Final Project Report

1. Introduction

Date	03 July 2024
Team ID	SWTID1720017249
Project Name	Panic Disorder Detection
Maximum Marks	1 Marks

1.1 Project overviews

Panic Disorder Detection-

Panic disorder is a type of anxiety disorder characterized by recurrent and unexpected panic attacks. Panic attacks are intense episodes of fear or discomfort that usually reach their peak within minutes and are accompanied by physical symptoms such as rapid heartbeat, shortness of breath, chest pain, dizziness, and a sense of impending doom.
Detecting panic disorder involves recognizing the signs and symptoms of panic attacks and assessing their frequency and impact on an individual's life.
Overall, the detection of panic disorder involves recognizing the symptoms of panic attacks, assessing their frequency and impact, and conducting a thorough evaluation by mental health professionals. Early detection and appropriate treatment can significantly improve the quality of life for individuals with panic disorder.

1.2 Objectives

- **Objective 1:** Develop a machine learning model to detect panic disorder based on patient symptoms and medical history.
- **Objective 2:** Try on several algorithms to train and test our model and use the one that gives us the highest accuracy.
- **Objective 3:** Integrate the model into a Flask web application that can take inputs from users and provide predictions.
- **Objective 4:** Ensure that the application is user-friendly and maintains the confidentiality of user data.
- **Objective 5:** Validate the model with real-world data to ensure its accuracy and reliability.

1. Project Initialization and Planning Phase

Date	03 July 2024
Team ID	SWTID1720017249
Project Name	Panic Disorder Detection
Maximum Marks	3 Marks

2.1 Define Problem Statements:

Many people struggle with unpredictable panic attacks that mess up their daily lives and make them feel worse overall. Not knowing what causes these attacks makes them even more anxious and frustrated. There's a need for a simple and reliable tool to help identify panic disorder signs, track panic attacks and offer ways to manage them better. An understanding and user-friendly platform could monitor these attacks in real-time, provide insights specific to each person, and offer practical help. This would empower people with panic disorder to take control, reduce their anxiety, and live better lives. By addressing these needs, we can create a service that truly helps people with panic disorder by giving them the tools to manage their condition effectively and build a positive relationship with our platform.

Problem Statement (PS)	I am (Customer)	I’m trying to	But	Because	Which makes me feel
PS-1	Someone who experiences frequent panic attacks	Understand what triggers my panic attacks so I can avoid them	The sudden and unpredictable nature of my attacks makes it difficult to identify any patterns or triggers	Without knowing what sets off my panic attacks, I live in constant fear of another episode, which only worsens my anxiety	Anxious, frustrated, and out of control
PS-2	Someone struggling with panic disorder that disrupts my daily life	Effectively manage my panic attacks when they occur	I often feel overwhelmed and lost during an attack, making it difficult to implement any coping mechanisms	There's a lack of readily available and user-friendly tools to guide me through managing a panic attack in real-time	Helpless, scared, and isolated during panic attacks
PS-3	Someone newly diagnosed with panic disorder.	Learn more about panic disorder and how to manage it effectively	The abundance of information online can be overwhelming and sometimes contradictory	I lack a reliable source of personalized insights and clear guidance specific to my situation	Confused, unsure, and anxious about managing my condition.

2. Project Initialization and Planning Phase

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

2.2. Business Requirements

To address the business requirements related to the detection of panic disorder, the following considerations should be incorporated:

1. **User Interface:**
   - Develop a user-friendly, intuitive interface tailored for mental health professionals to detect panic disorder.
   - The interface should facilitate easy input of patient data and allow seamless access to generated reports.
2. **Data Collection:**
   - Implement comprehensive data collection mechanisms to gather detailed information on symptoms, frequency, duration of panic attacks, and their impact on daily life.
   - Use structured questionnaires or surveys for patients and healthcare providers.
   - Ensure real-time data entry capabilities.
3. **Analytics and Algorithms:**
   - Develop robust algorithms and statistical models to analyze collected data for patterns indicative of panic disorder.
   - Leverage machine learning techniques to enhance detection accuracy and predictive capabilities.
   - Implement continuous learning to improve the system based on new data and feedback.
4. **Integration with Existing Systems:**
   - Ensure compatibility and seamless integration with existing electronic health record (EHR) systems and mental health management software.
   - Enable bi-directional data flow to facilitate comprehensive patient records and streamline diagnosis and treatment planning.
5. **Security and Privacy:**
   - Implement stringent security measures to protect sensitive patient data, including encryption, access controls, and regular data backups.
   - Ensure compliance with data protection regulations such as HIPAA and GDPR.

- Conduct regular security audits and vulnerability assessments.

6. **Reporting and Documentation:**
   - Generate comprehensive, easy-to-understand reports summarizing detection results.
   - Include insights on the likelihood of panic disorder, severity assessments, and recommended actions or treatment plans.
7. **Scalability and Performance:**
   - Design the system to handle significant data volumes and accommodate future growth in user demand.
   - Ensure the system delivers accurate and timely results, even with large numbers of concurrent users or data inputs.
   - Implement load balancing and performance optimization techniques.
8. **Collaboration and Communication:**
   - Enable secure collaboration features for mental health professionals to communicate and share insights.
   - Facilitate interdisciplinary discussions, case consultations, and treatment coordination.
   - Integrate messaging and notification systems for real-time updates and alerts.
9. **Training and Support:**
   - Provide comprehensive training materials, including user manuals, tutorials, and FAQs.
   - Offer ongoing technical support to address system-related issues and user inquiries promptly.
   - Conduct regular training sessions and webinars to keep users updated on new features and best practices.
10. **Compliance with Regulations:**
    - Ensure the system complies with relevant legal and regulatory requirements for healthcare data management and diagnostic practices.
    - Maintain up-to-date documentation of compliance measures and undergo regular audits.
    - Stay informed about changes in regulations and update the system accordingly.

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.

2. Project Initialization and Planning Phase

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

2.4. Social and Business Impact

Social Impacts:

1. **Improved Mental Health Diagnosis:** The panic disorder detection system can contribute to improved mental health diagnosis by providing accurate and timely identification of panic disorder. This can lead to early intervention and appropriate treatment, resulting in better outcomes for individuals suffering from panic disorder.
2. **Increased Accessibility to Diagnosis:** By leveraging technology, the panic disorder detection system can potentially increase accessibility to diagnosis. It can be deployed in various healthcare settings, including remote or underserved areas, making it easier for individuals to access mental health assessments and receive appropriate care.
3. **Reduced Stigma and Misdiagnosis:** Implementing an objective and reliable panic disorder detection system can help reduce stigma associated with mental health conditions. It can also minimize the risk of misdiagnosis, as the system relies on data-driven analysis rather than subjective judgment alone, promoting more accurate understanding and treatment of panic disorder.

Business Impacts:

1. **Enhanced Diagnostic Efficiency:** The panic disorder detection system can improve the efficiency of mental health diagnosis within healthcare organizations. It can automate data collection and analysis processes, enabling mental health professionals to streamline their workflow and allocate more time for personalized patient care.
2. **Cost Savings:** Timely diagnosis and intervention can prevent prolonged treatments, unnecessary hospitalizations, and complications, thereby reducing overall healthcare expenses.
3. **Improved Treatment Planning:** The panic disorder detection system's insights and reports can aid mental health professionals in developing personalized treatment plans for individuals diagnosed with panic disorder. This can enhance treatment effectiveness, patient adherence, and long-term outcomes, ultimately benefiting the business by building a reputation for quality care.

2. Project Initialization and Planning Phase

2.5 Project Proposal:

This project aims to develop a system for **detecting and managing panic disorder**. We propose a user-friendly approach with features for individuals to track and analyze their panic attacks, gaining valuable insights into their condition. This self-management focus can empower them to develop coping mechanisms. Additionally, the project will explore (with user consent) functionalities that could anonymously share data trends with healthcare professionals, potentially aiding in earlier detection of panic disorder.

