four nodes.

Additionally, the maximum clique in a network is the one with the most nodes — there cannot be another clique with more nodes [78]. For instance, in the undirected network depicted in Figure 3.1, there are three cliques: one with four nodes B, C, E, F, and two with three nodes each A, B, F, C, E, D. Because another clique has more nodes than the three-node clique, the three-node clique is not the maximum clique. As a result, the clique with four nodes B, C, E, F is the largest clique in the graph because no other clique has more than four nodes.

In the Depression Correlation Network, the term 'maximum clique' refers to the largest collection of entities or symptoms in which each entity correlates with every other entity in the same group. We would be able to better understand how the majority of these entities are interacting with one another and forming the basis of the disorder if we could find the greatest group of associated entities.

3.2 Centrality

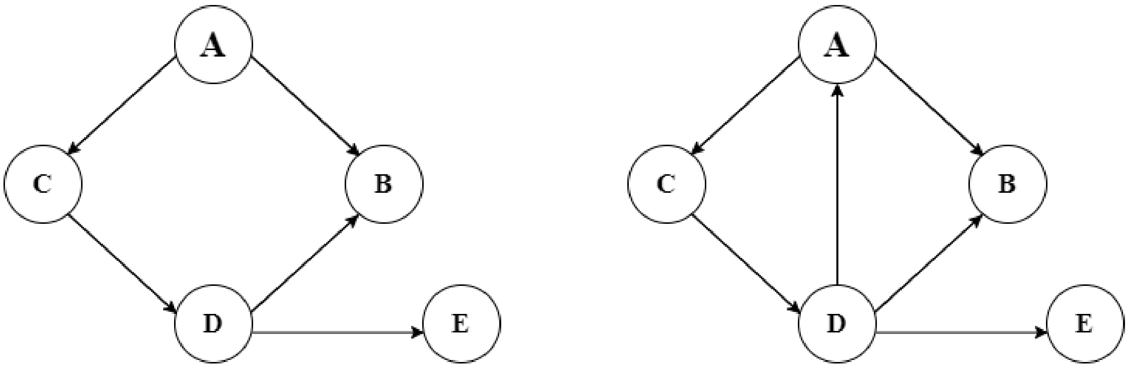
Measuring each node's significance and contribution to the network's overall functionality is crucial in a network with several nodes. Centrality is one of the many metrics that can be used to assess a node's function in a network. Degree centrality is a measure of the centrality or importance of a node (in this case, depressive symptoms from PHQ-9) within a network. It is based on the number of connections, or edges, that a node has with other nodes in the network. Additionally, it might show the level of impact or control that a certain symptom has over how the network's other symptoms interact with one another There are numerous ways to measure centrality. The two measurements below were used in our analysis:

- **Strength:** By calculating the strength of each symptom, you can assess the relative importance or influence of symptoms within the depressive symptom network. Symptoms with a higher degree of centrality have more connections or stronger correlations with other symptoms, indicating their potential significance in the network. This measure evaluates how much influence a given entity has over how other network elements interact with one another. The strength of a certain node in a weighted network is equal to the weights of all the edges incident to it. It displays the overall degree of relationship with a specific node. The degree to which a specific symptom is involved in the underlying dynamics of depressive symptoms is indicated by the network's strength in the case of the depression correlation. Because simply accounting for an association's existence is insufficient, we picked it above the simple degree of centrality. When determining the level of participation of a certain symptom, we must take into account each association's weight because not all associations have an identical degree of strength. For the reason that the fundamental dynamics of depression may be substantially influenced by symptoms that interact with other symptoms.

- **Betweenness Centrality:** Betweenness centrality is a measure of a node's centrality in a network based on the concept of shortest paths. It quantifies the extent to which a node lies on the shortest paths between pairs of other nodes in the network. Nodes with high betweenness centrality have a significant influence on the flow of information or resources within the network. The amount of times a specific node is on the shortest path connecting two other nodes is measured by betweenness. Through this metric, an entity's level of influence over how the other network elements interact with one another is measured. The betweenness centrality of a symptom may be of special interest in Depression Correlation among Cancer Patients to comprehend how it influences the interaction among other symptoms.

3.3 Directed Acyclic Graph (DAG)

DAG is a directed graph where the edges have a specific direction assigned to them and it is not possible to follow the directed edges in a loop to return to the same vertex. The term 'acyclic' refers to the absence of cycles in the graph, and 'directed' indicates that the edges have a specific direction. Therefore, it does not contain any directed cycles. In other words, it is a graph where the edges have a specific direction assigned to them and it is not possible to start at any vertex and follow the directed edges to return to the same vertex without traversing the same edge more than once. There are two examples shown in Figure 3.2a and Figure 3.2b that depict the difference between a Directed Acyclic graph and a Directed Cyclic Graph. Figure 3.2b is cyclic because return to node A is possible from the path A -> B -> D -> A or A -> C -> D -> A if we start from another node D, node A can be traversed more than once.
For correlation network illustration, undirected graphs are used in most cases. But Directed Acyclic Graphs depict casual interconnection among different nodes. In our study, DAGs suggested an association among various depressive symptoms in cancer patients, which eventually depicts the severity of depression along with the specific symptoms reflected to it. Thus, our motive behind generating directed networks is to depict the casual correlation between the severity of Depression and depressive symptoms from the PHQ-9 scale.



(a) Acyclic (b) Cyclic

Figure 3.2: Types of directed graph

3.4 Statistical Significance Test

As we collected a diverse dataset from cancer patients, we performed numerous statistical analyses in this study. We followed null hypothesis testing in our analysis. Null hypothesis testing, also known as statistical hypothesis testing, is a common method used in statistical inference to make decisions based on data. It involves formulating a null hypothesis, which represents a specific claim or assumption about a population parameter, and conducting a statistical test to assess the evidence against the null hypothesis [30]. The null hypothesis postulates that there is no distinction between certain populations parameters. For instance, we presuppose that there is no difference between the neurobiological activities of those who are screened for depression and those who are not, or between the sketch characteristics of other demographic groups. To confirm or disprove the null hypothesis, we conducted a variety of statistical tests.

Benjamin-Hochberg correction, also known as the False Discovery Rate (FDR) correction, is a method used in statistical hypothesis testing to control for multiple comparisons. It is named after its developers, Yoav Benjamini and Yosef Hochberg. The purpose of the Benjamin-Hochberg correction is to address the issue of increased false positives when performing multiple statistical tests simultaneously. When conducting numerous tests, the probability of obtaining false positive results by chance alone increases. The correction adjusts the p-values obtained from the individual tests to control the overall false discovery rate at a desired level [45]. The null hypothesis postulates that there is no distinction between certain population parameters. For instance, we presupposed that there is no difference between the neurobiological activities of those who are screened for depression and those who are not, or between the sketch characteristics of other demographic groups. To confirm or disprove the null hypothesis, we conducted a variety of statistical tests. Applying the Benjamini-Hochberg correction, the Depression Correlation Network among Cancer Patients derived the p-values from the correlation matrix. The p-values are obtained by squaring the correlations to obtain a value in the range [0, 1]. The correction adjusts the p-values based on the number of comparisons made and the desired significance level, α. It helps control the overall rate of false positives while identifying significant correlations more accurately.

Chapter 4

Methodology

In this Chapter, we present the details of our data collection and analysis. As per our study pipeline (Figure 4.1),

1. We screened participants for potential cases of depression using a depression screening tool
2. We collected free-hand sketches and EEG signals from participants suffering from various stages of cancer
3. We analyzed the collected data to comprehend the relationship between depression and its symptoms fully
4. We utilized preexisting machine learning models to screen for potential cases of depression among cancer patients

We scored the depression screening test and conducted the participant interviews with the assistance of an experienced psychiatrist. An artist helped us with both the qualitative analysis of the sketches as well as the sketching assignments. All these data collection processes were held under the supervision of an experienced oncologist. The Institutional Review Board (IRB) of the Bangladesh University of Engineering and Technology (BUET) reviewed and approved our research protocol.

4.1 Participants

Our study includes a diverse sample of individuals with various stages of cancer, as well as with different gender identities, socioeconomic backgrounds, and educational levels, to explore the utility of EEG and free-hand sketches from a more inclusive and diverse viewpoint.

Three of our interviewers (one male and two female) interviewed and collected data from cancer patients at the National Institute of Cancer Research Hospital (NICRH) and the Bangladesh Cancer Society Hospital and Welfare Home. With the help of the attending oncologist, we approached the patients there at random and requested their volunteer participation. After getting their verbal consent, we asked the physician whether they were capable enough at that moment to participate in the data collection process. We only proceeded with our interviews and other data collection

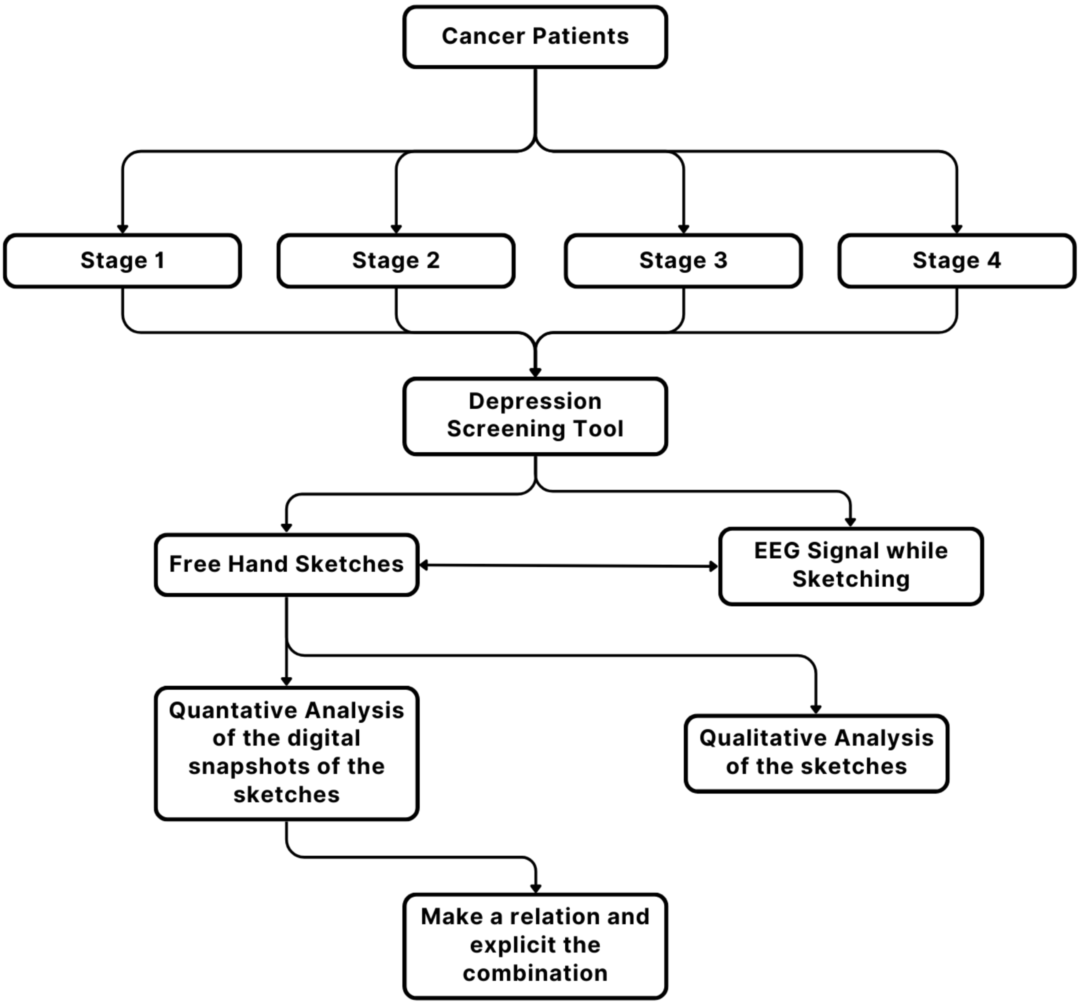


Figure 4.1: Research methodology

procedures after receiving approval to ensure everyone's safety. Initially, the patients were provided with a consent form consisting of two parts: one was an information sheet where a brief description of the purpose of the research, methodology, risks, benefits, reimbursements, confidentiality, and their right to participate voluntarily, refuse, or withdraw at any time was stated, and the other was the certificate of consent. The Bengali version of the consent form could be found in section 7.2. For the participants who were illiterate, the consent form was read to them with their caregivers observing the procedure. A member of the research team approached them for further procedures after they had had enough time to read, comprehend, discuss, and be ready to give signed consent.

We conducted the sessions in (1) the doctor's chamber or (2) the bedside of the patient, depending on the situation. At the NICRH, there were many patients admitted to the wards, making it impossible to collect data from the participant's bedside considering we would need to reduce the bias as much as possible while collecting EEG data. That's why we interviewed them at one of the oncologists' free chambers. The data collection procedure continued for multiple days from morning to evening to make the process more flexible for the participants without hampering the physicians' rounds or treatment procedures. At the Bangladesh Cancer Society Hospital and Welfare Home, the patients usually do not take admission and mostly come to their doctor's appointments or to receive their chemotherapy. As a result, the atmosphere in the wards was not loud, and we were able to collect the data from the patient's bedsides. The male patients were okay with the presence of the female interviewers. However, in the case of female patients, some of them felt hesitant, and some of the patients' caregivers requested female interviewers only. Respecting their requests, only female interviewers conducted the sessions with them. All the data collection procedures were held in Bengali, the mother tongue of both the interviewers and interviewees.

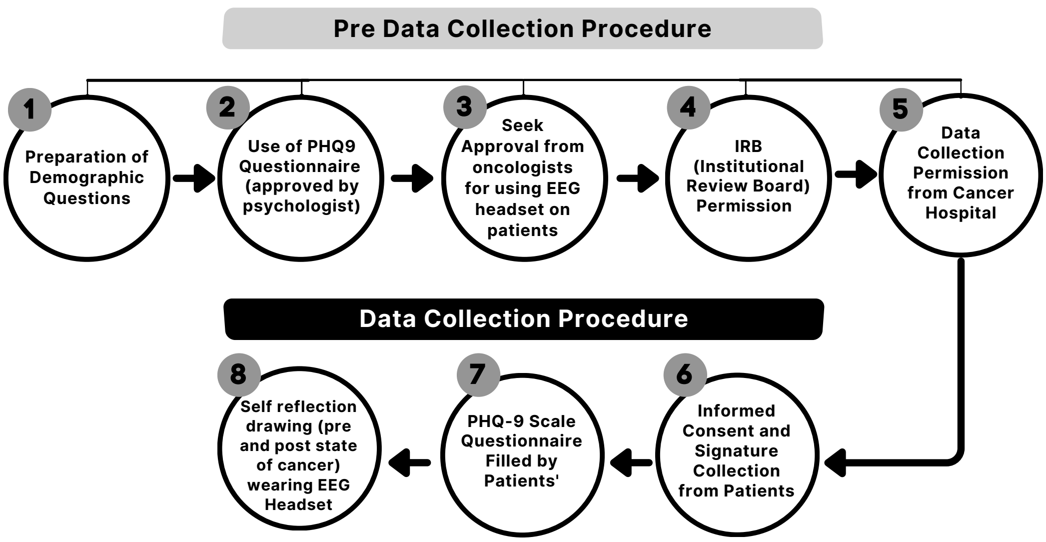


Figure 4.2: Our research pipeline

After the data collection was completed, we ran the Shapiro-Wilk normality test to determine whether our data was following a normal distribution or not and later selected parametric or non-parametric tests in accordance with the result.

4.2 Tools Used for Data Collection

Figure 4.3: Data Collection from Patients

Our data collection procedure involves several stages, including depression screening, EEG data collection, and free-hand sketches. The following provides a detailed description of each of them.

4.2.1 Depression Screening Tool

Many screening tools are currently available to evaluate the severity of depression and monitor people's depressive symptoms. Examples include PHQ-9, MINI, BDI, HDRS, MADRS, etc. [44]. Most of these scales are based on interviews, self-evaluation, and clinician observation. We selected the translated and validated PHQ-9 scale from the pool of screening instruments. The following were the main justifications for adopting the PHQ-9:

1. Unlike other surveys that require participants to answer a lot of questions, PHQ-9 delivers a brief, reasonable questionnaire [86].

2. It is easy to administer for its simplicity since the PHQ-9 is a depression module that scores each of the nine DSM-IV criteria from '0' (not at all) to '3' (nearly every day), providing a 0-27 severity score. It has been validated for use in primary care previously [32].

