1. Project Initialization and Planning Phase

Date	04 July 2024
Team ID	SWTID1720017249
Project Title	Panic Disorder Detection
Maximum Marks	3 Marks

2.3. Literature Survey

The study, titled "**Screening for and Detection of Depression, Panic Disorder, and PTSD in Public-Sector Obstetric Clinics**," assessed the detection and treatment rates of these conditions among pregnant women in public-sector obstetric clinics. Screening of 387 women revealed that only 26% of those with a positive psychiatric screen were recognized by their providers, with just 12% detection among those with suicidal ideation. Panic disorder and a history of domestic violence increased the likelihood of detection. While all women with panic disorder received or were receiving treatment, only 26% of those with depression did. The findings highlight low detection rates for depressive disorders in obstetric settings, underscoring the need for improved detection and referral practices.

The study "**Panic Disorder in Patients with Chest Pain: Prevalence and Detection**" reveals that up to 25% of patients with chest pain in emergency departments have panic disorder, with even higher rates in outpatient evaluations. Despite this prevalence, panic disorder often goes undiagnosed and untreated. A review of studies from 1970 to 2001 identified five variables associated with higher rates of panic disorder among chest pain patients: absence of coronary artery disease, atypical chest pain, female sex, younger age, and high self-reported anxiety. Affecting 1-4% of the U.S. population, panic disorder leads to recurrent panic attacks and significant behavioral changes, severely impacting quality of life and causing substantial disabilities. Symptoms like palpitations and chest pain mimic medical conditions, resulting in higher medical service usage. Patients frequently seek help in emergency or cardiology settings and undergo expensive cardiac workups without receiving a diagnosis. Identifying key variables can enhance the detection and treatment of panic disorder in patients with chest pain in general medical settings.

The research paper titled "**Automated Detection of Panic Disorder Based on Multimodal Physiological Signals Using Machine Learning**" by Eun Hye Jang, Kwan Woo Choi, Ah Young Kim, Han Young Yu, Hong Jin Jeon, and Sangwon Byun, explores the potential of machine learning in distinguishing panic disorder (PD) patients from healthy controls (HCs) using multimodal physiological signals. Data were collected from ECG, EDA, RESP, and PT during rest, stress, and recovery phases, with 11 features extracted from each phase. Five machine learning algorithms—logistic regression, k-nearest neighbor, support vector machine, random forest, and multilayer perceptron (MLP)—were tested. MLP achieved the highest accuracy of 75.61% with all 33 features. Linear regression identified ECG and PT features during stress and recovery as significant predictors of PD. These significant predictors improved the accuracy of other

algorithms compared to using ECG features alone. The study employed a nested cross-validation approach to enhance the reliability of the results. The findings demonstrate the potential of integrating multimodal physiological signals across different states to improve the accuracy of PD diagnosis. This research highlights the importance of combining various physiological measurements to enhance the classification and understanding of panic disorder.

The research paper titled "**Detecting Depression Using K-Nearest Neighbors (KNN) Classification Technique**" by Md Rafiqul Islam, Abu Raihan M. Kamal, Naznin Sultana, and Robiul Islam delves into the application of the K-Nearest Neighbors (KNN) algorithm in the realm of depression detection. With a focus on leveraging machine learning techniques for mental health assessment, the study contributes to the growing body of literature exploring innovative approaches to identifying and addressing depression. By building upon prior research that has demonstrated the potential of machine learning algorithms in detecting mental health conditions, the authors aim to shed light on the efficacy of KNN specifically in the context of depression diagnosis. The study situates itself within the broader landscape of mental health research, emphasizing the importance of early detection and intervention in managing depression effectively. By harnessing the power of data-driven methodologies, such as KNN classification, the researchers seek to enhance diagnostic accuracy and facilitate personalized treatment strategies for individuals grappling with depression. Through a systematic approach encompassing data preprocessing, feature selection, model training, and evaluation, the study showcases the utility of KNN in distinguishing between individuals with depression and those without. By harnessing the capabilities of KNN, the authors demonstrate the algorithm's ability to discern patterns and trends indicative of depression, thereby enabling clinicians and healthcare providers to make informed decisions regarding patient care and treatment planning. The results of the study reveal promising outcomes in terms of accuracy rates and sensitivity, underscoring the potential of KNN as a valuable tool in the arsenal of mental health professionals. By highlighting the strengths and limitations of the KNN algorithm in depression detection, the authors pave the way for future investigations aimed at refining and optimizing machine learning models for enhanced diagnostic precision. The study advocates for continued exploration of innovative methodologies that harness the power of data analytics and artificial intelligence to revolutionize mental health care delivery and improve patient outcomes. The research paper underscores the transformative potential of machine learning algorithms, such as KNN, in revolutionizing depression detection and treatment.

The research paper titled **"Predicting Dropout From Cognitive Behavioral Therapy for Panic Disorder Using Machine Learning Algorithms"** by Sei Ogawa explores the use of machine learning (ML) to predict dropout rates in cognitive behavioral therapy (CBT) for panic disorder (PD). Utilizing baseline data from 208 patients, the study applies two ML algorithms, random forest and light gradient boosting machine (LightGBM), to identify predictors of therapy dropout with high accuracy rates of 88% and 85%, respectively. Key predictors identified include personality traits measured by the NEO Five Factor Index and the severity of PD. The study highlights the potential of ML in enhancing clinical decision-making and addressing the challenge of attrition in therapeutic interventions. By integrating ML approaches like random forest and LightGBM, the research contributes to the broader field of mental health by offering robust, data-driven methods for improving patient retention in therapy and personalizing treatment strategies based on individual characteristics.

The research paper titled **"Predictors of Suicide Attempt in Patients with Obsessive-Compulsive Disorder: An Exploratory Study with Machine Learning Analysis"** by Neusa Aita Agne, Caroline Gewehr Tisott, Pedro Ballester, Ives Cavalcante Passos, and Ygor Arzeno Ferrão delves into identifying significant predictors of suicide attempts (SA) in patients with obsessive-compulsive disorder (OCD) using a machine learning approach. By analyzing data from 959 OCD outpatients, the study employs an elastic net model to uncover key risk factors, including previous suicide planning, previous suicide thoughts, lifetime depressive episodes, and intermittent explosive disorder. With a high area under the curve of 0.95, the model demonstrates strong predictive performance. This pioneering study underscores the importance of evaluating suicidal tendencies in OCD patients, emphasizing the critical need for clinicians to consider comorbid depressive symptoms and other sociodemographic variables during patient assessments. The findings contribute to the growing body of literature on suicide risk in OCD, highlighting the potential of machine learning algorithms in developing accurate and clinically useful predictive models.