Project Overview	
Objective	This project strives to develop a user-friendly system that tackles panic disorder. The primary focus is to empower individuals by equipping them with self-management tools. This will enable them to gain valuable insights into their condition and potentially develop improved coping mechanisms.
Scope	The project aims to develop a system that allows users to track and analyze panic attacks, providing data visualization tools to understand patterns. It may also explore the possibility of sharing anonymous data trends with healthcare professionals, but this feature falls outside the self-management focus and requires careful design to ensure user privacy.
Problem Statement	
Description	Individuals with panic disorder experience unpredictable panic attacks that significantly disrupt their daily lives. Recognizing the signs and symptoms of these attacks, tracking their frequency and severity, and accessing reliable information can be challenging. This lack of readily available tools and knowledge can lead to increased anxiety, feelings of helplessness, and difficulty managing their condition.
Impact	A user-friendly system addressing these challenges has the potential to empower individuals with panic disorder and significantly improve their quality of life. By equipping them with self-management tools, data-driven insights, and educational resources, the system can lead to reduced anxiety, improved coping mechanisms, and potentially earlier detection. This holistic approach empowers individuals to take control of their condition, ultimately leading to a better and healthier life.

Proposed Solution	
Approach	This project will utilize a user-centered design approach to develop a user-friendly system. Users can easily record details of their panic attacks (date, time, duration, symptoms, triggers) for analysis. Data visualization tools will help users identify trends and patterns in their panic attack frequency and severity. Additionally, the system will integrate informative content on panic disorder and coping techniques.
Key Features	-Users can effortlessly record details of panic attacks (date, time, duration, symptoms, triggers) for comprehensive analysis. -Interactive tools help users identify trends and patterns in their panic attack frequency and severity, fostering self-awareness. -The system integrates informative content on panic disorder, including symptoms, causes, and effective coping techniques, promoting user education.

Resource Requirements:

Resource Type	**Description**	**Specification/Allocation**
Hardware		
Computing Resources	CPU/GPU specifications, number of cores	T4 GPU
Memory	RAM specifications	8 GB
Storage	Disk space for data, models, and logs	1 TB SSD
Software		
Frameworks	Python frameworks	Flask
Libraries	Additional libraries	scikit-learn, pandas, numpy
Development Environment	IDE, version control	Jupyter Notebook, Git
Data		
Data	Source, size, format	Kaggle dataset, 120000, CSV

2. Project Initialization and Planning Phase

Date	04 July 2024
Team ID	SWTID1720017249
Project Name	Panic Disorder Detection
Maximum Marks	4 Marks

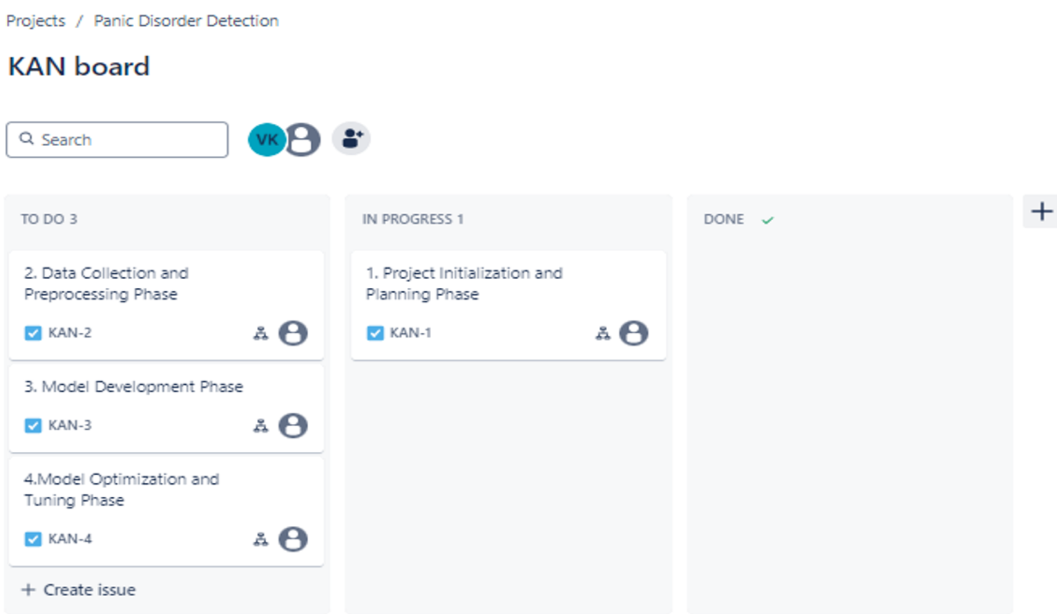
2.3 Initial Project Planning Template

Product Backlog, Sprint Schedule, and Estimation:

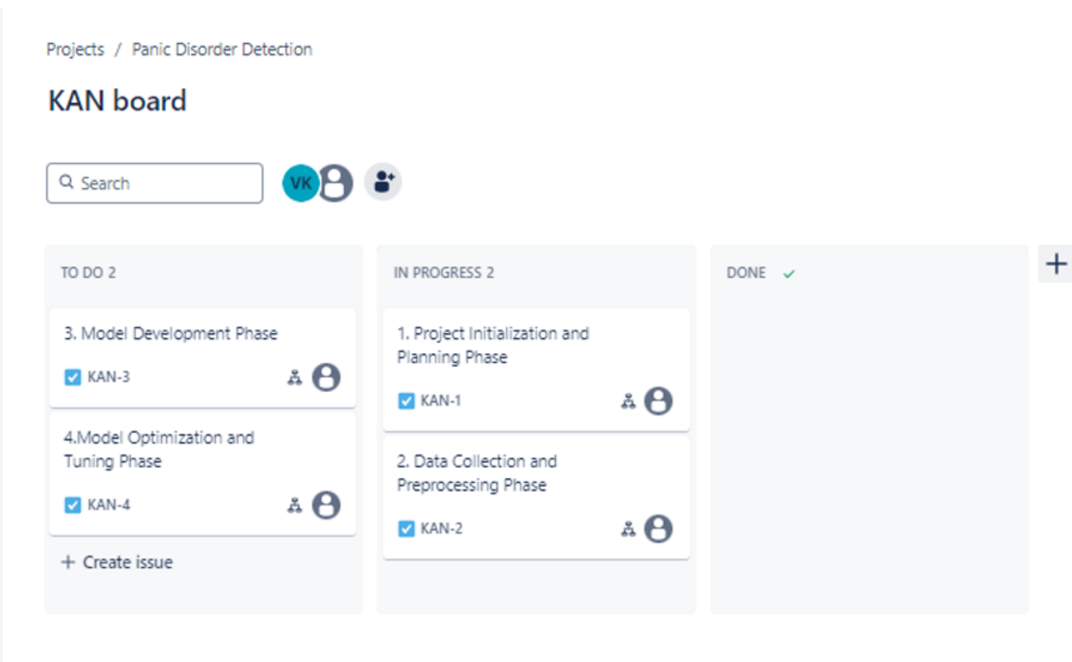
Sprint	Functional Requirement (Epic)	User Story Number	User Story / Task	Priority	Team Membe rs	Sprint Start Date	Sprint End Date (Planned)
Sprint-1	Project Initialization and Planning Phase	KAN-5	Define Problem Statements	High	Anshika	03/07/2024	04/07/2024
Sprint-1	Project Initialization and Planning Phase	KAN-6	Project Planning	Medium	Anusha	03/07/2024	04/07/2024
Sprint-1	Project Initialization and Planning Phase	KAN-7	Project Proposal	Medium	Suhani	04/07/2024	05/07/24
Sprint-2	Data Collection and Preprocessing Phase	KAN-8	Data Exploration and Preprocessing	High	Vidisha	06/07/2024	07/07/2024
Sprint-2	Data Collection and Preprocessing Phase	KAN-9	Data Quality	High	Anshika	06/07/2024	07/07/2024