3. Compared to other depression screening tests, which need administration times ranging from 45 to 120 minutes, PHQ-9 is said to take only approximately 5 to 10 minutes [75]. According to past studies, oncology patients frequently overlook psychological counselling sessions with lengthy administration times since they already had to spend a significant amount of time each day coping with numerous difficulties as a result of having one of the most chronic diseases [41].

4. PHQ-9 is compatible with the DSM-IV criteria [13].

5. The validity of the PHQ-9 has been assessed using a structured, independent interview conducted by a mental health professional (MHP). For severe depression, a PHQ-9 score of 10 or higher demonstrated 88% sensitivity and 88% specificity [26], [32].

6. PHQ-9 has been found effective in previous studies of depression screening among cancer patients [56].

Taking into account all of these aspects, the PHQ-9 scale was deemed to be a particularly acceptable instrument for evaluating depression in oncology patients receiving primary care in an emergency psychiatric setting. The PHQ-9 questionnaire [40] that we translated into Bengali includes the following questions:

1. How frequently, in the last two weeks,
   (a) Have you experienced a lack of interest or pleasure in doing things?
   (b) Have you felt down, depressed, or hopeless?
   (c) Have you had trouble falling asleep?
   (d) Have you felt tired or had low energy?
   (e) Have you experienced a poor appetite or overeating?
   (f) Have you felt like you are a failure or let down people close to you?
   (g) Have you had trouble concentrating?
   (h) Have you noticed a slowing down of your movements or speech?
   (i) Have you thought of self-harm or suicide?

2. How difficult has it been for you to participate in your daily activities?

All the question 1's sub-questions serve as the screening question and offer four options for participants to indicate their level of difficulty. The options were 'not at all', 'several days', 'more than half of the days', and 'nearly everyday' encoded with values ranging from 0 to 3, respectively. The last question is only answered if the participant previously checked at least one of the questions in number 1. It provides an indicator of the patient's overall impairment and is used to assess the treatment's effectiveness [40]. However, it was not considered when calculating the depression score.Upon completion of all the questions on the scale, a potential case of depression was recorded if the severity score was between 15-27 (Severity: 0-4 none, 5-9 mild, 10-14 moderate, 15-19 moderately severe, 20-27 severe) [13], [32].

Because of the possibility of having low literacy rates among the patient groups, we performed semi-structured one-on-one interviews with them using the PHQ-9 screening tool. For those who were capable and willing to fill out the form by themselves, we gave them the Bengali Questionnaire's self-report form. The questions can be found at section 7.2. The translation process was carried out in several steps:

1. To achieve conceptual equivalency, we held multiple focus group talks. In order to take the values, beliefs, and characteristics of the Bangladeshi community as well as the variations in how depression is presented and understood in Bangladesh into account, we tried to clarify each item on the PHQ-9 Questionnaire [80].

2. Next, the questionnaire was translated into Bengali by two native Bengali speakers - a veteran psychologist and an undergraduate student with prior experience in English translation. Based on the feedback from one of our esteemed collaborators, who is a renowned authority in oncology psychology in Bangladesh and has experience with research studies done in both Bengali and English, we made minor adjustments to the original translation.

3. A group formed by the authors, collaborators, and translators then compared and scrutinized the PHQ-9 questionnaire and its translated version, as well as the justifications and translational presumptions associated with them. In order to ensure the highest level of contextual and conceptual equivalence between the original English and Bengali translated versions of the questionnaire, they cross-checked the translation from the perspectives of both mental health and linguistic compatibility.

To encourage candid and spontaneous responses through organic and authentic conversations, our interviewers prioritized establishing strong connections with the patients. Additionally, we were careful to ensure that the patients were not overwhelmed by their own thoughts of despair, striving to create an environment where they felt comfortable and were able to maintain emotional composure.

4.2.2 EEG Headset

We acquired an affordable, consumer-grade, and transportable EEG headset called the Neurosky Mindwave Mobile Headset to accommodate the EEG data from cancer patients [67]. According to the International 10-20 system for positioning EEG electrodes, the headset has one main electrode at the FP1 site and a reference electrode linked to the ear [69]. It generates EEG power values for eight widely recognized brainwaves, including delta, theta, low alpha, high alpha, low beta, high beta, and gamma.

The NeuroSky device comes with ThinkGear technology, which employs sensor attachments to gather brain-wave impulses, amplify them, cancel out background noise and muscle activity, and then analyze all of the data on a single chip [69]. We utilized the ASIC EEG POWER INT data that had been processed and produced by the device at a 1 Hz sampling rate. It generates outputs for eight well-recognized brainwaves, including delta (0.5-2.75 Hz), theta (3.5-6.75 Hz), low alpha (7.5-9.25 Hz), high alpha (10-11.75 Hz), low beta (13-16.75 Hz), high beta (18-29.75 Hz), low gamma (31-39.75 Hz), and mid gamma (41-49.75 Hz) [53]. It is the ASIC counterpart of EEG. These values are only significant when compared to themselves and each other and have no units. Additionally, NeuroSky has eSenseTM proprietary technology for identifying mental states like concentration and relaxation [2].

For our research, we recorded the background EEG data from cancer patients of different cancer stages during their sketching sessions to gain knowledge about their mental states at that time. The majority of the participants willingly consented to wearing the non-invasive headset. However, a few of them raised concerns about the possibility of getting an electric shock from the device. To address these concerns, we ourselves wore the headsets, and other participants who had already finished their sessions also reassured them about the device's innocuous nature.

4.2.3 Free-hand Sketches

In addition to investigating the neurobiological indicators of depression in cancer patients, we used non-verbal expression (free-hand sketching) to pinpoint the underlying cognitive impairment. Due to their affordability, portability, ease of creation, and intricate visual depiction of an individual's experience, we chose free-hand sketches. This method is also appropriate due to its inexpensive overhead (it requires only a pencil and paper) for the uneducated and underprivileged community, which might lack literacy and technical skills [28], [66].

We chose **'self-reflection'** as the theme of the drawing. Every cancer type's health-related quality of life measure takes 'self-reflection' into account. It is known that certain cancer patients may have negative body evaluations after undergoing cancer treatments [48]. For people who have received treatment for any type of cancer, loss of body function and external changes in body shape have been linked to depression, which can increase communication challenges and feelings of social rejection [82]. Changes in physical appearance that may come from cancer and its treatments, could cause various psychological anguish depending on the patient's age, personality, gender, and culture. While some cancer patients may find changes in body function more depressing, others may find changes in appearance more upsetting [28], [66].

Self-portraits or basic sketches of one's own body image may represent a unique perception of the patient's viewpoint [48]. It provides an alternative form of verbal communication that can enable patients to analyze the significance of their mental condition by accessing information that the conscious mind may have denied and repressed [82]. The drawings may represent both positive and negative ideas about cancer, which might help people make more meaningful decisions and, hopefully, have better results. A sketch may be a beneficial tool in order to understand people's perspectives and experiences. This could be particularly true if they have verbal communication issues that are caused by functional or linguistic obstacles. In addition, it could make it easier for people to access and express various parts of their distress than using more conventional approaches [33].

In our research, we provided each participant with a piece of paper and a pencil. They were asked to draw 'how you saw yourself before cancer diagnosis' and 'how you see yourself now after cancer diagnosis.' Each participant was given a maximum of 15 minutes to complete in order to maintain uniformity among all. All the participants were able to complete both the sketches within the allocated time and did not asked for any extension.

We dedicated a considerable amount of time to ensuring the comfort of the participants by engaging them in participatory conversation. A few of the participants were hesitant at first, stating that sketching is not something they do on a regular basis and that they are not skilled enough. To address this, we reassured them that the purpose of the sketches was not to evaluate their drawing skills or literacy but rather to capture their unique perspectives. The participation of other participants, along with our assurances, served as a source of motivation and encouragement for them to overcome their reservations. Later, after finishing the sketches, one of them expressed that the sketching session reconnected her to the time she used to draw with her kid and thanked us for the opportunity.

4.3 Data Pre-processing and Analysis

We used a variety of quantitative and qualitative methods to analyze the collected data after properly de-identifying it. With the help of a psychiatrist and psychologist, we also analyzed the discussions and responses of the participants to the depression screening tool.

4.3.1 Sociodemographic Data

Participants' sociodemographic data were collected through printed survey questionnaires and then inputted into a Google Sheet, which was later turned into a Comma-Separated Values (CSV) file. There was some data that did not have any impact on the target value, such as patient name, current address, etc. Those columns were dropped to get a more manageable and compact dataset. The dataset also had several features with non-numeric values to make the questions more understandable for the participants. We encoded those values into numerical levels using Python libraries. After all the other features were encoded, we calculated the depression total by adding the officially assigned values per question of the PHQ-9 scale [40]. We then checked to which range of depression the total belonged and encoded the ranges as well. There were a few fields where we could expect null values. However, upon checking the dataset, there were none. So we did not need to impute any null values. Sklearn MinMaxScaler [117] of Python was used to scale the data so that any feature that may dominate and lead to a biased decision can be eliminated.

We used Cronbach's alpha [39], a measure of internal consistency, to validate our dataset. The dataset consisted of 22 items, and the value for Cronbach's alpha for the questionnaire is $\alpha = 0.77$. This value is in the higher range of 'acceptable' internal consistency (Table 4.1). Also, the range of values is [0.682, 0.844], indicating a 95% confidence interval for the true alpha value, which suggests that the calculated value is likely to be reasonably accurate.
We used the corr function of the pandas library [112] and the heatmap function of the seaborn [114] in order to find the heatmap and the correlation between the prevalence of depression and its symptoms. To identify the maximum clique in the network of depression and its symptoms, we utilized the find_cliques method of the Python networkx library [107]. We used the abbreviations of Table 4.2 to designate various symptoms of depression:

Cronbach's Alpha	Internal Consistency
$\alpha \geq 0.9$	Excellent
$0.9 > \alpha \geq 0.8$	Good
$0.8 > \alpha \geq 0.7$	Acceptable
$0.7 > \alpha \geq 0.6$	Questionable
$0.6 > \alpha \geq 0.5$	Poor
$0.5 > \alpha$	Unacceptable

Table 4.1: Reliability index interpretation for Cronbach's alpha [39]

Abbreviation	Symptoms	Abbreviation	Symptoms
Int	No interest in work	Fbd	Feeling bad about ownself
Hpl	Feeling down or hopeless	Con	Trouble concentrating
Slp	Trouble feeling asleep	Slw	Moving or speaking noticeably slowly
Eng	Little energy	Hrm	Self-harming thoughts
Apt	Poor appetite	Shar	Trouble in Sharing Pain with Others
DrpL	Depression Level		

Table 4.2: Depression Screening Symptoms and Abbreviations

4.3.2 EEG Signal

The EEG signals were transferred from the headset to a mobile phone using a Bluetooth connection. The mobile phone used was strongly password protected, dedicated only to the research purpose, and had no internet connection initialized to it as a way of protecting the highly sensitive biological information from any kind of remote attacks and unauthorized data transfers. Due to technical issues encountered during the data collection process, the EEG data obtained from three cancer patients became corrupted. The reported EEG values lack specific units and hold significance only in relation to one another and their own measurement. Therefore, we employed a method of calculating relative power by determining the absolute power within each frequency band and expressing it as a percentage of the total absolute power across all frequency bands [5].

To identify any differences or similarities in neurobiological markers of depression among the cancer patients, we compared EEG signals from depressed and non-depressed cancer patients while they were sketching the self-reflection pictures. The length of the collected EEG signals varied among different individuals. To ensure uniformity, we downsampled our data. Formally, downsampling refers to the process of reducing the sampling rate or resolution of a signal or dataset by selecting a subset of the original samples [99]. It involves decreasing the number of samples or observations in the dataset while attempting to retain essential information or characteristics of the original data. In the context of digital signal processing, downsampling is achieved by applying a low-pass filter to the original signal and then selecting samples at a lower rate. The low-pass filter removes high-frequency components that exceed the desired new sampling rate, preventing aliasing effects. Mathematically, downsampling can be represented as a discrete-time operation where a sequence of samples $x[n]$ is transformed into a new sequence $y[m]$ with a reduced sampling rate. The downsampling operation is typically denoted as $y[m] = x[Lm]$, where L is the downsampling factor [102].

We downsampled the EEG data to a desired sample rate of 50% and reduced high-frequency noise using a low-pass filter. High-frequency noise can come from various sources, including electromagnetic interference, muscle activity, or environmental factors [106]. To achieve this, we first calculated the Nyquist frequency by multiplying the original sampling frequency by 0.5. The Nyquist frequency represents the maximum frequency that can be accurately represented in the sampled data [98]. Next, we determined the cutoff frequency for the low-pass filter. In this case, the cutoff frequency (cutoff_freq) was calculated as 0.4 times the new sampling frequency (fs_new). Adjusting the cutoff frequency allowed us to control the amount of high-frequency noise we wanted to remove from the signal. Using the calculated Nyquist frequency and the cutoff frequency, we designed a Butterworth filter with a specified filter order. The filter coefficients (b and a) were obtained, which define the transfer function of the filter. Finally, we applied the Butterworth filter to the EEG data. Each band of the data was filtered using the filter coefficients to reduce high-frequency noise. The resulting filtered signals were then downsampled by the specified decimation factor. By calculating the Nyquist frequency, determining the appropriate cutoff frequency, and designing the Butterworth filter [100], we were able to effectively filter the EEG data and reduce high-frequency noise, ultimately achieving our goal of downsampling and improving the quality of the signals.

We compared the original and scaled EEG data and to validate the similarity between them, we checked the feature similarity. We explored a deep Learning based approach with a pre-trained Convolutional Neural Network (CNN) named VGG16 to extract features from the graph images [118]. VGG16 extracts features from the graph images, and then, we calculated the cosine similarity between the extracted features from the graphs. High similarity values indicate more similar results. The cosine similarity metric is used to measure the similarity between the feature vectors of the two images [116]. Cosine similarity computes the cosine of the angle between the vectors, indicating how similar the images are in terms of their visual content. Based on the calculation, we can determine whether the two graph images are considered similar or not.

We calculated the percentage difference for each feature between the EEG data while drawing in our theme of 'before cancer phase self-reflection' and 'after cancer phase self-reflection'. As we collected the data for the two segments separately, we tried to distinguish the EEG features of these two phases for all the patients with percentage differences. We utilized the features of the Python library DataFrame to calculate the percentage difference. To calculate the percentage difference for a specific feature, we used the formula:

$$\text{Percentage Difference} = \frac{After - Before}{Before} * 100\% \tag{4.1}$$

We compared EEG data from 'Before' and 'After' sessions for multiple participants. The Python code we used reads the CSV files containing the data for each participant and calculates the percentage difference for each feature column. A positive percentage difference indicates an increase, while a negative percentage difference indicates a decrease. The code manually calculates the percentage difference by subtracting the 'Before' values from the 'After' values, dividing by the 'Before' values, multiplying by 100, and storing the results in the result_df DataFrame. Statistical information is extracted from the results, including the count of samples that show an increase or decrease for each feature. This information provides insights into the changes observed in the EEG data before and after, specific sessions for each participant. Then we generated comparison graphs for the EEG trends using data from the extracted features from the percentage difference in EEG trends between two conditions. We utilized the pandas library to read the files and extract the trend names. It then calculates the number of rows and columns required to arrange the subplots based on the number of trends. The matplotlib library is used to create a figure with subplots for each trend. For each trend, the code plots the values for increased and decreased conditions on the corresponding subplot. The titles, labels, and legends are set accordingly. The resulting plot is saved as a PNG file, and it is also displayed for visualization.

4.3.3 Free-Hand Sketches

Different qualitative and quantitative analyses were performed on the free-hand sketches drawn by tour participants.

Qualitative Analysis

To facilitate the qualitative interpretation of sketches, we formed a multidisciplinary team comprising researchers, a psychologist, and an artist. This interdisciplinary composition of our team enabled us to draw insights from various perspectives, incorporating psychological, artistic, and research-based expertise. We adopted the critical visual methodology framework developed by Rose as a guide for our analysis. This framework has previously been proven effective in comprehending the experiences of individuals with chronic pain through their artistic depictions [52], [95]. According to Rose's framework, the interpretation of a visual image involves three distinct aspects: the process of its creation, its visual characteristics, and the perception and interpretation of the image itself.

Our approach to the interpretation placed specific emphasis on the compositional aspects of sketches, aiming to minimize biases in understanding the implied messages conveyed by the artists through their artwork [4], [61]. To achieve this, we utilized our own as well as participant-given written annotations as valuable sources of insight. We cross-checked our understanding using a set of predetermined questions pertaining to sketch content, organization, and expression. Along with that, we initially assigned numbers to the sketches according to their contents, and through discussion and multiple review processes, we collaboratively grouped those into various common themes.