Sprint-2	Data Collection and Preprocessing Phase	KAN-10	Raw Data Sources and Data Quality	High	Anusha	07/07/2024	08/07/2024
Sprint-3	Model Development Phase	KAN-11	Feature Selection	Medium	Suhani	07/07/2024	08/07/2024
Sprint-3	Model Development Phase	KAN-12	Exploratory Data Visual Analysis	Low	Vidisha	08/07/2024	09/07/2024
Sprint-3	Model Development Phase	KAN-12	Initial Model Training Code	Low	Anshika	08/07/2024	09/07/2024
Sprint-3	Model Development Phase	KAN-13	Model Validation and Evaluation	High	Anusha	08/07/2024	09/07/2024
Sprint-3	Model Development Phase	KAN-14	Model Selection	Low	Suhani	09/07/2024	10/07/2024
Sprint-4	Model Optimization and Tuning Phase	KAN-15	Model Optimization	Low	Vidisha	09/07/2024	10/07/2024
Sprint-4	Model Optimization and Tuning Phase	KAN-16	Tuning Phase	Low	Anusha	09/07/2024	10/07/2024

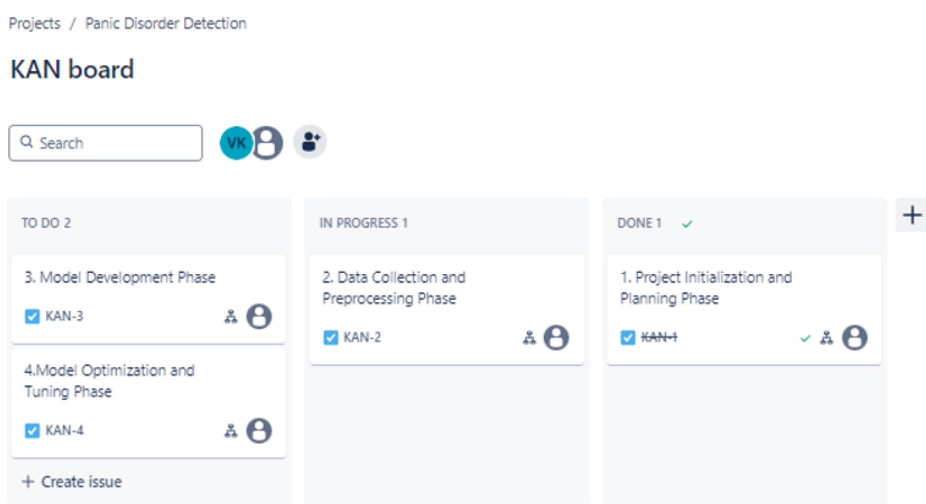
Project Initialization and Planning Phase



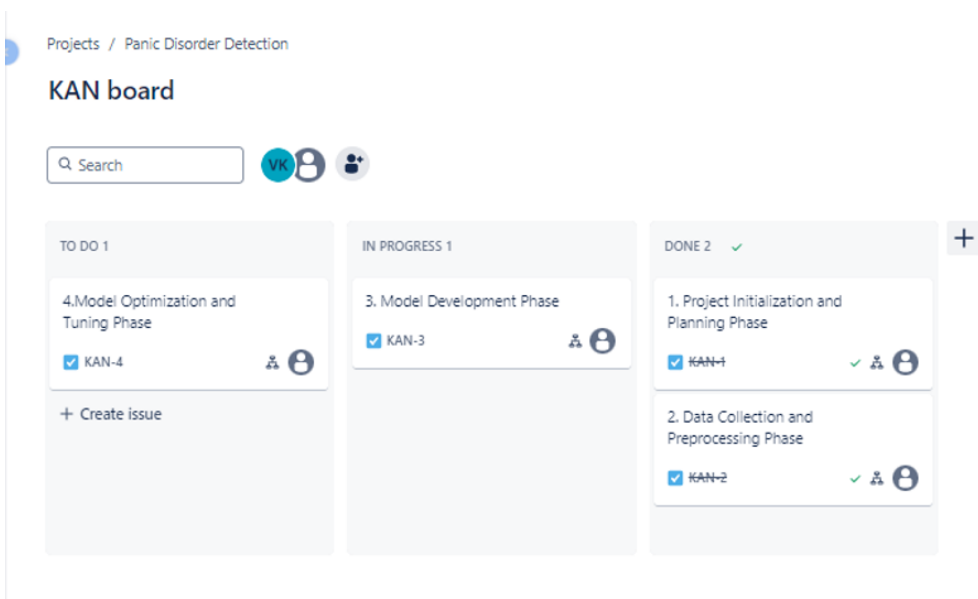
Project Initialization and Planning Phase **and** Data Collection and Preprocessing Phase



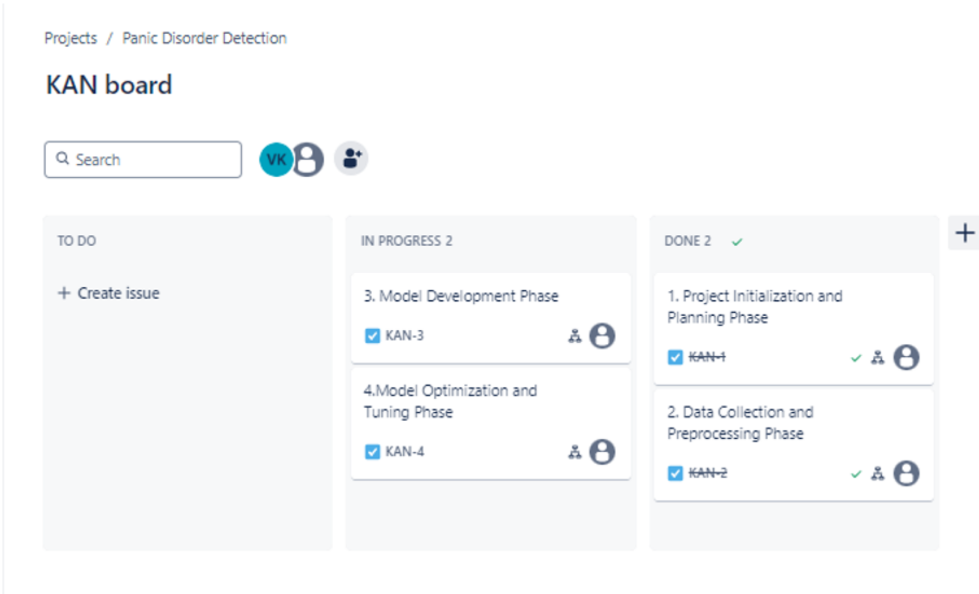
Data Collection and Preprocessing Phase



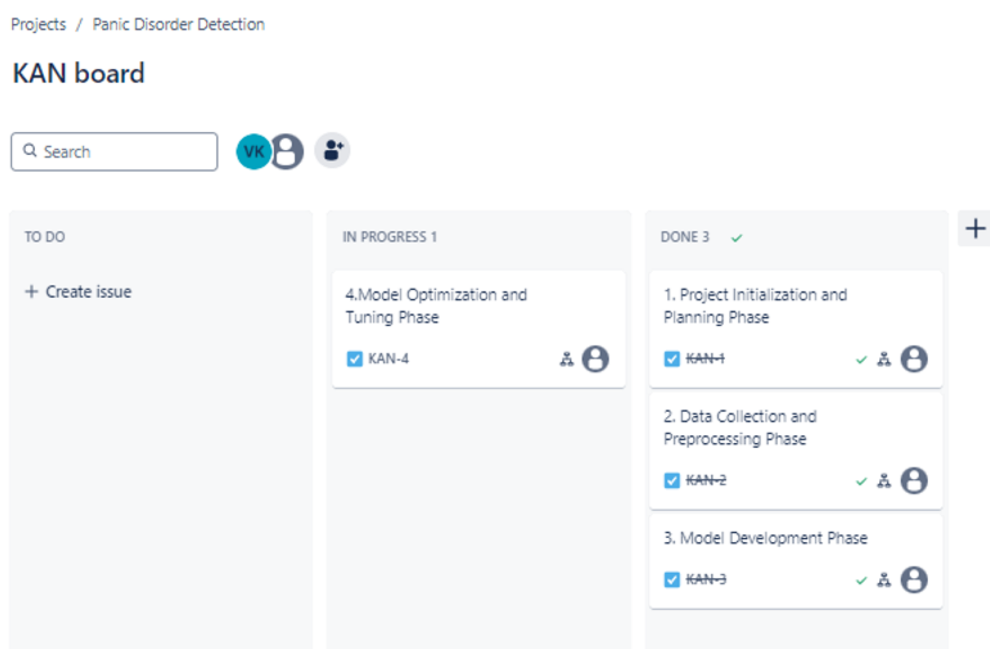
Model Development Phase



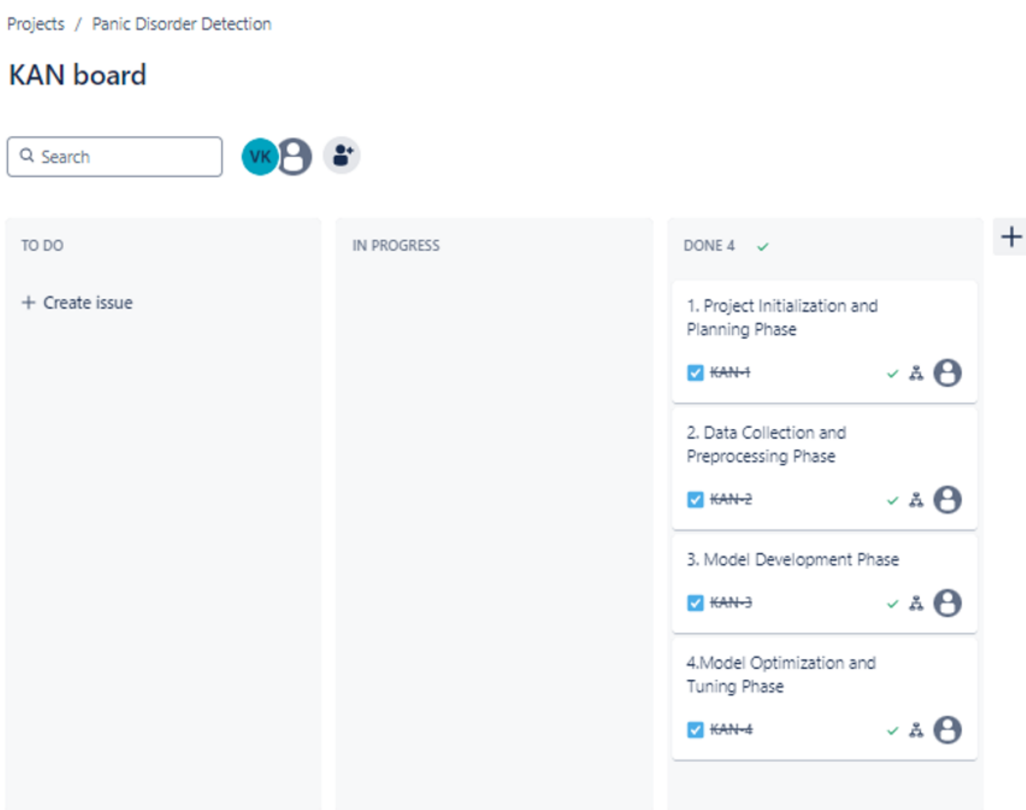
Model Development Phase **and** Model Optimization and Tuning Phase



Model Optimization and Tuning Phase



All Phases Completed



3. Data Collection and Preprocessing Phase

Date	06 July 2024
Team ID	SWTID1720017249
Project Title	Panic Disorder Detection
Maximum Marks	2 Marks

3.1 Data Collection Plan & Raw Data Sources Identification Report

Elevate your data strategy with the Data Collection plan and the Raw Data Sources report, ensuring meticulous data curation and integrity for informed decision-making in every analysis and decision-making endeavor.

Data Collection Plan:

Section	Description
Project Overview	This machine learning project aims to tackle panic disorder through machine learning for early detection support. A user-friendly system will collect physiological data (heart rate, respiration) and user-reported symptoms during potential attacks. This data, along with information from a panic disorder dataset on Kaggle, will be used to train machine learning models. These models will then analyze user data in real-time, searching for patterns indicative of panic attacks. By identifying these patterns early, users can be empowered to seek professional help and potentially improve their management of panic disorder.
Data Collection Plan	- A user-friendly system will collect real-time physiological data (heart rate, respiration) and user-reported symptoms during potential panic attacks. This allows the system to learn about the user's specific experiences. -Search for datasets containing data points relevant to panic attacks, such as self-reported anxiety levels, physiological responses during

	anxiety episodes, etc.
Raw Data Sources Identified	PanicAttackDetect utilizes two raw data sources. First, a user-friendly system will collect real-time physiological data (heart rate, respiration) and user-reported symptoms during potential panic attacks. This captures the user's specific experiences. Secondly, publicly available panic disorder datasets from Kaggle will be used. This injects additional information on panic attacks, enriching the training process for the machine learning models. Combining these sources aims to create a robust system for identifying patterns indicative of panic attacks.

Raw Data Sources Identified:

Source Name	Description	Location/URL	Format	Size	Access Permissions
Kaggle Dataset	This dataset contains 120000 records about Panic disorder patients.The dataset contains two files. Panic_Disorder_training:-This file contains 100000 labeled records. Panic_Disorder_testing: -This file contains 20000 labeled records.	https://www.kaggle.com/datasets/muhammadshahidazeem/panic-disorder-detection-dataset/data	CSV	15.03 MB	Public

3. Data Collection and Preprocessing Phase

Date	06 July 2024
Team ID	SWTID1720017249
Project Title	Panic Disorder Detection
Maximum Marks	2 Marks

3.2 Data Quality Report:

The Data Quality Report will summarize data quality issues from the selected source, including severity levels and resolution plans. It will aid in systematically identifying and rectifying data discrepancies.

Data Source	Data Quality Issue	Severity	Resolution Plan
Kaggle Dataset	Missing values in the ’Medical History’,’Psychiatric History’ and ’Substance Use’	High	Replacing Missing Values with Specific Strings
Kaggle Dataset	Categorical data in the dataset	Moderate	Encoding must be done in the data