Quantative Analysis

The free-hand sketches were captured and converted into digital images using a mobile phone camera (specifically, the Xiaomi Redmi Note 10 Pro). We monitored the digital images' proper alignment and clarity. We selected and agreed upon six sketch indicators whose relevance had previously been tested to identify potential cases of depression and similar psychological cases. Those were:

1. Hair density
2. Body outline (boldness, dual stroke)
3. Lip line (smile curve, frown)
4. Presence of tears
5. Lower body sketch
6. Overall body weight depiction

As free-hand sketches are very irregular in general and each feature of free-hand sketches can vary from person to person and even within two sketches drawn by the same person, detecting every feature computationally was not possible. We detected some of these indicators using computational methods and others using manual processing techniques.

- **Computation methods:** To assess the boldness of the sketches, we applied the binary thresholding technique to convert the sketches into binary images [110]. The distanceTransform function of the Python OpenCV library [108], in combination with the Numpy library [72], was utilized to calculate the median stroke and determine the boldness value of each sketch.

  In order to detect hair density, we applied the Morphological Closing Operation, Histogram Analysis Algorithm, and Watershed Algorithm methods. The morphological closing operation and the Watershed algorithm both require the images to be converted to grayscale. So we applied Binary Thresholding to the images. Then, Morphological Closing [111] was used to fill small gaps in the images, enabling a more accurate assessment of hair density. The operation counts the number of black and white pixels, sums them up, and calculates hair density as the ratio of hair pixels to total pixels. Similarly, the Watershed algorithm [109] segments hair from the background, counts the number of hair pixels and total pixels in the hair mask and finally computes hair density as the ratio of hair pixels to total pixels. In the case of the histogram analysis algorithm, it computes the histogram of the images, and then hair density is computed as the ratio of black pixel count to total pixel count.

- **Manual Processing Techniques:** For the indicators which needed manual detection, two researchers and one artist each evaluated the sketches individually first and cross-checked with one another at the end. If the identification matched, the presence number was counted, else, the team re-evaluated the sketches. We also utilized the National Institutes of Health (NIH) Image-J software [104] for the sketch analysis and initiated it by importing the scanned images into the software. We performed various measurements, including vertical length, horizontal length, the total area of the sketch, area of the damaged portion, percentage of the damaged area, and total area change percentage, to gain a comprehensive understanding of the differences between non-depressed and depressed cancer patients sketches, as well as to evaluate the changes within each individual's before and after ones. To calculate the area of the whole sketch and the area of the damaged portion, we manually traced the outside perimeters of the drawn sketches and any part of the drawing considered as damaged or changed. The software then provided the corresponding area measurements in pixels. We derived the percentage of the damaged area by dividing the calculated damaged area by the total area of images drawn as post-self-reflection. This metric helped quantify the extent of the damage or change in the sketches. Furthermore, we assessed the area change percentage by calculating the difference between the areas of pre and post-drawn images and dividing it by the area of the pre-drawn image. We used Wilcoxon Signed-Rank tests [64] to determine if there were statistically significant variations in horizontal lengths, vertical lengths, and total areas between before and after sketches of non-depressed and depressed patients.

With the help of the pre-trained VGG-16 model of Keras [118] and the Python Scipy library [36], we preprocessed the before and after sketches of each patient with the same preprocessing function used to train the VGG-16 model on the imagenet dataset [105] and extracted the feature vectors for each set of images. Using Python scikit-learn, cosine similarity [116] was computed to identify the similarity level between the self-reflection images before and after their cancer diagnosis. The output is a value between 0 and 1, where 0 means no similarity and 1 means the two images are identical. The closer the value is to 1, the more similar the images are in terms of their visual features. Next, given the non-linearity and limited size of our dataset, we opted for Support Vector Machine (SVM), Random Forest, and Convolutional Neural Network (CNN) models with five-fold cross-validation. We developed these models to identify potential cases of depression among cancer patients using computationally and manually extracted sketch features and demographic data. Later, to enhance the accuracy of the predictions, we combined sketch features and EEG data during the sketching process. Through rigorous experimentations, we figured out that Random Forest with five-fold cross-validation demonstrated superior performance in identifying potential cases of depression among cancer patients based on the combination of sketch features and EEG data.

Chapter 5

Findings

Of the 75 participants approached to take part in the study, 66 participants provided written consent and took part in the data collection procedure. This represents an 88% response rate. There was no particular association between the age group and a lower likelihood of participating. Sociodemographic variables for n=66 are presented in Table 5.1.

5.1 Perspective, Cancer, and Depression

During our interviews, we had the privilege of hearing firsthand accounts from participants who openly shared personal experiences about the profound impact of their cancer diagnosis on them and their family members' lives. These stories revealed a range of struggles and challenges that differed based on the gender of the patients. Male patients spoke about the financial hardships they encountered as they were not able to continue their jobs anymore. Many expressed concerns about their ability to provide for their families and the pressure they felt to ensure their daughters were married off before their own demise. A 48-year-old patient with stage 4 cancer shared,

"I used to own five shops in the market back in the day. None are left. This monster (cancer) took everything from me. Now I don't even have money to buy rice. It would be better to die than experience this."

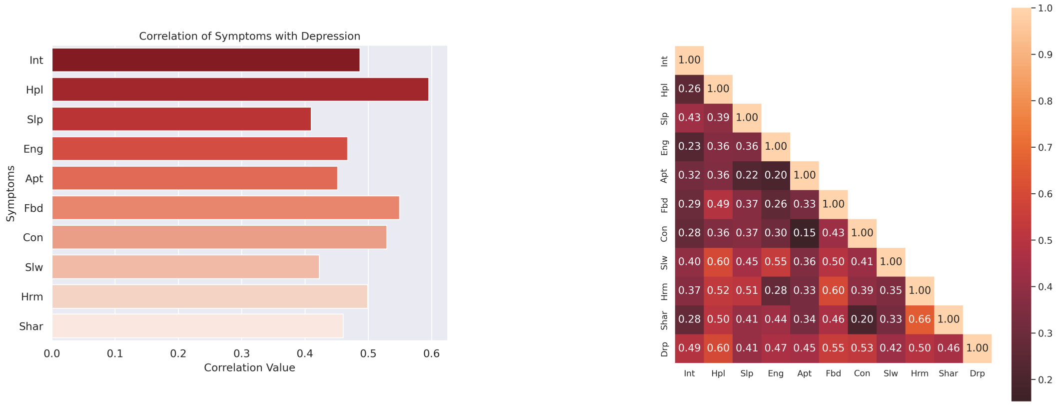
The female patients also highlighted financial struggles but often emphasized the physical and emotional toll of their illness. They described how their weaknesses and physical limitations hindered their ability to fulfill their traditional caregiving roles with the family. Some even shared heart-wrenching stories of divorce and the challenges they faced in maintaining their sense of self-worth and identity. The impact on their appearance, such as hair loss or bodily changes, contributed to feelings of despair and a diminished sense of self-esteem. A 28-year-old patient with stage 3 cancer said,

"I have a three-year-old son. He cries in fear whenever he sees me. I didn't stand in front of a mirror for who knows how many days."

In addition, some participants provided unique perspectives on their journey to

Variable	Value
Age, n (%)	
18-24	15 (22.72)
25-44	16 (24.24)
45-64	18 (27.27)
65+	17 (25.75)
Gender, n (%)	
Male	36 (54.54)
Female	30 (45.45)
Others	0 (0)
Highest Level of Education, n (%)	
<SSC/Equivalent	16 (24.24)
SSC/Equivalent	10 (15.15)
HSC/Equivalent	11 (16.67)
Diploma/Equivalent	12 (18.18)
Bachelor/Equivalent	6 (9.09)
Masters/Equivalent	5 (7.58)
Ph. D/Equivalent	6 (0.09)
Employment Status, n (%)	
Employed (Full-time/Part-time/Homemaker/Voluntary)	48 (72.73)
Unemployed	12 (18.18)
Retired or other (Disability)	6 (9.09)
Marital Status, n (%)	
Unmarried	6 (9.09)
Married	47 (71.21)
Widowed	8 (12.12)
Divorced	5 (7.57)
Total Child Count, mean	2.52
Economical Status, n (%)	
Low-Income	26 (39.39)
Medium Income	25 (37.87)
High Income	15 (22.72)
Cancer Stage, n (%)	
Stage 01	25 (37.88)
Stage 02	20 (30.30)
Stage 03	19 (28.79)
Stage 04	2 (3.03)
Operation Status after Cancer Diagnosis, % needed	36 (54.54)
Family History of cancer, % yes	29 (43.94)
Loan, % yes	26 (39.39)

Table 5.1: Sociodemographic variables for 66 cancer patients. Age categories [2], Economical status categories [83]



(a) Correlation between depression and its symptoms

(b) Correlation Heatmap

Figure 5.1: Correlation & Heatmap between depression and its symptoms

cope with cancer and its effects. A 20-year-old patient with stage 3 cancer told us,

"Life is a gift of Allah. No matter how much I have to suffer or how many days I will be alive, I want to live every day to the fullest."

It is important to note that these stories reflect the diverse experiences and perspectives of the individuals interviewed. While certain themes may emerge based on gender or age, it is essential to recognize that each person's journey with cancer is unique, and their struggles may encompass a broader range of factors beyond those we got to know.

From our collected data, we analyzed the responses of the participants to the PHQ-9 scale to measure the prevalence of depression among them. Table 5.2 depicts the depression level status of the sample size screened through the aforementioned screening scale.

Depression Levels	Male (% of male)	Female (% of female)	Total, n (%)
None	9 (25)	6 (20)	15 (22.72)
Mild	9 (25)	2 (6.67)	11 (16.67)
Moderate	8 (22.22)	10 (33.33)	18 (27.27)
Moderately Severe	6 (16.67)	8 (26.67)	14 (21.21)
Severe	4 (11.11)	4 (13.33)	8 (12.12)

Table 5.2: Depression level status of n = 66 cancer patients screened through PHQ-9 scale

In order to represent the interrelationship between depression and its symptoms among cancer patients, we used maximal clique identification and correlation heatmaps. In the heatmap, the lighter colours indicate higher correlation, and the darker colors indicate lower correlation values (Figure 5.1b).

5.2 Networks based on Depression among Cancer Patients

5.2.1 Correlation Network (CNDCP)

We created the Correlation Network of Depression among Cancer Patients (CNDCP) in Figure 5.2 in order to comprehend the dynamics between depression level and the depressive symptoms derived from the PHQ-9 questionnaire scale. In the generated undirected graph, the edges show significant Benjamin-Hochberg correction correlation between depression Level and its associated symptoms. The width and color variation of the edges indicate how strongly two nodes (symptoms) are correlated. The wider the edge, the stronger the association.

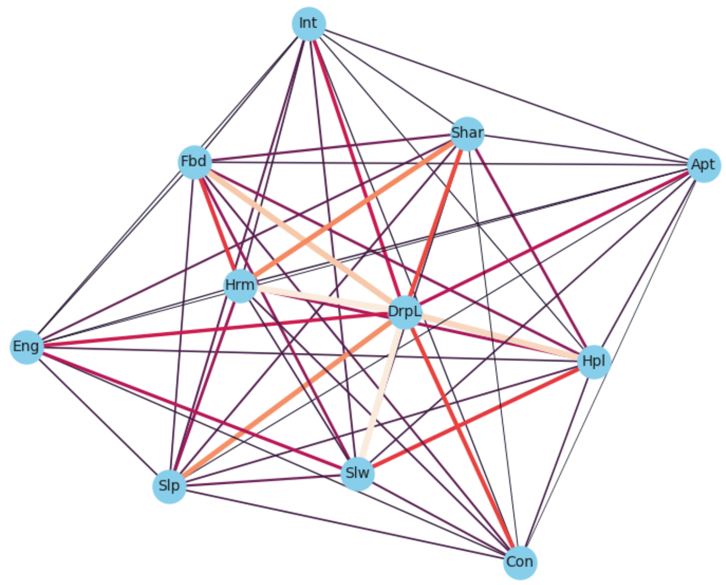


Figure 5.2: Correlation network based on Benjamini-Hochberg corrected statistically significant correlations (r $\geq$ 0.75, P $<$ 0.25)

As shown by CNDCP (Figure 5.2), there is a strong correlation (wider edges) between depression level and all other psychiatric symptoms. The lower correlation is seen between Depression and 'Poor Appetite' (r = 0.37), and Depression Level and 'Trouble in Sharing' (r = 0.41). The nodes for 'Self-harm Thoughts' (r = 0.74), 'Moving or Speaking Noticeably Slow' (r = 0.65), 'Hopelessness' (r = 0.58) and 'Feeling Bad about Oneself' (r = 0.57) show the highest association in this graph. The nodes 'Trouble Sleeping' (r = 0.52) and 'Lack of Interest' (r = 0.47) have also shown significant associations with Depression Levels. This graph does not show any negative correlation. The cluster of 'Self-harming Thoughts', 'Feeling Bad about Oneself', 'Moving or Speaking Noticeably Slow', 'No Interest in Work', 'Lack of Concentration', and 'Hopelessness' supported the DSM-IV clinical theory regarding depression [101]. A maximum clique with a significant relationship between depression levels and its symptoms was found in our network of cancer patients' depression correlations (Figure 5.3). Here, we demonstrated how borders that are

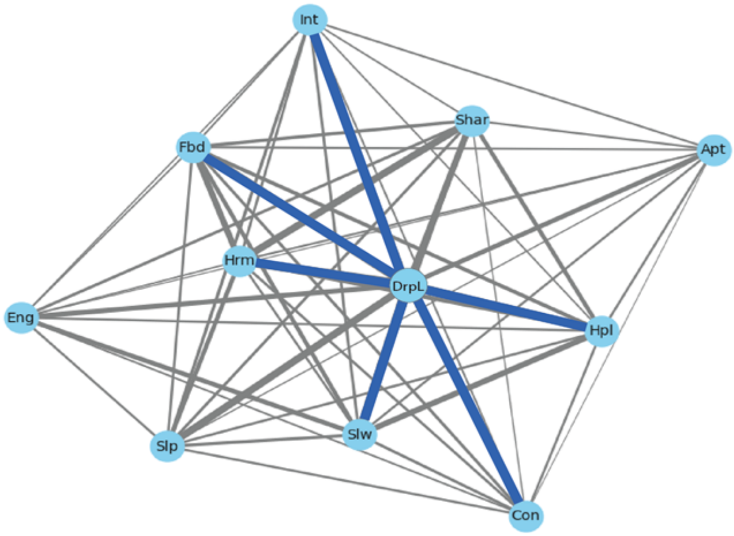


Figure 5.3: Maximum Clique in the Correlation Network of Depression among Cancer Patients

wider and darker have a stronger correlation. We found one maximum clique of 7 entities and 6 symptoms along with depression level. The symptoms in the maximum clique are- 'Self Harming Thoughts', 'Moving or Speaking Noticeably Slow', 'Feeling Bad about Oneself', 'Hopelessness', 'No Interest in Work', and 'Lack of Concentration'. According to the DSM-IV criteria, this maximum clique successfully groups the symptoms associated with depression [101].

5.2.2 Partial Correlation Network (PCNDCP)

Next, In our study, we aimed to explore the relationships between depression and its associated symptoms among cancer patients by developing the Cancer Patients' Depression Partial Correlation Network (PCNDCP). This network analysis allowed us to identify the direct interactions between depression and various symptoms, shedding light on their interconnectedness. The network derived from the depressive symptoms of the cancer patients appears in Figure 5.4. The edges in this network represent Benjamini-Hochberg corrected statistically significant partial correlations ($r \geq 0.75$, $P < 0.25$) among different entities. Only the stronger partial correlations are represented in this graph. We can see the Parital Correlation Network (Figure 5.4) is less dense, i.e., contains fewer edges than the Correlation Network of Depression among Cancer Patients (Figure 5.2). In this graph, we have eradicated the interconnected edges of different symptoms and depicted the symptoms vastly and directly correlated with depression level only. By eliminating the interconnected edges of different symptoms, we highlighted the symptoms that were highly and directly correlated with depression. This refined representation provides a clearer understanding of the symptomatology associated with depression among cancer patients.