3. Data Collection and Preprocessing Phase

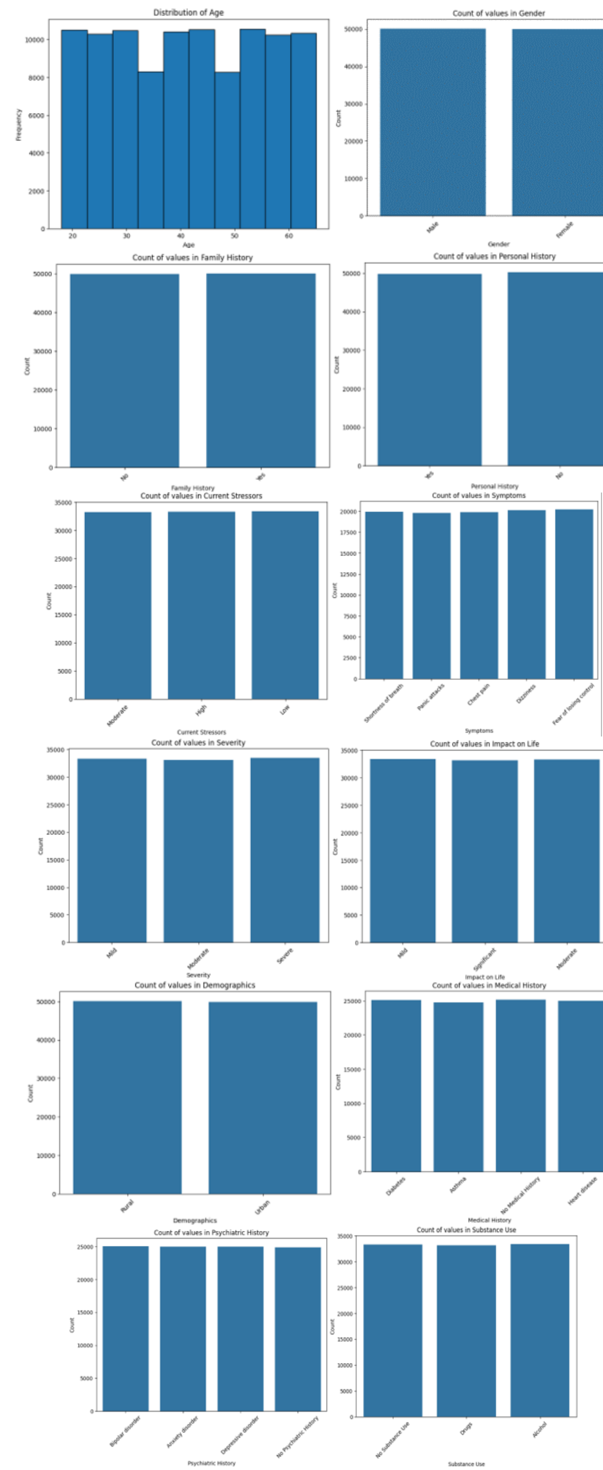
Date	06 July 2024
Team ID	SWTID1720017249
Project Title	Panic Disorder Detection
Maximum Marks	6 Marks

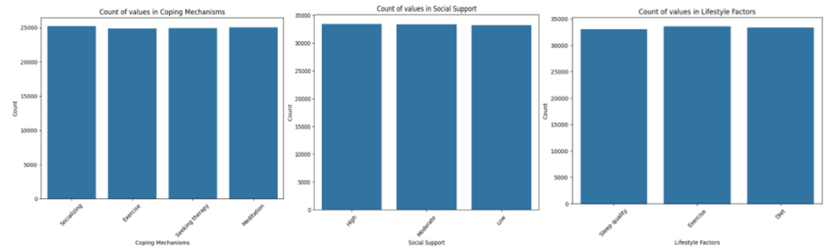
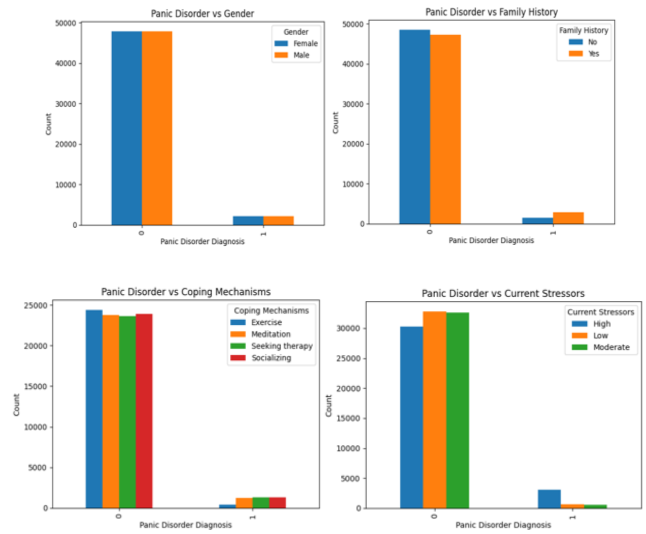
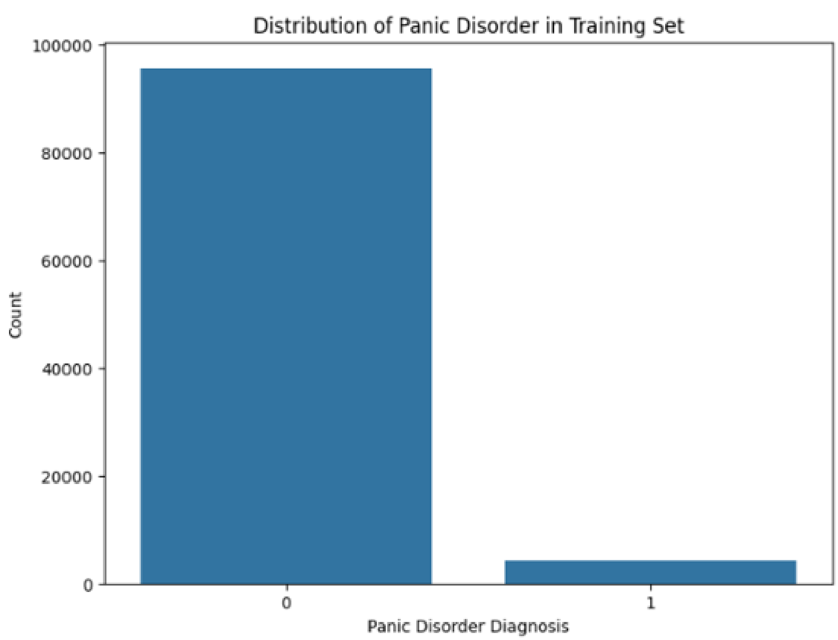
3.3 Data Exploration and Preprocessing:

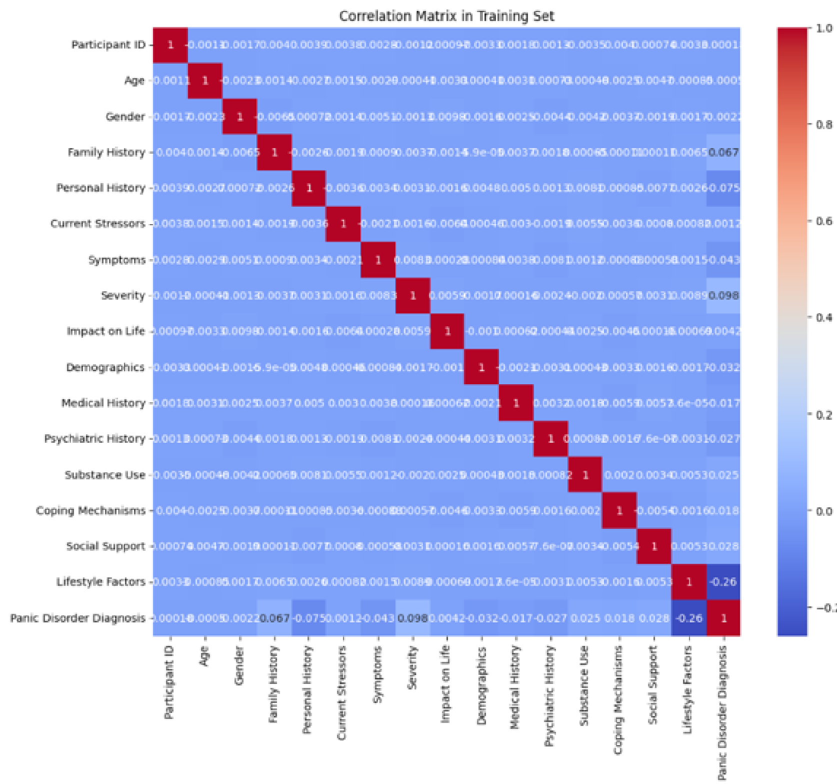
Dataset variables will be statistically analyzed to identify patterns and outliers, with Python employed for preprocessing tasks like normalization and feature engineering. Data cleaning will address missing values and outliers, ensuring quality for subsequent analysis and modeling, and forming a strong foundation for insights and predictions.