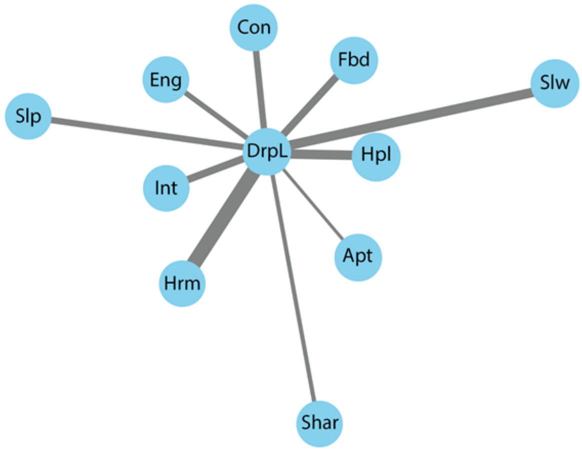


Figure 5.4: Partial Correlation Network of Depression among the cancer patients

5.2.3 Bayesian Regulatory Network

Figure 5.5 shows the Regulatory Network of Depression among Cancer Patients. We constructed the Regulatory Network of Depression among Cancer Patients using Bayesian inference based on the depressive symptoms reported by the cancer patients. This network model uncovers a complex structure of relationships between depression and its associated symptoms. Through this model, we gain a deeper understanding of the interconnections and can make more confident inferences about the directions of these associations. This enables us to infer the directions of several associations more securely.
The varying thickness of the edges in the network indicates the degree of confidence in the predicted flow of information and potential causation in the depicted direction. Several significant features are evident in this regulatory network.

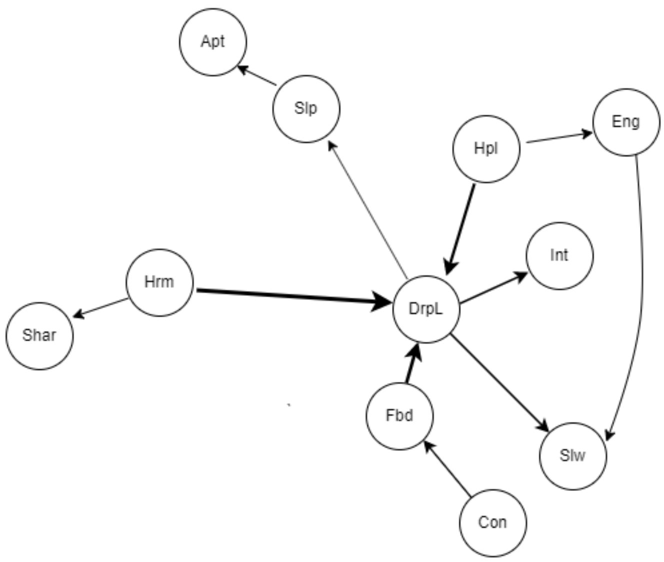


Figure 5.5: Directed Acyclic Graph of Bayesian Regulatory Network of depression and the symptoms

First, ‘Feeling Bad about Oneself’, ‘Self Harming Thoughts’, ‘Hopelessness’ related stimuli are the significant consistences of depression. From the prediction, we notice, ‘Self-harming Thoughts’ stimuli projects the most constituency of depression among Cancer Patients. The network directly constitutes the connection between ‘Difficulty in Sharing Things’ and ‘Self-harming Thoughts’, which refers to a significant factor in suicidal tendency. Many studies have found out the reason of trouble sharing the pain with others has lead to self-harm or suicide [97]. This network predicts the correlation between ‘Lack of Energy’ and ‘Moving or Speaking Noticeably Slow’, which is another logical connection.
The Regulatory Network of Depression among Cancer differs from both Correlation Network and Partial Correlation Network in a number of ways. As per the Regulatory Network, depression is directly associated with three depressive symptoms: ‘Hopelessness’, ‘Feeling Bad about Oneself’, and ‘Self-harming Thoughts’.

5.3 Centrality

To measure the importance of symptoms in the Correlation Network of Depression among cancer patients, we used two centrality measurements: strength (Figure 5.6) and betweenness (Figure 5.7).

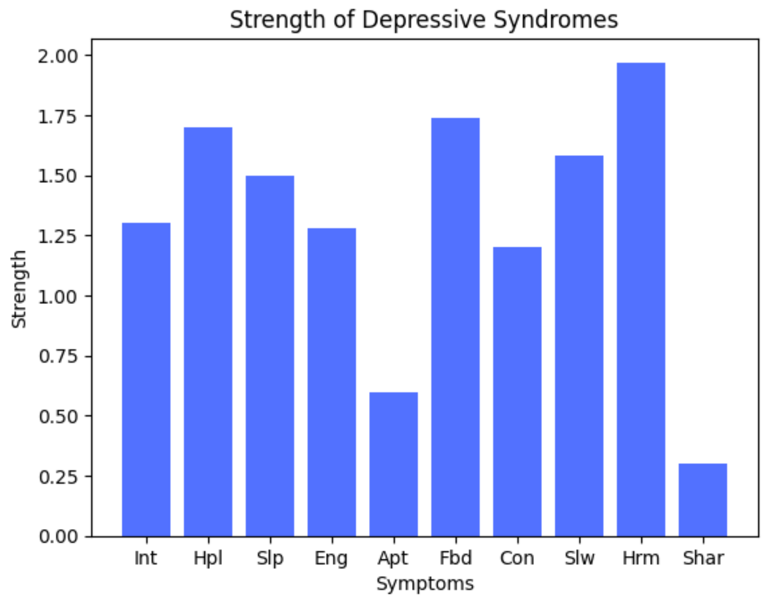


Figure 5.6: Strength of depressive syndromes in the Correlation Network of Depression among Cancer Patients

‘Self-harming Thoughts’, ‘Feeling Bad about Oneself’ and ‘Hopelessness’ turn out to be highly central symptoms from the ‘Strength and Betweenness Centrality’ score. The importance of these specific features is also strongly visible in the Correlation Network and Partial Correlation Network of Depression among Cancer Patients. Among all the depressive symptoms, ‘Self-harming Thoughts’ has the highest betweenness score as it directly interconnects with most of the other depressive symptoms. On the contrary, we have found out from the Strength Centrality graph of that, ‘Trouble in Sharing the Pain with Others’ and ‘Poor Appetite’ tend to have the least positive strength score. There is no negative score in both of the degree centrality measurements. Negative centrality scores indicate the poorly interconnected nodes or the nodes without connection [57]. As there are no negative centrality measures in these graphs, it depicts that all the nodes are interconnected.

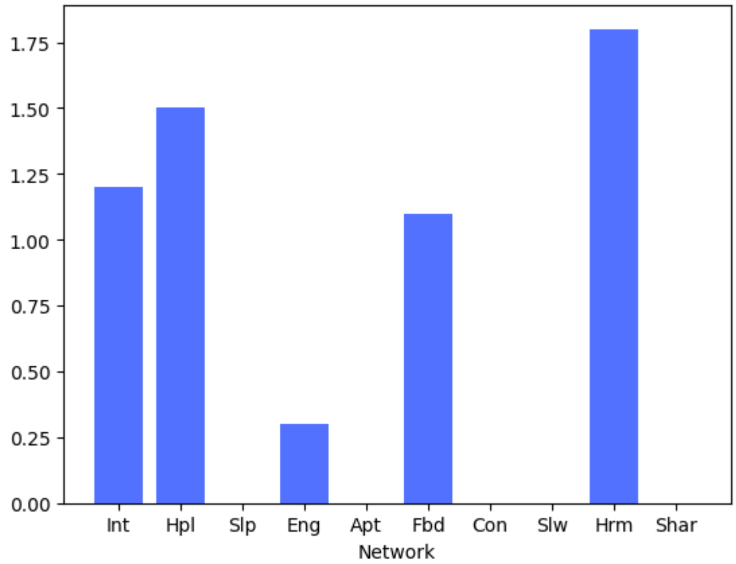


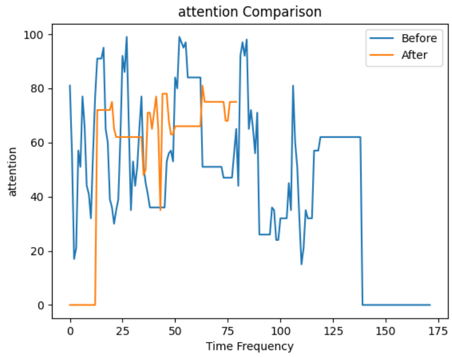
Figure 5.7: Betweenness centrality graph of Correlation Networks of Depression among Cancer Patients

5.4 Analysis on EEG signals of Cancer Patients

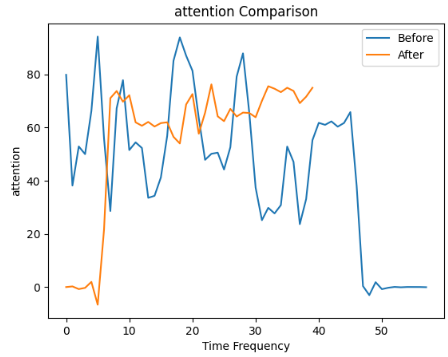
5.4.1 Comparison of the Original and Scaled EEG signals

After employing bandpass filter and downsampling, the processed data illustrated the same features (i.e., increase or decrease of frequencies) as the original data. The headset we used, the Neurosky Mindwave Mobile Headset, collects EEG data in 13 bands which are 'eegRawValue', 'eegRawValueVolts', 'attention', 'meditation', 'blinkStrength', 'delta', 'theta', 'alphaLow', 'alphaHigh', 'betaLow', 'betaHigh', 'gammaLow', 'gammaMid'. We utilized the features from 8 bands 'attention', 'meditation', 'delta', 'theta', 'alphaHigh', 'alphaLow', 'betaLow', and 'betaHigh' which depicted significant features for the depressed group in our analysis. The comparison graphs are attached in Figure 5.8, Figure 5.9, and Figure 5.10.

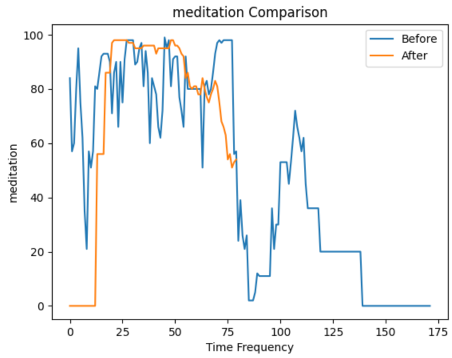
Later, at the end of the validation, we found out that, most of the generated graphs from the original and scaled EEG data yield up to 96% similarity. So, it can be said that our scaled EEG data is appropriate.



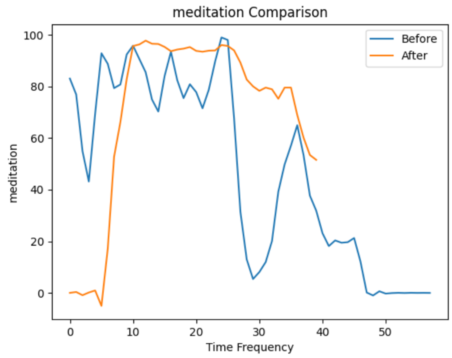
(a) Original 'attention' data from patient p1



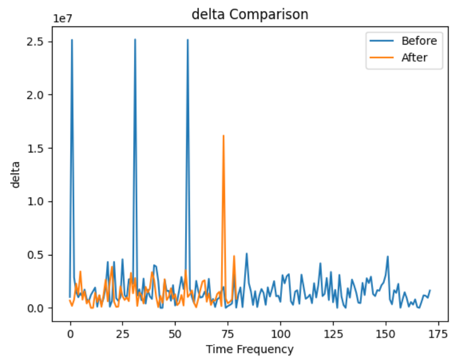
(b) Scaled 'attention' data from patient p1



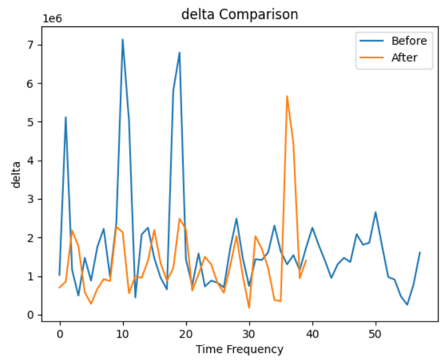
(c) Original 'meditation' data from patient p1



(d) Scaled 'meditation' data from patient p1

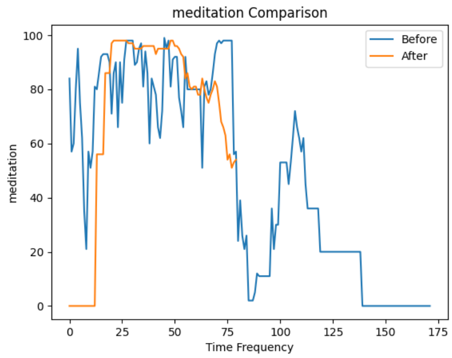


(e) Original 'delta' data from patient p1

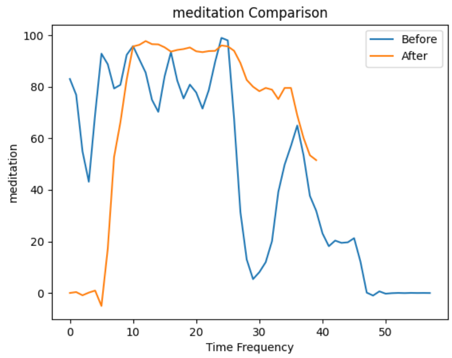


(f) Scaled 'delta' data from patient p1

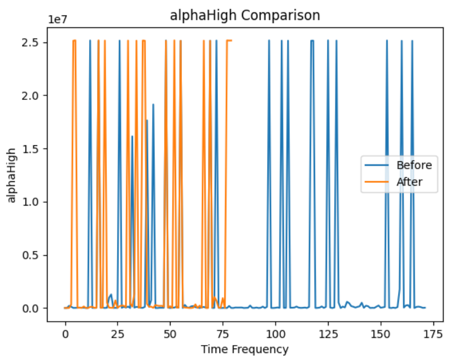
Figure 5.8: Comparison between original and scaled EEG signals of 3 bands (attention, meditation, delta) from one patient while sketching the before and after self-reflection sketch



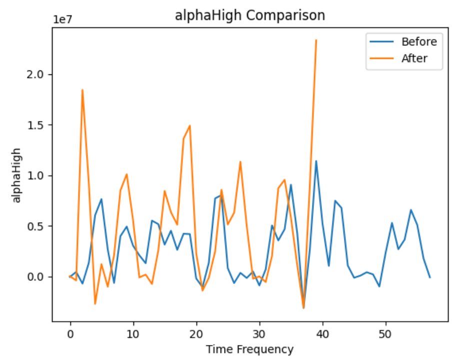
(a) Original 'theta' data from patient p1



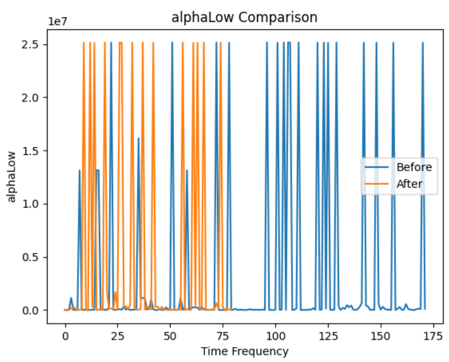
(b) Scaled 'theta' data from patient p1



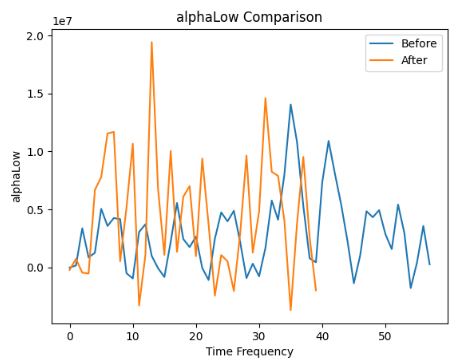
(c) Original 'alphaHigh' data from patient p1



(d) Scaled 'alphaHigh' data from patient p1

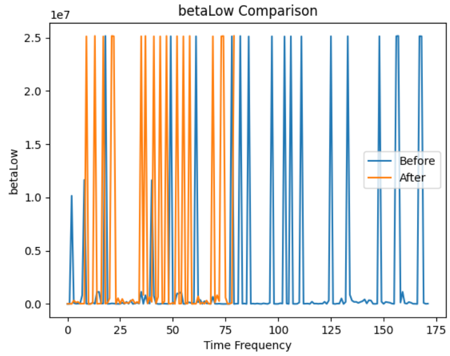


(e) Original 'alphaLow' data from patient p1

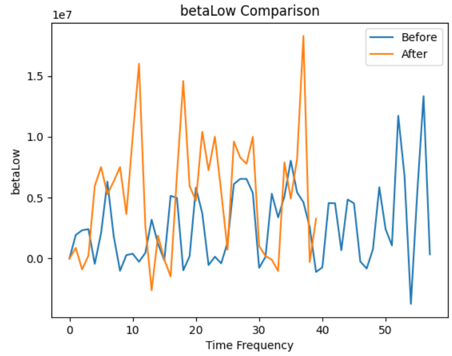


(f) Scaled 'alphaLow' data from patient p1

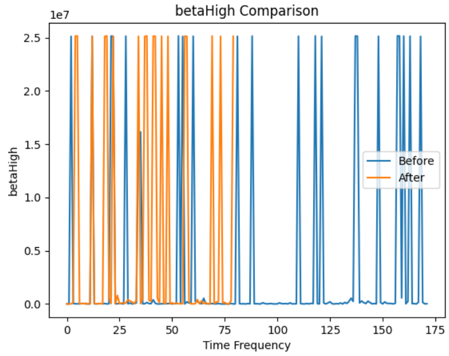
Figure 5.9: Comparison between original and scaled EEG signals of 3 bands (theta, alphaLow, alphaHigh) from one patient while sketching the before and after self-reflection sketch



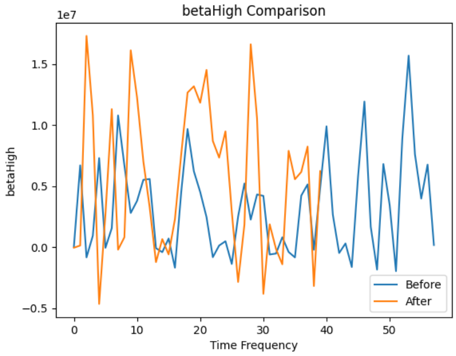
(a) Original 'betaLow' data from patient p1



(b) Scaled 'betaLow' data from patient p1



(c) Original 'betaHigh' data from patient p1

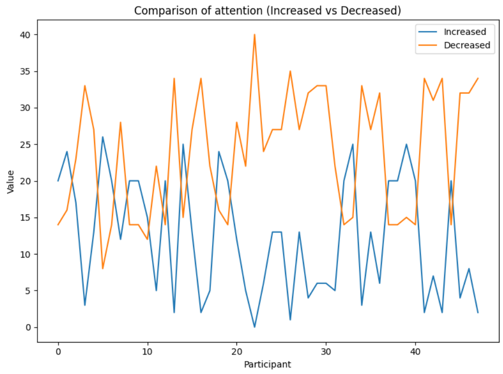


(d) Scaled 'betaHigh' data from patient p1

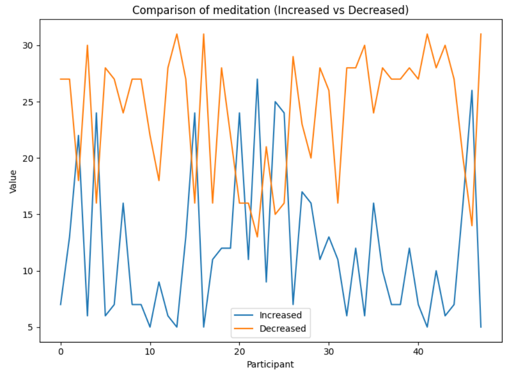
Figure 5.10: Comparison between original and scaled EEG signals of 2 bands (betaLow, betaHigh) from one patient while sketching the before and after cancer phase of self-reflection

5.4.2 Percentage Difference of EEG data while sketching Before and After-phase of cancer

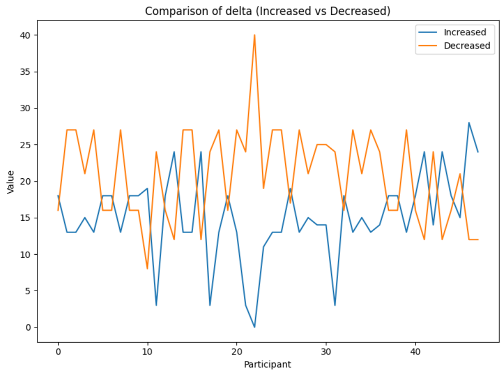
The percentage difference extracted features for each EEG band in our entire dataset. The curves in Figure 5.11 actually represent the ratio of patients experiencing an increase or decrease in EEG values. Upon observing the curves, it is evident that for the alphaLow, alphaHigh, betaLow, betaHigh, and theta bands, the number of patients with an increasing change in EEG values is higher compared to those with a decreasing change. Conversely, in the case of the delta, attention, and meditation bands, the opposite pattern is observed, with a higher proportion of patients showing a decrease in EEG values.



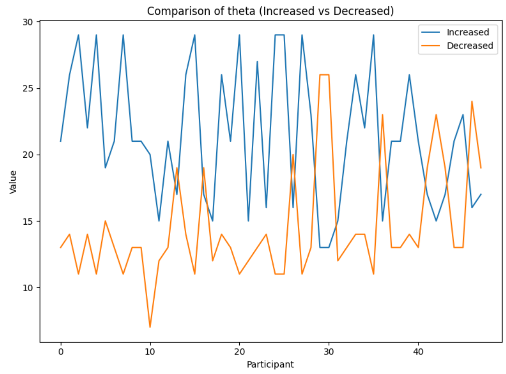
(a) Comparison of ‘attention’ EEG data



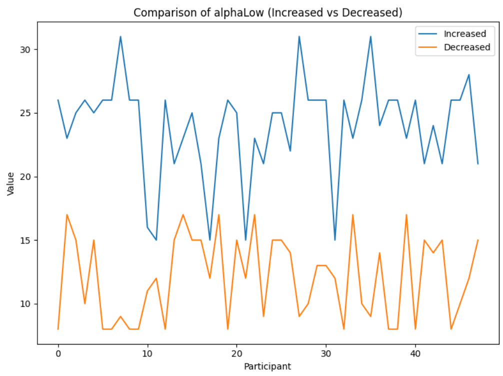
(b) Comparison of ‘meditation’ EEG data



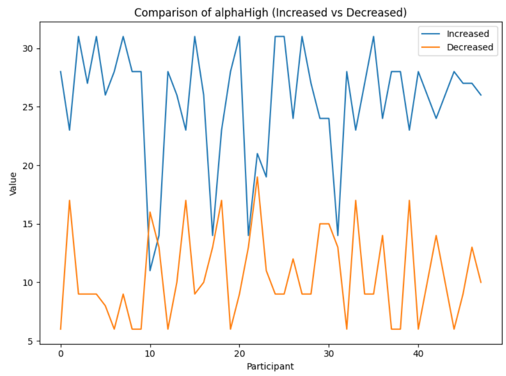
(c) Comparison of ‘delta’ EEG data



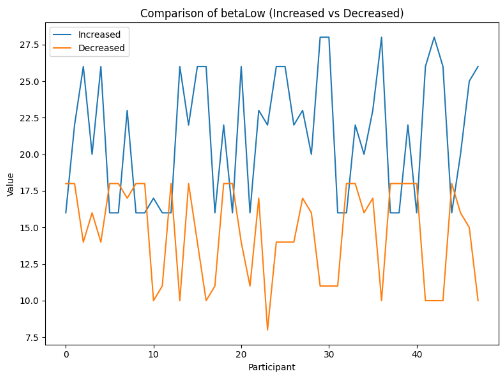
(d) Comparison of ‘theta’ EEG data



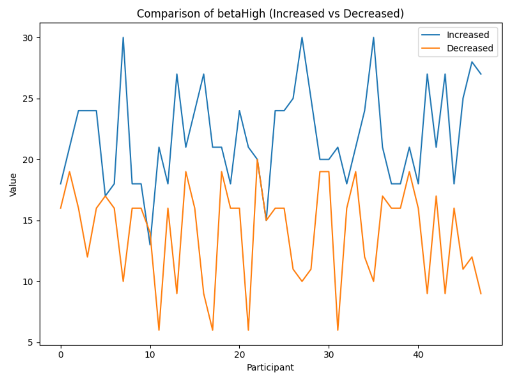
(e) Comparison of ‘alphaLow’ EEG data



(f) Comparison of ‘alphahigh’ EEG data



(g) Comparison of ‘betaLow’ EEG data



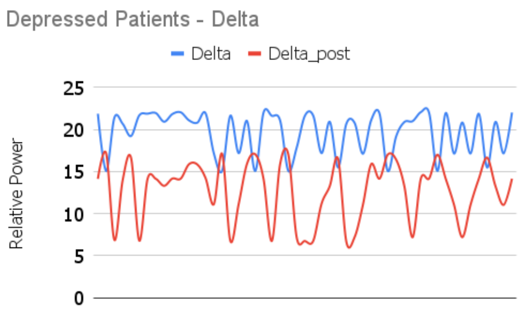
(h) Comparison of ‘betaHigh’ EEG data

Figure 5.11: Percentage change graphs of eight EEG bands

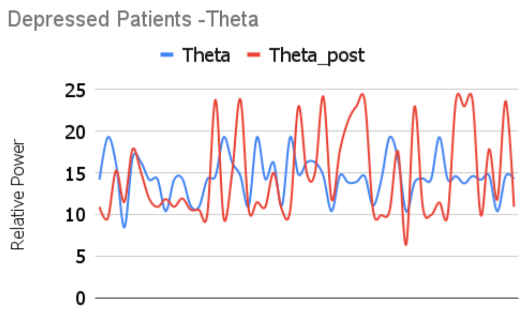
5.4.3 Relative EEG Power during Sketching Session

We have found some common patterns in the EEG band values of potentially depressed participants. These EEG data were taken while the participants sketched theirs before and after self-reflection.

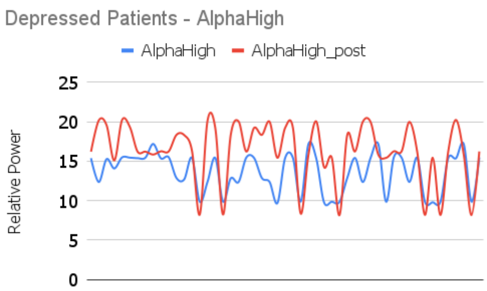
- We observed an increase in the alpha, beta, and theta bands while drawing the after-self-reflection sketches compared to the before-self-reflection ones (Figure 5.12).
- We observed a decrease in the delta band while drawing the after-self-reflection sketches compared to the before-self-reflection ones (Figure 5.12).



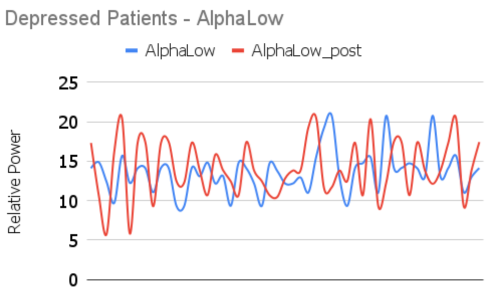
(a) Delta Band



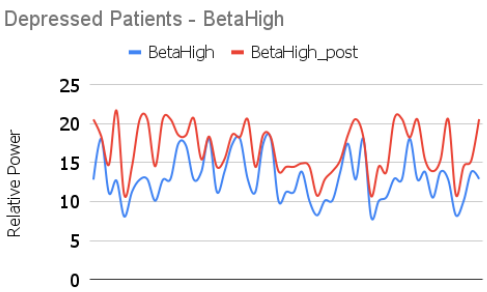
(b) Theta Band



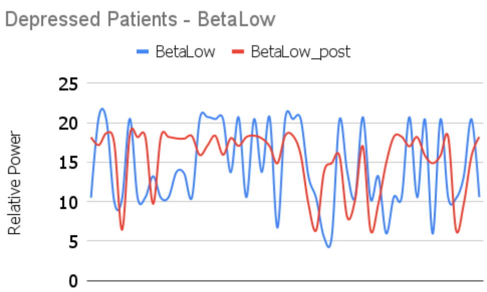
(c) AlphaHigh Band



(d) AlphaLow Band



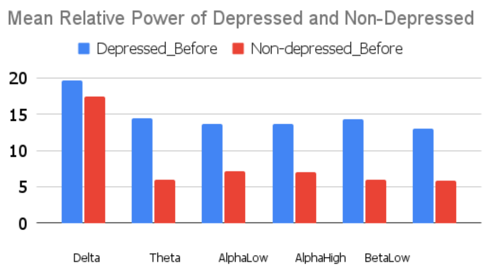
(e) BetaHigh Band



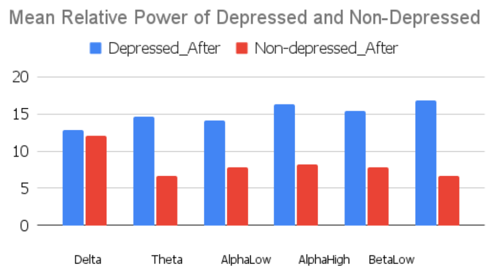
(f) BetaLow Band

Figure 5.12: Smoothed Line Charts of Relative EEG Power Values

As for the non-depressed patients, we observed a lower mean relative EEG power in all bands than that of the depressed patients in the case of both before and after self-reflection sketches (Figure 5.13).



(a) Mean Relative Power during Before-Self-Reflection Sketch

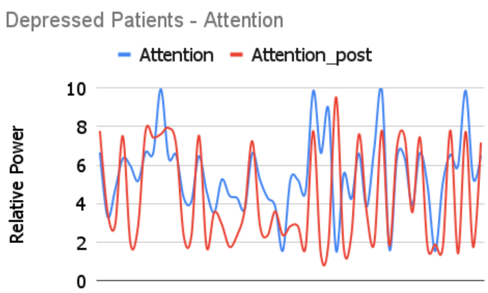


(b) Mean Relative Power during After-Self-Reflection Sketch

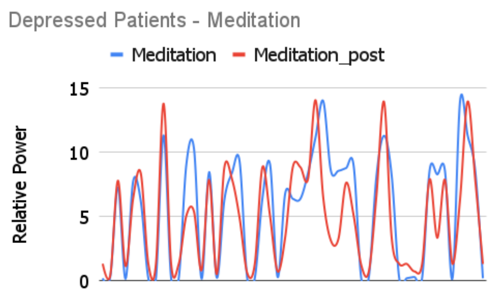
Figure 5.13: Mean Relative Power Comparison of Depressed and Non-Depressed during Before and After-Self-Reflection Sketches

5.5 Attention and Relaxation Levels

In addition to examining the EEG bands, we also investigated the levels of attention and meditation exhibited by the participants during the sketching sessions.
Those who are depressed show a significant decrease in attention while drawing the after-self-reflection sketches compared to the before-self-reflection ones (Figure 5.14). As for the meditation level during after-self-reflection sketching sessions, we could not find any specific pattern in it, rather, it sometimes varied and other times remained similar.



(a) Attention Band



(b) Meditation Band

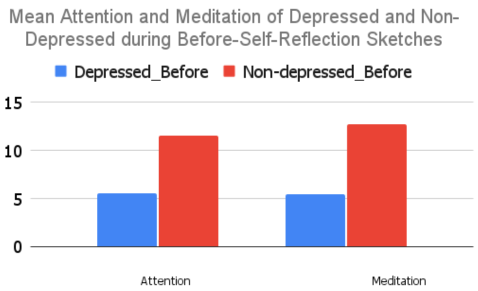
Figure 5.14: Smoothed Line Charts of Attention and Meditation Band Values

We noted that attention and meditation levels in regard to the non-depressed patients exhibited higher mean values compared to the depressed patients (Figure 5.15). This observation held true for both the sketches of before and after self-reflection, with after values being slightly less than the before ones.

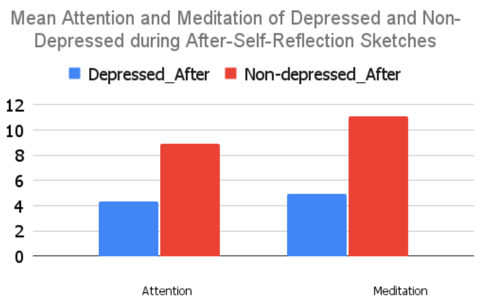
5.6 Visual Analysis of the Free-Hand Sketches

Through a visual examination of all the free-hand sketches, we searched for any potential non-verbal features using which we could divide the sketches into common themes. We got four prominent themes as such (Table 5.3).