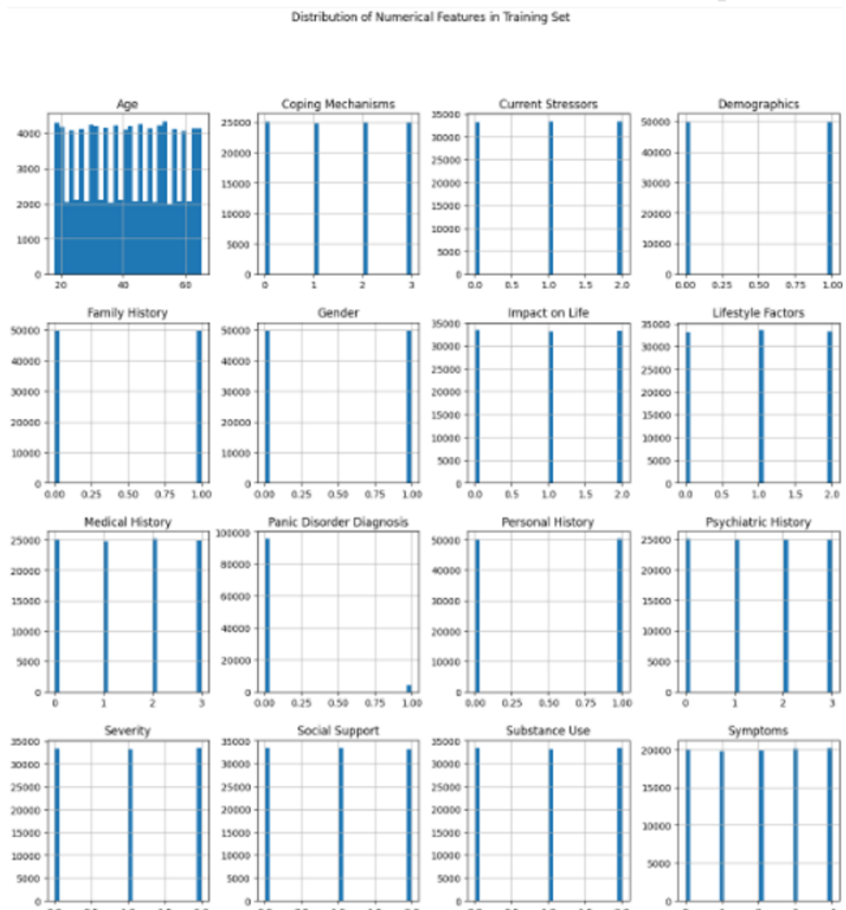
Section	**Description**
Data Overview	Dimension: 100000 rows x 17 columns Descriptive statistics:

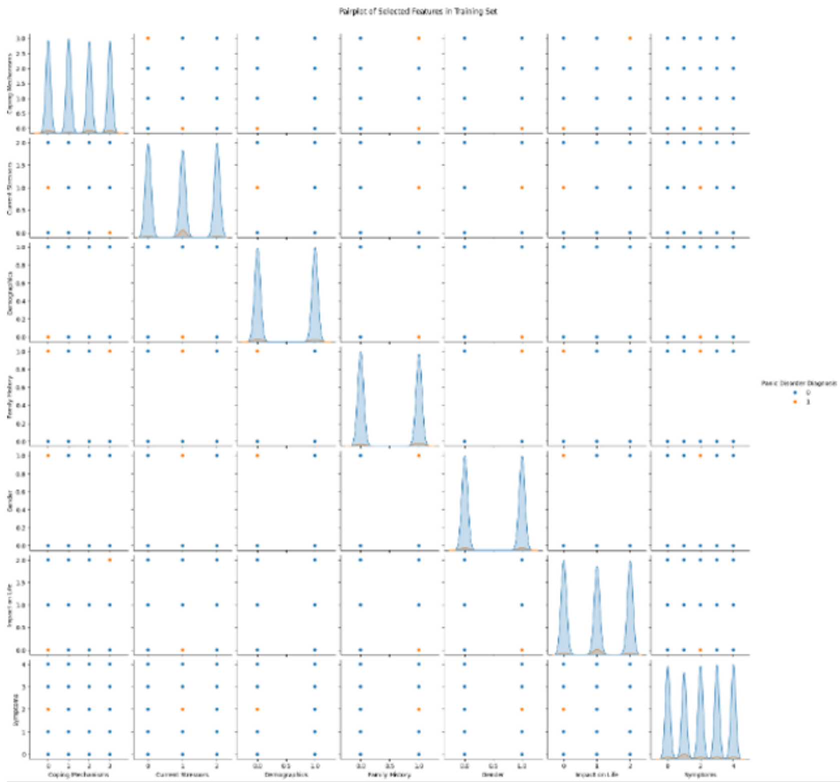
	Participant ID	Age	Gender	Family History	Personal History	Current Stressors	Symptoms	Severity	Impact on Life	Demographics	Medical History	Psychiatric History	Substance Use
count	100000.000000	100000.000000	100000	100000	100000	100000	100000	100000	100000	100000	100000	100000	100000
unique	NaN	NaN	2	2	2	3	5	3	3	2	4	4	3
top	NaN	NaN	Male	Yes	No	Low	Fear of losing control	Severe	Mild	Rural	No Medical History	Bipolar disorder	Alcohol
freq	NaN	NaN	50052	50042	50210	33409	20236	33510	33452	50087	25173	25058	33445
mean	50000.500000	41.454300	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
std	28867.657797	13.839204	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
min	1.000000	18.000000	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
25%	25000.750000	29.000000	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
50%	50000.500000	41.000000	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
75%	75000.250000	53.000000	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
max	100000.000000	65.000000	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

Univariate Analysis	

<table>
<tr>
<td></td>
<td>
</td>
</tr>
<tr>
<td>Bivariate Analysis</td>
<td>
</td>
</tr>
<tr>
<td>Multivariate Analysis</td>
<td>
</td>
</tr>
</table>


Correlation Matrix in Training Set
Participant ID
Age
Gender
Family History
Personal History
Current Stressors
Symptoms
Severity
Impact on Life
Demographics
Medical History
Psychiatric History
Substance Use
Coping Mechanisms
Social Support
Lifestyle Factors
Panic Disorder Diagnosis


Distribution of Numerical Features in Training Set
Age
Coping Mechanisms
Current Stressors
Demographics
Family History
Gender
Impact on Life
Lifestyle Factors
Medical History
Panic Disorder Diagnosis
Personal History
Psychiatric History
Severity
Social Support
Substance Use
Symptoms

	Pairplot of Selected Features in Training Set Coping Mechanisms Current Stressors Demographics Family History Gender Impact on Life Symptoms Panic Disorder Diagnosis 0 1

Outliers and Anomalies

```
train.isnull().sum() #Determining

Participant ID                 0
Age                            0
Gender                         0
Family History                 0
Personal History               0
Current Stressors              0
Symptoms                       0
Severity                       0
Impact on Life                 0
Demographics                   0
Medical History            25173
Psychiatric History        24921
Substance Use              33374
Coping Mechanisms              0
Social Support                 0
Lifestyle Factors              0
Panic Disorder Diagnosis       0
dtype: int64
```

```
test.isnull().sum() #Determining t

Participant ID                0
Age                           0
Gender                        0
Family History                0
Personal History              0
Current Stressors             0
Symptoms                      0
Severity                      0
Impact on Life                0
Demographics                  0
Medical History            5001
Psychiatric History        4989
Substance Use              6617
Coping Mechanisms             0
Social Support                0
Lifestyle Factors             0
Panic Disorder Diagnosis      0
dtype: int64
```