- **Self-Reflection showing Appearance:** Approximately 61% of the participants sketched their appearance in order to represent themselves before and



(a) Mean Attention and Meditation during Before-Self-Reflection Sketch



(b) Mean Attention and Meditation during After-Self-Reflection Sketch

Figure 5.15: Mean Attention and Meditation Value Comparison of Depressed and Non-Depressed during Before and After-Self-Reflection Sketches

Theme	Count, n (%)	Sketches from Different Depression Levels (%)				
		None	Mild	Moderate	Moderately Severe	Severe
Appearance	40 (61)	18	23	25	22	12
Activities	10 (15)	10	10	50	10	20
Line Art	9 (14)	45	11	33	0	11
Damaged Area	7 (10)	44	0	0	56	0

Table 5.3: Distribution of sketches across different themes

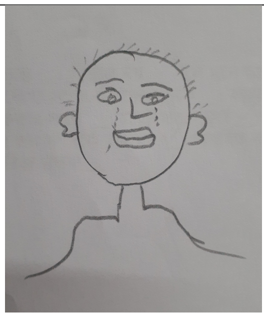
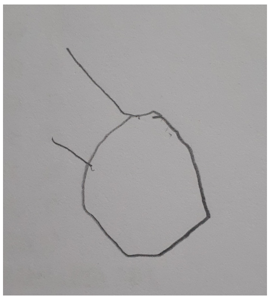
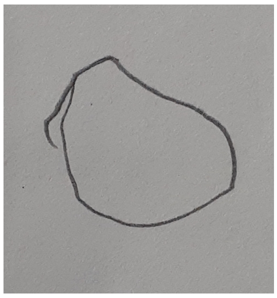
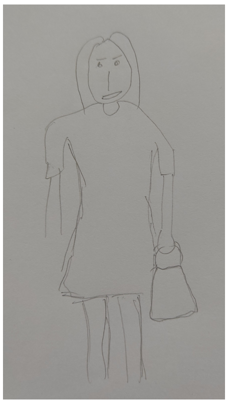
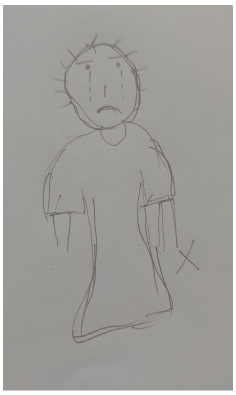
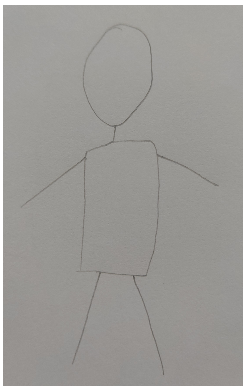
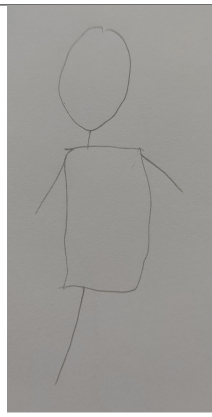
Before	After	Before	After
 (a) Appearance	 (b) Appearance	 (c) Damaged Area	 (d) Damaged Area
 (e) Activities	 (f) Activities	 (g) Line Art	 (h) Line Art

Table 5.4: Presence of different themes in the free-hand sketches of the patients

after they learned about being diagnosed with cancer (Table 5.4a, Table 5.4b). These sketches varied in terms of body parts included, ranging from full body views to the lower half of the body, and some focused solely on the face and above. Notably, some of the sketches also captured the changes in the participants' preferences, such as growing long beards or adopting attire adhering to religious customs or traditions, etc.

- **Self-Reflection in Activities:** In 15% of sketches, the participants expressed their limitations in engaging in various activating due to their cancer diagnosis (Table 5.4e, Table 5.4f). These depictions showcased the challenges they faced in farming, shopping, household tasks, and other aspects of daily life. Inversely, in the after images, many portrayed the presence of cannulas in their arms, crutches, or amputations, symbolizing the physical hindrances that hampered their participation in previously enjoyed activities.

- **Self-Reflection as Line Art:** Among the participants, 14% of them opted to represent themselves only through line art, without including any specific human features (Table 5.4g, Table 5.4h). Surprisingly, 45% of them are non-depressed participants, with 75% belonging to cancer stage 1. It can be hypothesized that they might have experienced difficulty identifying significant changes in their self-reflection before and after their cancer diagnosis, resulting in minimal emphasis in their sketches.

- **Self-Reflection and Damaged Area:** 10% of participants focused exclusively on illustrating the changes in the damaged areas of their bodies associated with cancer (Table 5.4c, Table 5.4d). These sketches depicted the increase in tumour or cyst sizes, or in the case of female patients who underwent mastectomies, the removal of their breasts.

5.7 Computing Methods to Interpret Free-Hand Sketching

5.7.1 Line Boldness

Among the 66 patients included in the study, it was observed that 40 of them had a higher boldness value in the before images. Within this group, 33% of them were non-depressed participants, while 67% were diagnosed with depression. This may be attributed to the participants' inclination towards portraying happier moments in their sketches, resulting in increased pressure and boldness in their before sketches. On the contrary, 22 patients' sketches exhibited a higher boldness value in after sketches, indicating the patients' subconscious tendency to accentuate the areas that have changed, such as amputations or disfigurements, resulting from cancer and its treatments.

Parameters	Values	
	Non-depressed	Depressed
Before and After Horizontal Lengths	0.3027	0.0003
Before and After Vertical Lengths	0.6386	0.0012
Before and After Drawn Area	0.934	0.0002

Table 5.5: Comparison of Wilcoxon Signed-Rank Test on Dimensional Measurements between Depressed and Non-depressed Patients' Sketches

5.7.2 Hair Density

The application of three different methods, namely the morphological closing operation, histogram analysis algorithm, and watershed algorithm, did not yield definite results in our study. All the outputs were zero (0). It might be because the algorithms employed may not possess the required flexibility to effectively handle the irregular and nuanced nature of the free-hand sketches.

5.7.3 ImageJ Results

Features of Sketches

We used the Wilcoxon signed-rank test on horizontal length, vertical length, and total area of before and after sketches for both non-depressed and depressed participants in order to assess whether their population mean ranks differ (Table 5.5). The significance level considered was 0.05.
The results of the Wilcoxon signed-rank test for depressed patients consistently yielded p-values less than 0.05, indicating strong evidence to reject the null hypothesis. This suggested that the mean ranks of the related samples significantly differ, with all the dimensions getting significantly smaller in the after sketches. On the contrary, for non-depressed patients, all the test results yielded p-values higher than the significance level. This lack of statistical significance implies that there was not enough evidence to reject the null hypothesis, meaning there was no significant difference in the mean ranks of the related samples.
While analyzing the relation between the depression level and the damage percentage in after-images changed, we found that non-depressed patients exhibited the least amount of percentage change, while patients with moderately severe depression demonstrated the highest. The intermediate levels of depression showed gradual increases in the values. Notably, participants with severe depression showed a decrease in the percentage change (Figure 5.16).

Cosine Similarity

The mean values of cosine similarity with respect to depression level are given in the Table 5.6.
The consistent decrease in mean cosine similarity with depression level suggested that as the depression level intensified from none to severe, there were greater dissimilarities between the self-reflection sketches, indicating a more pronounced impact of depression on the participants' portrayal of themselves.

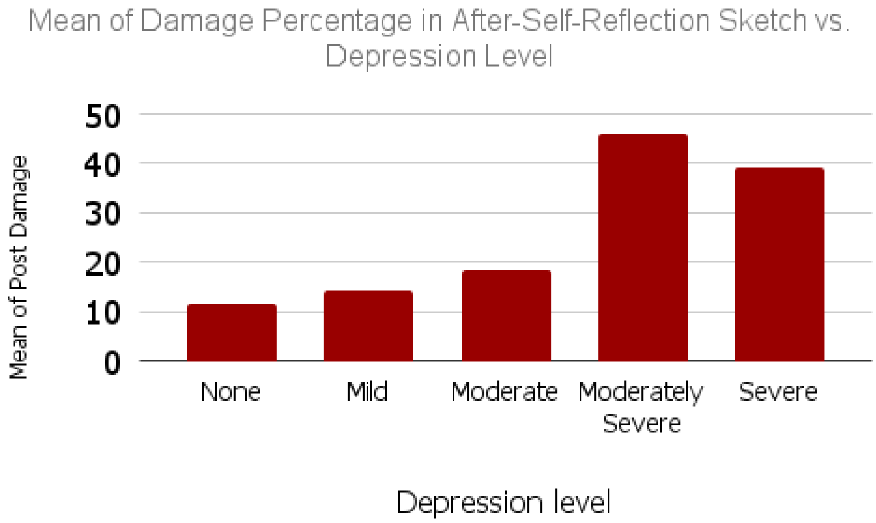


Figure 5.16: Variation of Mean Damage Percentage in After-Self-Reflection Sketch with respect to Depression Level

Depression Level	Mean of Cosine Similarity
None	0.68
Mild	0.55
Moderate	0.52
Moderately Severe	0.45
Severe	0.39

Table 5.6: Mean of Cosine Similarity value based on Depression Level

5.8 Screening Potential Cases of Depression Among Cancer Patients

We trained multiple machine learning models with various inputs in order to find their potential regarding depression screening.

5.8.1 Random Forest

Initially, we used the demographic data along with the sketch features to train the random forest model with five-fold cross-validation. This model gave an accuracy of 74% with high weighted precision, recall, F1-score, and AUC (Table 5.7). After the incorporation of EEG data with the sketch features, the random forest model showed highly improved values in every sector. However, as it uses randomness in feature selection and our sample size was smaller, its accuracy fluctuated a lot.

5.8.2 Convolutional Neural Network (CNN)

Similar to the previous model, the convolutional neural network model was also trained with demographic data and sketch features at first, and the model gave 85% accuracy in the case of five-fold cross-validation. Its accuracy increased to 93% with higher weighted precision, recall, F1-score, and AUC (Table 5.7) after it was trained with EEG data along with the previous ones.

5.8.3 Support Vector Machine (SVM)

SVM with five-fold cross-validation gave an accuracy of 85%. Even though the accuracy is the same as CNN, it has higher values in terms of precision, recall, F1-score, and AUC (Table 5.7), while we utilized the demographic data and sketch features for training the model at the beginning. After the EEG incorporation, it also made substantial enhancements in all aspects and showed greater accuracy, precision, recall, F1-score, and AUC.

Model	Accuracy	Precision	Recall	F1-Score	AUC	Percentage Change
Random Forest (Demographic data +Sketch Features)	0.742	0.762	0.738	0.742	0.871	26.549
Random Forest (Demographic data +Sketch Features + EEG)	0.939	0.947	0.934	0.938	0.992	
SVM (Demographic data + Sketch Features)	0.857	0.867	0.86	0.811	0.928	8.284
SVM (Demographic data + Sketch Features + EEG)	0.928	0.964	0.928	0.928	0.969	
CNN (Demographic data + Sketch Features)	0.857	0.733	0.76	0.737	0.875	8.284
CNN (Demographic data + Sketch Features + EEG)	0.928	0.9	0.96	0.911	0.938	

Table 5.7: Weighted performance measurements of different models developed for potential depression screening

Chapter 6

Discussion

6.1 Collective Observation

In our study, depression was prevalent in 77% of cancer patients. This is greater than the previously found depression rate (56.2%) among cancer patients in this region [113]. An earlier study [94] reported several somatic, psychological, social, and sociodemographic factors associated with the high prevalence of depression among cancer patients. During the interviews, these factors were also reported by the participants.

- Psychological distress: Nearly 85% of our participants expressed psychological distress while sharing their changed experiences after the diagnosis. This percentage of people also includes those who are not identified as depressed according to the depression screening scale PHQ-9. This might be because of the unknown nature of the illness, the fear of dying, and how the effects of treatment may affect the patient's quality of life.

- Physical symptoms: A variety of physical symptoms, including pain, fatigue, sleep disturbances, and appetite loss, are experienced by cancer patients. These signs and symptoms have an impact on the patient's disposition and aid in the onset of depression. During the study, 80% of the participants indicated that they felt fatigued, 69% had trouble falling asleep, and had a poor appetite.

- Age: Previous research indicates that older cancer patients are more likely than younger ones to experience depression [96]. This could be the result of the additional challenges older patients have to deal with, such as comorbidities and age-related physical limitations. In this study, 94% of participants aged over 65 were diagnosed with depression, compared to 71% of participants aged 18 to 44.

- Gender and Cancer Type: Studies have found that female cancer patients are more likely to experience depression than males [43]. In the case of this study, 80% of females are diagnosed as depressed, compared to 75% of males. This might be due to a range of factors, including hormonal changes, social support, coping mechanisms, etc.

In addition to these, a higher risk of depression is also associated with cancer types because of the aggressive nature of various types, their poor prognosis, and the limited treatment options available.

- Treatment-related side-effects: The side-effects of cancer treatment such as operations, chemotherapy, and radiation therapy include hair loss, trouble concentrating, nausea, vomiting, fatigue, etc. [91]. These side effects lead to a change in self-perception and hopelessness. 71% of the participants reported their loss of concentration in daily activities and felt "they are now a person they do not recognize."

- Social isolation: Cancer patients experience social isolation due to their debilitating health conditions that make them incapable of taking part in daily activities and socializing. About 89.5% of participants said that they do not feel any interest in work and think this makes their daily lives somewhat difficult.

6.2 Neurobiological Signatures of Depression

To address the problems that arise when using conventional questionnaire-based diagnostic tools for depression, we investigated alternative methods for conducting depression screening. We compared the EEG signals obtained during before-self-reflection sketching to the after-self-reflection sketching of individuals with and without depression. The relative strengths of various brainwaves were found to vary significantly. The following provides a general summary of our findings.

- **Alpha Activity:** When comparing the EEG signals of the before-self-reflection sketching session with the after-self-reflection ones of those cancer patients who have mild to moderate depression, we found depression is associated with a significant increase in both relatively low and high alpha power. This supports the finding of the earlier study that patients with depressive disorder demonstrated higher alpha power in the frontal/prefrontal regions [58]. It can be hypothesized that the functional connectivity in high-frequency bands may have been enhanced in depressed patients as a compensatory mechanism to compensate for functional deficits in the frontal and parietal/temporal/occipital regions' low-frequency connections and maintain normal cognitive function.

  Besides, the participants who are moderately severe and severely depressed showed a decrease in their relative alpha power. This corroborates the earlier study that a low level of alpha power is associated with anxiety, high stress, and insomnia in major depressive disorder (MDD) patients [103]. Moreover, another study on MDD patients states that decreased alpha power can be associated with treatment response [51]. Even though our study did not inquire about the types of medications the participants are on, the decrease in relative alpha power might be because of that.

- **Beta Activity:** Multiple earlier studies associated insomnia, anxiety, and stress with increased beta activity [14], [103]. Accordingly, the participants who reported trouble sleeping showed a significant increase in their relative low beta power. Moreover, the participants with difficulty concentrating showed a significant increase in their relative low beta power. This coincides with an earlier finding, where significantly increased relative beta power was observed among the refugees with concentration difficulties [115].

Throughout the sketching session, the participants with depression had a higher relative power in their high beta frequency band than those without. This might be because they are more vulnerable to the continuous recalling of sensitive times and struggles associated with them. This is consistent with the findings from a previous study where increased levels of high beta activity were found during anxiety or periods of emotional intensity [19], [37].

- **Theta Activity:** A previously conducted study correlated antidepressant treatment outcome with an increase in the EEG theta band power [51]. Also, it is reported that MDD patients show significantly higher coherence in the theta frequency band [42]. This is also evident in our samples. Even though there was no significant variance in the theta activity of the participants with depression, they showed a higher relative theta power throughout.

- **Delta Activity:** A decrease in relative delta power was found when comparing the EEG signals of the before-self-reflection sketching session with the after-self-reflection ones of those cancer patients who have depression. Even a previous study discovered decreased functional connectivity between frontal and parietal/temporal/occipital sites in the delta frequency band in depressed patients, which may suggest an impairment in the connection between the frontal and parietal/temporal/occipital regions [58].

- **Attention and Meditation Levels:** In our study, participants showed significantly lower mean attention values while sketching before-self-reflection sketches than after-self-reflection ones. This might be a result of the fact that they had to pay closer attention or concentrate harder when they started outlining to decide what and how they would draw. With time, their ability to concentrate may deteriorate, or they may become too worn out to be interested in the sketches.

  The meditation levels of the participants did not have any specific patterns; rather, they varied significantly per individual. Those who were spontaneous during the sketching session had a higher mean value of meditation. This might be because the sketching activity made them excited about trying new things and helped them divert their minds from stress and anxiety. Many studies have suggested similar benefits of art therapy in treating psychological distress and depression [29], [76], [88] by using various sensory stimuli as part of therapeutic techniques. Accordingly, our study raises the possibility that adding creative activities like sketching to depression treatment may enhance the patients' cognitive function. However, the participants who felt uneasy or guarded while sketching displayed a lower meditation mean value. This could be a result of their severe psychiatric morbidity, which prevented them from benefiting from a single sketching session, or as a result of pressure to sketch without any practice or prior planning.