Data Preprocessing Code Screenshots

Loading Data

```
train=pd.read_csv('panic_disorder_dataset_training.csv')
train.head() #print the first 5 rows of the training dataset
```

	Participant ID	Age	Gender	Family History	Personal History	Current Stressors	Symptoms	Severity	Impact on Life	Demographics	Medical History	Psychiatric History	Substance Use	Coping Mechanisms	Social Support	Lifestyle Factors	Panic Disorder Diagnosis
0	1	38	Male	No	Yes	Moderate	Shortness of breath	Mild	Mild	Rural	Diabetes	Bipolar disorder	NaN	Socializing	High	Sleep quality	0
1	2	51	Male	No	No	High	Panic attacks	Mild	Mild	Urban	Asthma	Anxiety disorder	Drugs	Exercise	High	Sleep quality	0
2	3	32	Female	Yes	No	High	Panic attacks	Mild	Significant	Urban	Diabetes	Depressive disorder	NaN	Seeking therapy	Moderate	Exercise	0
3	4	64	Female	No	No	Moderate	Chest pain	Moderate	Moderate	Rural	Diabetes	NaN	NaN	Meditation	High	Exercise	0
4	5	31	Male	Yes	No	Moderate	Panic attacks	Mild	Moderate	Rural	Asthma	NaN	Drugs	Seeking therapy	Low	Sleep quality	0

Handling Missing Data

```
train.replace('None', pd.NA, inplace=True)
train['Medical History'].fillna('No Medical History', inplace=True)
train['Psychiatric History'].fillna('No Psychiatric History', inplace=True)
train['Substance Use'].fillna('No Substance Use', inplace=True)
```

```
test.replace('None', pd.NA, inplace=True)
test['Medical History'].fillna('No Medical History', inplace=True)
test['Psychiatric History'].fillna('No Psychiatric History', inplace=True)
test['Substance Use'].fillna('No Substance Use', inplace=True)
```

Data Transformation

```
le = {}
for column in train.columns:
    if train[column].dtype=='object':
        le[column] = {}
        c = 0
        for i in train[column].unique():
            le[column][i] = c
            c += 1
        train[column] = train[column].map(le[column])
le = {}
for column in test.columns:
  if test[column].dtype == object:
    le[column] = {}
    c = 0
    for i in test[column].unique():
      le[column][i] = c
      c += 1
    test[column] = test[column].map(le[column])
```

Feature Engineering

```
x_train=train.iloc[:,1:-1] #Dependent variables of the training dataset
y_train=train.iloc[:,-1] #Independent variables of the training dataset
x_test=test.iloc[:,1:-1] #Dependent variables of the testing dataset
y_test=test.iloc[:,-1] #Independent variables of the testing dataset
```

```
class_0_indices = x_train[y_train == 0].index #negative class
class_1_indices = x_train[y_train == 1].index #positive class

undersample_indices = np.random.choice(class_0_indices, size=class_1_indices.shape[0], replace=False)

x_train_undersampled = pd.concat([x_train.loc[undersample_indices], x_train.loc[class_1_indices]])
y_train_undersampled = pd.concat([y_train.loc[undersample_indices], y_train.loc[class_1_indices]])

# Print before and after balancing
print("Before balancing", Counter(y_train))
print("After balancing", Counter(y_train_undersampled))
```

Save Processed Data

```python
# Perform Chi-Square test on undersampled data
f_p_values = chi2(x_train_undersampled, y_train_undersampled)
p_values = pd.Series(f_p_values[1], index=x_train_undersampled.columns)
p_values.sort_values(ascending=True, inplace=True)
print(p_values)

# Manually selected features based on the analysis
selected_features = ['Coping Mechanisms', 'Current Stressors', 'Demographics', 'Family History', 'Gender', 'Impact on Life', 'Symptoms']

# Create a DataFrame with selected features
x_train_selected = x_train_undersampled[selected_features]
x_test_selected = x_test[selected_features]

# Print the selected features and their corresponding p-values
print("Selected Features and their p-values:")
print(p_values[selected_features])
```

4. Model Development Phase

Date	07 July 2024
Team ID	SWTID1720017249
Project Title	Panic Disorder Detection
Maximum Marks	5 Marks

4.1 Feature Selection Report

In the forthcoming update, each feature will be accompanied by a brief description. Users will indicate whether it's selected or not, providing reasoning for their decision. This process will streamline decision-making and enhance transparency in feature selection.

Feature	Description	Selected (Yes/No)	Reasoning
Age	Age of the individual	No	Not selected; p-value not provided, implying non-significance.
Psychiatric History	History of psychiatric disorders	Yes	Selected; very low p-value (1.917349e-10), indicating high significance.
Lifestyle Factors	Lifestyle habits and factors	Yes	Selected; extremely low p-value (0.000000e+00), indicating very high significance.
Social Support	Availability and quality of social support	Yes	Selected; very low p-value (1.144308e-06), indicating high significance.
Substance Use	Usage of substances such as alcohol or drugs	Yes	Selected; very low p-value (1.294024e-06), indicating high significance.
Personal History	Personal history of the individual	Yes	Selected; extremely low p-value (2.747857e-39), indicating very high significance.
Medical History	Medical history of the individual	Yes	Selected; low p-value (3.300026e-04), indicating significance.
Severity	Severity of the condition	Yes	Selected; extremely low p-value (3.994025e-57), indicating very high significance.
Coping Mechanisms	Coping mechanisms used by the individual	Yes	Selected; low p-value (8.106781e-03), indicating significance.
Current Stressors	Current stressors affecting the individual	Yes	Selected because of significance
Demographics	Demographic information	Yes	Selected; low p-value (1.826159e-07), indicating significance.

Family History	Family history of psychiatric or medical conditions	Yes	Selected; very low p-value (1.322812e-25), indicating high significance.
Gender	Gender of the individual	Yes	Selected because of significance
Impact on Life	Impact of the condition on the individual's life	Yes	Selected because of significance
Symptoms	Symptoms experienced by the individual	Yes	Selected; very low p-value (1.475430e-27), indicating high significance.

4. Model Development Phase

Date	09 July 2024
Team ID	SWTID1720017249
Project Title	Panic Disorder Detection
Maximum Marks	6 Marks

4.2 Model Selection Report

In the forthcoming Model Selection Report, various models will be outlined, detailing their descriptions, hyperparameters, and performance metrics, including Accuracy or F1 Score. This comprehensive report will provide insights into the chosen models and their effectiveness.

Model Selection Report:

Model	Description	Hyperparameters Used	Best Params
Gradient Boosting	Gradient Boosting model with hyperparameter tuning using GridSearchCV	n_estimators: [100, 200, 300], learning_rate: [0.01, 0.1, 0.2], max_depth: [3, 4, 5], min_samples_split: [2, 5, 10], min_samples_leaf: [1, 2, 4], subsample: [0.8, 0.9, 1.0]	{'n_estimators': value, 'learning_rate': value, 'max_depth': value, 'min_samples_split': value, 'min_samples_leaf': value, 'subsample': value}
XGBoost	XGBoost model with hyperparameter tuning using GridSearchCV	n_estimators: [100, 200, 300], learning_rate: [0.01, 0.1, 0.2], max_depth: [3, 4, 5], subsample: [0.8, 0.9, 1.0], colsample_bytree: [0.8, 0.9, 1.0], gamma: [0, 0.1, 0.2]	{'n_estimators': value, 'learning_rate': value, 'max_depth': value, 'subsample': value, 'colsample_bytree': value, 'gamma': value}
Decision Tree	Decision Tree model with hyperparameter tuning using GridSearchCV	criterion: ['gini', 'entropy'], splitter: ['best', 'random'], max_depth: [None, 10, 20, 30, 40, 50], min_samples_split: [2, 5, 10], min_samples_leaf: [1, 2, 4], max_features: [None, 'auto', 'sqrt', 'log2']	{'criterion': value, 'splitter': value, 'max_depth': value, 'min_samples_split': value, 'min_samples_leaf': value, 'max_features': value}

4. Model Development Phase

Date	09 July 2024
Team ID	SWTID1720017249
Project Title	Panic Disorder Detection
Maximum Marks	4 Marks

4.3 Initial Model Training Code, Model Validation and Evaluation Report

The initial model training code will be showcased in the future through a screenshot. The model validation and evaluation report will include classification reports, accuracy, and confusion matrices for multiple models, presented through respective screenshots.