Common Indicators	Sub Category	Presence of Indicators (%) in Non-depressed Patients		Presence of Indicators (%) in Depressed Patients	
		Before Sketch	After Sketch	Before Sketch	After Sketch
Hair Density	Normal/ Same as before	67	33	81	7
	Increase	0	0	0	3
	Decrease	0	20	0	69
	Not Present	33	47	19	21
Body Outline	Double Stroke	26	30	48	84
Lip Line	Upward	53	29	75	16
	Downward	0	25	0	61
	Not Present	47	46	25	23
Tears		0	13	0	35
Sketch of Lower Body		56	47	43	26
Body Weight Depiction	Increase	0	20	0	2
	Decrease	0	20	0	72
	Normal/Same as Before	100	60	100	26

Table 6.1: Summary of Indicators' Presence from Free-Hand Sketches in Percentage

6.3 Implications of Free-Hand Sketches

Our study also focused on examining the changes in selected indicators between non-depressed and depressed individuals by analyzing theirs before and after self-reflection sketches.

6.3.1 Variation in Free-Hand Sketches

The sketches of before and after self-reflection of depressed and non-depressed participants showed observable differences in several indicators, including hair density (normal, increase, decrease, not present), body outline (dual stroke), lower body sketch (present, not present), lip line (upward, downward, not present), presence of tears, and overall body weight depiction (increase, decrease, same as before). Table 6.1 showed a brief summary of the findings.

- **Hair Density:** Loss of hair is frequently associated with cancer and the medications, and procedures used as treatment. The majority of the participants showed a noticeable thinning of hair in their after-self-reflection sketches, reinforcing the association between cancer and hair loss. Furthermore, the difference in hair density (from normal to decreased) was more prevalent in the after-sketches of depressed participants compared to the non-depressed participants.

- **Body Outline:** Some of the participants drew their heads and bodies with double-stroked, bold, shaky, and non-contiguous outlines in both their before and after sketches. However, while the presence of dual strokes in the body outline increased by only 4% in non-depressed participants' before to after sketches, the percentage almost doubled in depressed participants (from 48% to 84%).

  Generally, a body outline signifies a perceived barrier between the individual and their environment. Previous studies have associated the use of bold or doubled outlines in drawings with anxiety and external pressure [6], [34]. Some studies also found it in the drawings done by groups known to have depression and high anxiety levels [9], [27], [47], [50]. On the other hand, a detached, non-contiguous, shaky, or omitted outline was linked with internal anxiety by existing research [27]. The presence of these features in both sketches could be attributed to the participants not being accustomed to drawing or the pressure they felt when asked to sketch without any prior practice.

- **Lower body** The lower body in figure drawing is often associated with stability, balance, and a solid foundation. Previous studies have linked the signs of non-stable standing and distorted or omitted legs in drawings to a sense of instability experienced by certain groups, who perceived the world as unstable and uncertain [60]. However, in the case of our study, even though there was a decrease in the percentage from before to after images of both non-depressed and depressed participants, we could not consider this indicator as a substantial insight. That is because a significant number of sketches initially did not include any lower body sketch. Therefore, it was difficult to determine the extent to which depression or other mental distress contributed to the omission of the lower body in the after-self-reflection sketches.

- **Lip Line:** Existing studies found that self-figure drawings of individuals who struggle with expressing their feelings or have difficulty in communication were often characterized by emphasized or omitted lips [24], [81]. Additionally, the use of smile and frown curves in drawings is a common way to represent happiness and sadness, respectively. In our study, we observed a significant decrease in the percentage of sketches with upward or smile curves and an increase in the percentage of sketches with downward or frown curves in the after-self-reflection sketches. This change was particularly prominent among participants diagnosed with depression, as their sketches exhibited greater differences in the percentage change.

- **Eyes and the Presence of Tears:** Eyes, being a fundamental means of communication with the outside world, play a remarkable role in self-reflection sketching. Different depictions of eyes, such as omission, hollow shapes, shaded areas, or the presence of tears, can convey various emotions and psychological states, including helplessness, depression and anxiety, fears, denial of reality, difficulties in reality testing, and interpersonal relations [3], [23]. Previous studies have identified similar eye depictions in drawings by colon cancer patients as an expression of a sense of helplessness [25]. In our collected sketches, we observed that a substantial number of participants depicted shaded, hollow eyes, and 35% of depressed and 13% of non-depressed patients drew tears in their after-self-reflection sketches to express their continuously deteriorating psychological conditions.

- **Body Weight Depiction:** Weight loss is a common symptom associated with cancer. Among the after-self-reflection sketches, 20% of non-depressed patients indicated weight loss, whereas, the number was 72% in that of the depressed patients.

These findings suggested that depressed cancer patients might perceive similar changes as more pronounced and impactful compared to non-depressed patients due to their weakened emotional state.

6.3.2 Screening Depression Based on Free-Hand Sketches

Considering our relatively smaller sample size, we opted for cross-validation instead of using 'test on test data' to obtain a more comprehensive and reliable estimation of the model's performance across different data subsets. Among the models trained using only demographic data and sketch features, the Support Vector Machine model (SVM) with five-fold cross-validation demonstrated the best performance (accuracy: 0.857, precision: 0.867, recall: 0.86, F1-score: 0.811, AUC: 0.928). However, when tested on test data, the Random Forest model exhibited similar performance measures (accuracy: 0.850, precision: 0.860, recall: 0.826, F1-score: 0.834, AUC: 0.935) compared to cross-validation results (accuracy: 0.742, precision: 0.752, recall: 0.738, F1-score: 0.742, AUC: 0.871). This discrepancy could be attributed to the model's tendency to overfit on a smaller dataset or to perform better on a specific test set that aligns with the characteristics of the corresponding training data.

Furthermore, integrating EEG data into the models led to significant improvements in accuracy, precision, recall, F-1 score, and AUC. The Random Forest model trained with sketch features and EEG data using five-fold cross-validation achieved impressive performance measures (accuracy: 0.939, precision: 0.947, recall: 0.934, F1-score: 0.938, AUC: 0.992), surpassing a previously developed Random Forest model for depression screening based on clinical, laboratory, and sociodemographic data (accuracy: 0.89, sensitivity: 0.90, AUC: 0.87) [89]. This underscores the potential of incorporating sketch features alongside EEG data to enhance the model's performance. Moreover, the SVM model yielded an accuracy of 0.928, a precision of 0.964, a recall of 0.928, an F1-score of 0.928, and an AUC of 0.969. This accuracy is nearly the same as that of a previously developed depression screening model based solely on EEG data (accuracy: 93.54%). However, it is worth mentioning that Acharya et al. [62] employed left EEG data, whereas we utilized relative EEG power values collected from the pre-frontal region.

Chapter 7

Reflections

7.1 Conclusion

Depression and cancer are two profound life-altering experiences, and their co-occurrence is associated with various somatic, psychological, social, and sociodemographic factors. In this study, we explored and demonstrated the potential of non-verbal measures, specifically free-hand sketching, and EEG, as effective means of identifying depression among cancer patients. We used computational algorithms and manual processing techniques to discover any underlying nonverbal cues in free-hand sketches and unveil the neurobiological signatures of depression through EEG signals collected through a portable and easy-to-use EEG headset. Our analyses revealed the correlation between depression and its symptoms, potential neurobiological signatures associated with depression, and how much an individual's psychological conditions can affect the presence of nonverbal cues in the free-hand sketches. Our developed Support Vector Machine and Random Forest models demonstrated promising accuracy in screening potential cases of depression. We anticipate this study could pave the way for larger-scale research on this relatively newer depression screening approach focused on the minimization of cultural and linguistic barriers and open up new opportunities for interdisciplinary research. Moreover, where there is a low patient-to-oncology psychiatrist ratio, the outcomes of this study have the potential to bridge the gap between oncologists and psychiatrists. It can assist in the initial screening of depression and aid physicians in supporting patients' experiences and emotional well-being along with physical health care, throughout their journey to recovery.

7.2 Avenues for Future Work

Despite the promising outcomes of our study, it has several limitations that need to be acknowledged, indicating areas for future research. The most significant limitation is the smaller sample size. As an exploratory research regarding the use of this relatively unexplored approach, the sample size of 66 participants was determined based on feasibility within the compact time frame. It also surpassed the median average number of participants in previous drawing research [55]. However, this sample size may not have been sufficient to support robust statistical analysis between the questionnaires and the sketches. Further studies with larger sample sizes would allow for more conclusive findings.

Another limitation pertains to the influence of the drawing instructions provided to the participants. They were instructed to create simple pencil sketches without using color. However, it is important to acknowledge that the choice of drawing materials and options for expression, such as color, could have influenced the participants' drawings and potentially yielded different findings [21]. Future studies could consider providing a wider range of drawing materials to allow for greater flexibility and diversity in artistic expression. Furthermore, despite providing reassurance that the activity was not an assessment of their drawing skills, some individuals may have still felt hesitant or self-conscious about their abilities. This initial hesitation could have impacted the way participants approached the task and potentially influenced their drawings.

The study design included a single sitting for both the 'before' and 'after' self-reflection sketches. To gain a more comprehensive understanding of participants' evolving perceptions and depictions over time, future research should consider incorporating multiple time points and conducting the sessions in several settings. This would provide deeper insights into the participants' experiences. Besides, an individual's previous self-esteem and the mentalities of their surroundings may affect the sketch features of 'self-reflection' post-cancer diagnosis positively or negatively. These factors can correlate with several variables that are related to but distinct from depression.

It is also important to note that previous research on non-clinical participants has shown that certain structural and formal aspects of sketches, such as size, line, and placement, tend to be less variable compared to content-related features, such as body details, clothing, etc. [1]. In our study, while no significant differences in dimensional measurements were observed among non-depressed patients, depressed patients' sketches depicted contrasting findings. Further research involving clinical patients is needed in order to validate any potential relationship between these sketch aspects and the participant's mental and physical conditions.

Additionally, due to the higher prevalence of depression among cancer patients, our dataset was skewed towards more depressed individuals than non-depressed individuals. Despite attempts to balance the classes through oversampling, undersampling, and both during model training, the performance of the models worsened. Therefore, we plan to collect more data from non-depressed cancer patients in the future. Also, in our study, we worked with depressed and non-depressed groups within cancer patients. In the future, we plan to include healthy individuals with and without depression to understand the underlying differences among all these groups.

In terms of the technology used, we utilized a consumer-grade, single-electrode, portable EEG headset. While these devices offer affordability and user-friendliness, the quality of the data they produce is not as high as that of devices with a greater number of electrodes or sensors. Moreover, further research should focus on assessing the acceptability of EEG devices among users and addressing any initial stigma associated with their use before integrating them into mainstream clinical diagnosis. Besides, to make the manual processing of free-hand sketches more computationally efficient, there is a need to develop custom-trained models that can effectively handle the irregular nature of free-hand sketches and accurately identify the presence of relevant indicators. We aim to do it in the future.

Appendices

Questionnaire

ক্যান্সার রোগীদের তথ্য সংগ্রহ ফরম (* আবশ্যিক)

০১. ফরম নাম্বার:

০২. তথ্য সংগ্রহের তারিখ:

০৩. তথ্য সংগ্রহের সময়:

০৪. আপনার নাম (ঐচ্ছিক):

০৫. আপনার বয়স (বছর)*:
- ○ ১৮ - ২৪
- ○ ২৫ - ৪৪
- ○ ৪৫ - ৬৪
- ○ ৬৫ বছরের বেশি

০৬. আপনার লিঙ্গ* :
- ○ পুরুষ
- ○ নারী
- ○ অন্যান্য
- ○ প্রকাশ করতে অনিচ্ছুক

০৭. আপনার সাথে যোগাযোগের নাম্বার (ঐচ্ছিক):

০৮. আপনার বর্তমান ঠিকানা (অন্তত জেলা):

০৯. আপনার স্থায়ী ঠিকানা (অন্তত জেলা):

১০. আপনার সর্বোচ্চ শিক্ষাগত যোগ্যতা*:
(যেকোনো একটি বৃত্ত চিহ্নিত করুন)
- ○ হাই স্কুল/এসএসসি/ও-লেভেল/ঈবতেদায়ি/সমমানের ডিগ্রির নিচে
- ○ হাই স্কুল/এসএসসি/ও-লেভেল/ঈবতেদায়ি/সমমানের ডিগ্রি
- ○ কলেজ/এইচএসসি/এ-লেভেল/আলীম/সমমানের ডিগ্রি
- ○ ডিপ্লোমা/সমমানের ডিগ্রীর উপরে
- ○ ব্যাচেলর/ফাযিল/সমমান ডিগ্রী
- ○ মাস্টার্স/কামিল/সমমান ডিগ্রী
- ○ পিএইচডি/সমমান ডিগ্রী

১১. আপনার পেশা*:
(সকল প্রযোজ্য বৃত্ত চিহ্নিত করুন)
- ○ বেকার
- ○ অবসরপ্রাপ্ত
- ○ কৃষক
- ○ শিক্ষার্থী
- ○ শিক্ষক
- ○ গৃহিণী
- ○ ডাক্তার/ডেন্টিস্ট/নার্স/ফার্মাসিস্ট/ স্বাস্থ্যসেবা ক্ষেত্রে নিযুক্ত
- ○ প্রতিরক্ষা কর্মকর্তা (সেনাবাহিনী/পুলিশ/অনুরূপ চাকরি)
- ○ প্রতিরক্ষা কর্মচারী (কর্মকর্তা নয়) (সেনা/পুলিশ/অনুরূপ চাকরিতে)
- ○ সরকারী কর্মকর্তা
- ○ সরকারি কর্মচারী (কর্মকর্তা নয়)
- ○ বেসরকারী কর্মকর্তা
- ○ বেসরকারী কর্মচারী (কর্মকর্তা নয়)
- ○ ব্যবসায়ী (বড় ব্যবসা)
- ○ ব্যবসায়ী (ছোট ব্যবসা)
- ○ অন্যান্য ____

১২. আপনার ধর্ম*:
(যেকোনো একটি বৃত্ত চিহ্নিত করুন)
- ○ ইসলাম
- ○ হিন্দু
- ○ খ্রিস্টান
- ○ বৌদ্ধ
- ○ অন্যান্য ____

১৩. আপনার বৈবাহিক অবস্থা*:
(যেকোনো একটি বৃত্ত চিহ্নিত করুন)
- ○ অবিবাহিত
- ○ বিবাহিত
- ○ বিধবা
- ○ তালাকপ্রাপ্ত
- ○ অন্যান্য ____

১৪. আপনার সন্তান সংখ্যা*: _______

১৫. আপনার মাসিক আয় (বাংলাদেশি টাকায়)*:
(যেকোনো একটি বৃত্ত চিহ্নিত করুন)
- ○ ২০,৬০০ এর কম
- ○ ২০,৬০১ - ৫১,৬০০
- ○ ৫১,৬০০ এর বেশি

১৬. আপনি কি ধরনের ক্যান্সারে আক্রান্ত? *
- ○ রক্তের ক্যান্সার
- ○ জরায়ুমুখে ক্যান্সার
- ○ চামড়ায় ক্যান্সার
- ○ ফুসফুসের ক্যান্সার
- ○ প্রস্টেট ক্যান্সার
- ○ স্তন ক্যান্সার
- ○ থাইরয়েড ক্যান্সার
- ○ অন্যান্য ____

১৭. আপনি ক্যান্সারের কোন স্তরে আক্রান্ত? *
- ○ জানা নেই
- ○ ১
- ○ ২
- ○ ৩
- ○ ৪
- ○ প্রকাশ করতে অনিচ্ছুক

১৮. আপনার কি হাসপাতালে ভর্তি হতে হয়েছে/হয়েছিল? *
- ○ হ্যাঁ
- ○ না
- ○ প্রকাশ করতে অনিচ্ছুক

১৯. আপনার কি অপারেশন করতে হয়েছে/হয়েছিল?*
- ○ হ্যাঁ
- ○ না
- ○ প্রকাশ করতে অনিচ্ছুক

২০. আপনার পরিবারের সদস্যদের কেউ কি ক্যান্সারে আক্রান্ত/আক্রান্ত ছিলেন? *
- ○ জানা নেই
- ○ হ্যাঁ
- ○ না
- ○ প্রকাশ করতে অনিচ্ছুক

২১. আপনি কি আপনার চিকিৎসার ব্যাপারে পরিবারের সদস্যদের থেকে যথেষ্ট সমর্থন পান? *

- হ্যাঁ
- না
- প্রকাশ করতে অনিচ্ছুক

২২. আপনি কি হাসপাতালের ফি পরিশোধে কোন সমস্যার সম্মুখীন হচ্ছেন/হয়েছেন? *

- কখনোই না
- প্রায় না
- মাঝে মাঝে
- প্রায় প্রতিবারই
- প্রত্যেকবার

২৩. আপনার কি কোন ঋণ রয়েছে? *

- হ্যাঁ
- না
- প্রকাশ করতে অনিচ্ছুক

ক্যান্সার রোগীদের তথ্য সংগ্রহ ফরম (* আবশ্যিক)

বাংলা বিষণ্নতা মাত্রা পরিমাপক

বিগত দুই সপ্তাহে আপনি কত সময় নিচের যেকোন একটি সমস্যার সম্মুখীন হয়েছেন (আপনার উত্তর নির্দেশ করার জন্য ✓ চিহ্ন ব্যাবহার করুন)		একেবারেই না	কিছুদিন	অর্ধেকেরও বেশী সময়	প্রায়ই প্রতিদিন
১	কাজ করতে কম আগ্রহ বা আনন্দ	০	১	২	৩
২	মন খারাপ, হতাশা বা আশাহীন বোধ করা	০	১	২	৩
৩	ঘুম আসতে বা ঘুমিয়ে থাকতে সমস্যা (ঘুম ভেঙে যাওয়া) অথবা অতিরিক্ত ঘুমানো	০	১	২	৩
৪	ক্লান্ত বোধ করা বা কম শক্তি পাওয়া	০	১	২	৩
৫	রুচি কমে যাওয়া বা স্বাভাবিক এর তুলনায় বেশী খাওয়া	০	১	২	৩
৬	নিজের সম্পর্কে খারাপ বোধ করা অথবা নিজেকে ব্যর্থ মনে করা অথবা নিজেকে বা পরিবারকে হেয় মনে করা	০	১	২	৩
৭	কোন কিছুর প্রতি মনোযোগে সমস্যা (যেমনঃ খবরের কাগজ পড়া বা টেলিভিশন দেখা . . .)	০	১	২	৩
৮	এত ধীরে চলাফেরা করা বা আস্তে কথা বলা যা অন্য মানুষেরা খেয়াল করে/নজরে আসে	০	১	২	৩
৯	আপনার কি এমন মনে হয় যে, বর্তমান অবস্থার চাইতে মরে যাওয়াটাই ভালো অথবা নিজেকে আঘাত করতে ইচ্ছা করে	০	১	২	৩
	মোট =				

আপনি যদি কোন সমস্যায় পড়ে থাকেন, তাহলে সমস্যাগুলো আপনার দৈনন্দিন কাজ, বাসার জিনিসপত্রের যন্ত্র বা অন্য লোকের সাথে মেশা কতটা কঠিন করেছে?

একেবারেই কঠিন নয় ☐ কিছুটা কঠিন ☐ বেশী কঠিন ☐ অতিমাত্রায় কঠিন ☐

Consent Form

Brac University, Dhaka 1212, Bangladesh, Phone: (8802) 58810383

এই সম্মতি ফর্মটি বাংলাদেশের ক্যান্সার আক্রান্ত রোগীদের জন্য যারা **"Beyond Words: An Exploration of Free-hand Sketches and EEG-based Neurobiological Signatures to Unveil the Underlying Depression among Cancer Patients"** শীর্ষক গবেষণায় অংশগ্রহণ করছেন।

প্রধান গবেষকের নাম:

গবেষকবৃন্দের নাম:

অংশ ০১: তথ্য পত্র

ভূমিকা

আমরা, সৈয়দ জুহায়ের হোসেন, আনিকা তাহসিন মায়ামী এবং আনিকা প্রিয়দর্শিনী মৃত্তিকা, ব্র্যাক বিশ্ববিদ্যালয়ে শেষ বর্ষে অধ্যয়নরত শিক্ষার্থী। আমরা ক্যান্সার রোগীদের মনস্তাত্বিক দিক নিয়ে গবেষণা করছি, যা এই দেশে প্রায়শই সম্বোধন করা হয় না। আমি আপনাকে গবেষণা সম্পর্কিত কিছু তথ্য দিচ্ছি এবং আপনাকে এই গবেষণার অংশ হতে আমন্ত্রণ জানাচ্ছি। আপনাকে তৎক্ষণাৎ সিদ্ধান্ত নিতে হবে না, এবং আপনি সিদ্ধান্ত নেওয়ার আগে স্বাচ্ছন্দ্য বোধ করেন এমন যে কারো সাথে পরামর্শ করতে পারেন।

এই সম্মতি ফর্মে আপনার বুঝতে কষ্ট হতে পারে এমন শব্দ থাকতে পারে। এমন পরিস্থিতিতে অনুগ্রহ করে আমাকে থামতে বলবেন এবং আমি সময় নিয়ে আপনাকে ব্যাখ্যা করবো। যদি পরবর্তীতে আপনার কোন প্রশ্ন থাকে, তাহলে আপনি অন্য গবেষক বা আমার কাছে জিজ্ঞাসা করতে পারেন।

গবেষণার উদ্দেশ্য

ক্যান্সার রোগীরা প্রায়শই তাদের রোগ এবং অন্যান্য কারণে উদ্বেগ, বিষণ্ণতা, মানসিক চাপ ইত্যাদিতে ভোগেন। আমরা যত তাড়াতাড়ি সম্ভব তাদের মনস্তাত্বিক দিকগুলি বুঝতে সাহায্য করার উপায়গুলি খুঁজে পেতে চাই, যাতে এটি তাদের পুনরায় সুস্থতা অর্জনের পথে বাধা হয়ে না দাড়াতে পারে। আমরা বিশ্বাস করি, আপনি এই বিষয়ে আপনার ব্যক্তিগত অভিজ্ঞতা আমাদের জানানোর মাধ্যমে এই গবেষণায় গুরুত্বপূর্ণ অবদান রাখতে পারেন। আপনার এবং অন্যদের ব্যক্তিগত সংগ্রাম কীভাবে আপনাদের এবং পুরো চিকিৎসা ব্যবস্থাকে প্রভাবিত করছে সে সম্পর্কে আমরা জানতে চাই।

গবেষণায় অন্তর্ভুক্ত কার্যক্রম

এই গবেষণাটি ১৫ মিনিটের সাক্ষাৎকার এবং ০৫ মিনিটের চিত্র অঙ্কন পর্বে বিভক্ত।

অংশগ্রহণকারী নির্বাচন

আপনাকে এই গবেষণায় অংশ নেওয়ার জন্য আমন্ত্রণ জানানো হচ্ছে কারণ আমরা মনে করি যে একজন রোগী হিসাবে আপনার অভিজ্ঞতা আমাদের একই রকম শারীরিক এবং মানসিক অবস্থার মাঝে দিয়ে জীবন অতিবাহিত করা অনন্যদের সংগ্রামকে আরও গভীরভাবে বুঝতে সাহায্য করবে।

স্বতঃস্ফূর্ত অংশগ্রহণ

এই গবেষণায় অংশগ্রহণে আপনি কোনভাবে বাধ্য নন। আপনি অংশগ্রহণ করবেন কি না সেটা সম্পূর্ণ আপনার নিজস্ব সিদ্ধান্ত। আপনি যদি অংশগ্রহণ না করার সিদ্ধান্ত নেন, তাহলেও এই হাসপাতালে আপনার প্রাপ্ত সমস্ত পরিষেবা পূর্বের মতই অব্যাহত থাকবে।

পদ্ধতি

আমরা আপনাকে এই গবেষণা প্রকল্পে অংশ নিয়ে ক্যান্সার রোগীদের মানসিক অবস্থা সম্পর্কে আমাদের আরও জানতে সাহায্য করার অনুরোধ জানাচ্ছি। আপনি যদি অংশগ্রহণে সম্মতি দেন, তাহলে আপনাকে সাক্ষাৎকার গ্রহণকারীদের একজনের সাথে একটি সাক্ষাৎকারে অংশগ্রহণ করতে অনুরোধ করা হবে।

সাক্ষাৎকার চলাকালীন আমি বা অন্য একজন সাক্ষাৎকার গ্রহণকারী আপনার সাথে হাসপাতালের কক্ষে আরামদায়ক জায়গায় বসবো। যদি আপনি ইচ্ছা প্রকাশ করেন তাহলে, সাক্ষাৎকারটি আপনার বিছানার পাশেও নেয়া যেতে পারে। আপনি যদি সাক্ষাৎকার চলাকালীন কোনও প্রশ্নের উত্তর দিতে না চান তবে আপনি তা বলতে পারেন এবং সাক্ষাৎকার গ্রহণকারী সেই অনুযায়ী পরবর্তী প্রশ্নে চলে যাবেন। সাক্ষাৎকার চলাকালীন সময়ে সাক্ষাৎকার গ্রহণকারী ছাড়া অন্য কেউ উপস্থিত থাকবে না, যদি না আপনি অন্য কাউকে সেখানে উপস্থিত রাখতে চান। রেকর্ড করা তথ্য অত্যন্ত গোপনীয়, এবং গবেষণা দল ছাড়া আপনার সাক্ষাৎকারের সময় নথিভুক্ত তথ্য অন্য যে কারো নাগালের বাইরে রাখা হবে। পুরো সাক্ষাৎকারটি রেকর্ড করা হবে, তবে তাতে নাম দিয়ে কাউকে চিহ্নিত করার উপায় রাখা হবে না। রেকর্ডটি একটি সম্পূর্ণ ইন্টারনেট বিচ্ছিন্ন মোবাইল ফোনে সংরক্ষণ করে রাখা হবে। গবেষণা দল ছাড়া অন্য কেউ রেকর্ডগুলো ব্যাবহার করতে পারবে না।

ঝুঁকি

আমরা আপনাকে আমাদের সাথে কিছু অত্যন্ত ব্যক্তিগত এবং গোপনীয় তথ্য শেয়ার করতে বলছি, এবং আপনি কিছু বিষয় নিয়ে কথা বলতে অস্বস্তি বোধ করতে পারেন। কিন্তু আপনাকে ইচ্ছার বিরুদ্ধে কোনো প্রশ্নের উত্তর দিতে হবে না বা সাক্ষাৎকারে অংশ নিতে হবে না। কোনো প্রশ্নের উত্তর না দেওয়ার বা সাক্ষাৎকারে অংশ নিতে অস্বীকার করার জন্য আপনাকে আমাদের কোনো কারণ দেখাতেও হবে না।

সুবিধা

এই সাক্ষাৎকারে অংশগ্রহণ করার ফলে আপনার সরাসরি কোন উপকার হবে না, তবে আপনার অংশগ্রহণ আমাদের ক্যান্সার রোগীদের বিষন্নতা এবং মনস্তাত্ত্বিক দিকগুলি শনাক্তকরণ এর উপায় খুঁজে পেতে সাহায্য করবে।

প্রতিদান

গবেষণায় অংশ নিতে আপনাকে কোনো আর্থিক সহায়তা দেওয়া হবে না।

গোপনীয়তা

আমরা গবেষণা দলের বাইরের কারো সাথে আপনার প্রদান করা তথ্য আলোচনা করবো না। এই গবেষণা প্রকল্প থেকে আমরা যে তথ্য সংগ্রহ করি তা অত্যন্ত গোপন রাখা হবে। আপনার যেকোনো তথ্যে আপনার নামের পরিবর্তে একটি নম্বর থাকবে। শুধুমাত্র গবেষকরা জানতে পারবেন আপনার নম্বর কী এবং আমরা সেই তথ্যটির যথাযথ গোপনীয়তা নিশ্চিত করব।

ফলাফল জানানো

আপনি আজ আমাদের যা বলবেন তার কিছুই গবেষণা দলের বাইরের কারো সাথে শেয়ার করা হবে না। এই গবেষণা থেকে আমরা যে জ্ঞান পেয়েছি তা জনসাধারনকে জানানোর আগে আপনার এবং আপনার সম্প্রদায়কে জানানো হবে। প্রতি অংশগ্রহণকারী ফলাফলের একটি সারসংক্ষেপ পাবেন। এর পরে, আমরা ফলাফল প্রকাশ করব যাতে অন্যান্য আগ্রহী ব্যক্তিরা গবেষণা থেকে শিখতে পারেন।

প্রত্যাখ্যান বা প্রত্যাহার করার অধিকার

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আপনি যদি না চান, তবে আপনাকে এই গবেষণায় অংশ নিতে হবে না এবং অংশগ্রহণ করা বেছে নেওয়া, আপনার চিকিৎসাকে কোনোভাবেই প্রভাবিত করবে না। আপনি যে কোনো সময় সাক্ষাৎকারে অংশগ্রহণ করা বন্ধ করতে পারেন। সাক্ষাৎকারের শেষে আমরা আপনাকে আপনার মন্তব্যগুলি পর্যালোচনা করার একটি সুযোগ দেব, এবং আপনি সেগুলির কিছু অংশ সংশোধন বা অপসারণ করতে বলতে পারেন ।

কার সাথে যোগাযোগ করবেন
আপনার কোন প্রশ্ন থাকলে, আপনি এখন বা পরে তা জিজ্ঞাসা করতে পারেন। আপনি যদি পরে প্রশ্ন জিজ্ঞাসা করতে চান, আপনি নিম্নলিখিত যেকারো সাথে যোগাযোগ করতে পারেন:

নাম: সৈয়দ জুহায়ের হোসেন
ই -মেইল: syed.zuhair.hossain@g.bracu.ac.bd
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নাম: আনিকা প্রিয়দর্শিনী মৃত্তিকা
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অংশ ০২: সম্মতি স্বাক্ষরপত্র

আমি পূর্বোক্ত তথ্য পড়েছি, বা এটি আমাকে পড়ে শোনান হয়েছে। আমি এটি সম্পর্কে প্রশ্ন জিজ্ঞাসা করার সুযোগ পেয়েছি, এবং আমাকে যে যে প্রশ্ন জিজ্ঞাসা করা হয়েছে, তার উত্তর আমার সন্তুষ্টির সাথে নথিভুক্ত করা হয়েছে। আমি স্বেচ্ছায় এই গবেষণায় অংশগ্রহণ করার সম্মতি দিচ্ছি।

অংশগ্রহণকারীর নাম ____________________
অংশগ্রহণকারীর স্বাক্ষর ____________________
তারিখ ______________________________
দিন/ মাস/ বছর

নিরক্ষর হলে:
আমি অংশগ্রহণকারীকে সম্মতি ফর্মটি সঠিকভাবে পড়ে শোনাতে দেখেছি এবং অংশগ্রহণকারী প্রশ্ন জিজ্ঞাসা করার সুযোগ পেয়েছেন। আমি নিশ্চিত করছি যে, অংশগ্রহণকারী স্বাধীনভাবে নিজস্ব সম্মতি দিয়েছেন।

সাক্ষীর নাম _____________

অংশগ্রহণকারীর টিপসই:

সাক্ষীর স্বাক্ষর ______________

তারিখ ______________________________

দিন/ মাস/ বছর

সম্মতি গ্রহণকারী গবেষক/ব্যক্তির বিবৃতি

আমি অংশগ্রহণকারীর কাছে তথ্য পত্রটি সঠিকভাবে পড়েছি এবং সর্বোচ্চ চেষ্টা করেছি যেন অংশগ্রহণকারী এই সেশনে কী করা হবে তা বুঝতে পারে।
আমি নিশ্চিত করছি যে, অংশগ্রহণকারীকে গবেষণা সম্পর্কে প্রশ্ন জিজ্ঞাসা করার সুযোগ দেওয়া হয়েছিল এবং অংশগ্রহণকারীর দ্বারা জিজ্ঞাসা করা সমস্ত প্রশ্নের সঠিক উত্তর দেওয়ার সর্বোচ্চ চেষ্টা করা হয়েছে। আমি নিশ্চিত করছি যে, অংশগ্রহণকারীকে সম্মতি দিতে বাধ্য করা হয়নি এবং সম্মতিটি স্বাধীনভাবে এবং স্বেচ্ছায় দেওয়া হয়েছে।

এই সম্মতি ফর্মের একটি অনুলিপি অংশগ্রহণকারীকে প্রদান করা হয়েছে।

সম্মতি গ্রহণকারী গবেষক/ব্যক্তির নাম__________________________

গবেষক/সম্মতি গ্রহণকারী ব্যক্তির স্বাক্ষর____________________________

তারিখ ______________________________

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