Initial Model Training Code:

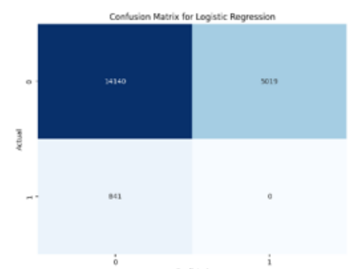
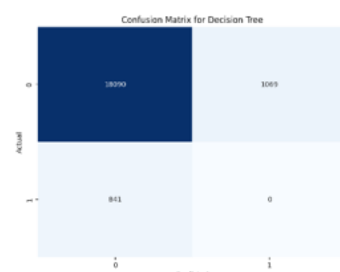
Training and Testing The Model In Multiple Algorithms

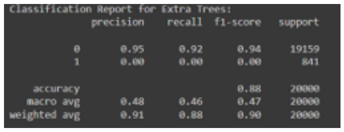
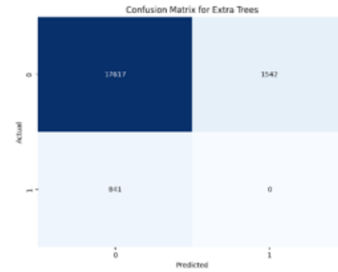
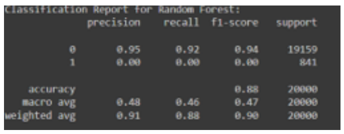
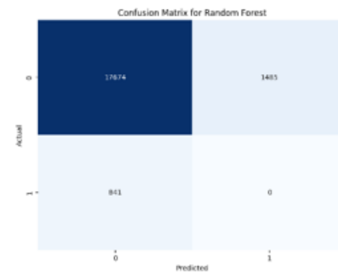
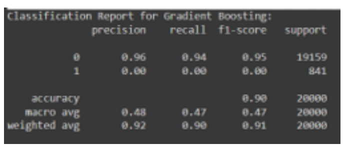
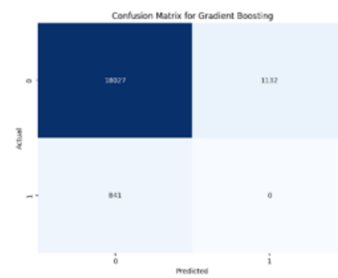
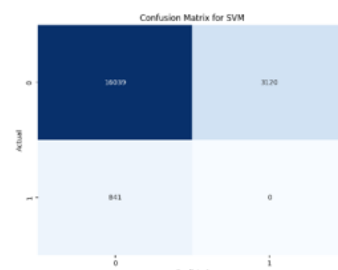
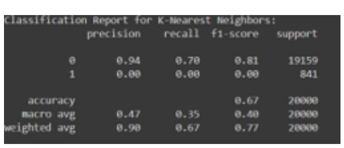
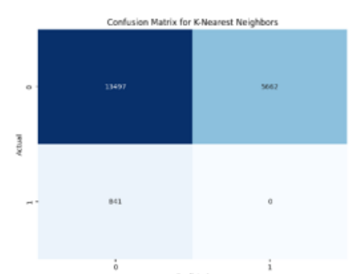
```
[ ] # Assuming x_train, x_test, y_train, y_test are defined and preprocessed

    # Initialize models
    models = {
        'Logistic Regression': LogisticRegression(),
        'Decision Tree': DecisionTreeClassifier(),
        'Extra Trees': ExtraTreesClassifier(),
        'Random Forest': RandomForestClassifier(),
        'Gradient Boosting': GradientBoostingClassifier(),
        'SVM': SVC(),
        'K-Nearest Neighbors': KNeighborsClassifier(),
        'XGBoost': XGBClassifier()
    }
```

Testing and Comparing Model With Multiple Evaluation Metrics

```python
# Train and evaluate each model
for model_name, model in models.items():
    model.fit(x_train_selected, y_train_selected)
    y_pred = model.predict(x_test_selected)

    # Calculate accuracy
    accuracy = accuracy_score(y_test_selected, y_pred)
    print(f"{model_name} - Accuracy: {accuracy:.4f}")

    # Display confusion matrix
    plt.figure(figsize=(8, 6))
    cm = confusion_matrix(y_test, y_pred)
    sns.heatmap(cm, annot=True, cmap='Blues', fmt='d', cbar=False)
    plt.title(f"Confusion Matrix for {model_name}")
    plt.xlabel('Predicted')
    plt.ylabel('Actual')
    plt.show()

    # Display classification report
    print(f"Classification Report for {model_name}:")
    print(classification_report(y_test_selected, y_pred))
```

Model Validation and Evaluation Report:

<table>
<tr><th>Model</th><th>Classification Report</th><th>Accuracy</th><th>Confusion Matrix</th></tr>
<tr><td>Logistic Regression</td><td>Classification Report for Logistic Regression:
precision recall f1-score support
0 0.94 0.74 0.83 19159
1 0.00 0.00 0.00 841
accuracy 0.71 20000
macro avg 0.47 0.37 0.41 20000
weighted avg 0.90 0.71 0.79 20000</td><td>70.70</td><td>
</td></tr>
<tr><td>Decision Tree</td><td>Classification Report for Decision Tree:
precision recall f1-score support
0 0.96 0.94 0.95 19159
1 0.00 0.00 0.00 841
accuracy 0.90 20000
macro avg 0.48 0.47 0.47 20000
weighted avg 0.92 0.90 0.91 20000</td><td>90.45</td><td>
</td></tr>
</table>

<table>
<tr>
<td>Extra Trees</td>
<td>
<table>
<tr><th colspan="5">Classification Report for Extra Trees:</th></tr>
<tr><th></th><th>precision</th><th>recall</th><th>f1-score</th><th>support</th></tr>
<tr><td>0</td><td>0.95</td><td>0.92</td><td>0.94</td><td>19159</td></tr>
<tr><td>1</td><td>0.00</td><td>0.00</td><td>0.00</td><td>841</td></tr>
<tr><td>accuracy</td><td></td><td></td><td>0.88</td><td>20000</td></tr>
<tr><td>macro avg</td><td>0.48</td><td>0.46</td><td>0.47</td><td>20000</td></tr>
<tr><td>weighted avg</td><td>0.91</td><td>0.88</td><td>0.90</td><td>20000</td></tr>
</table></td>
<td>88.09</td>
<td>
</td>
</tr>
<tr>
<td>Random Forest</td>
<td>
<table>
<tr><th colspan="5">Classification Report for Random Forest:</th></tr>
<tr><th></th><th>precision</th><th>recall</th><th>f1-score</th><th>support</th></tr>
<tr><td>0</td><td>0.95</td><td>0.92</td><td>0.94</td><td>19159</td></tr>
<tr><td>1</td><td>0.00</td><td>0.00</td><td>0.00</td><td>841</td></tr>
<tr><td>accuracy</td><td></td><td></td><td>0.88</td><td>20000</td></tr>
<tr><td>macro avg</td><td>0.48</td><td>0.46</td><td>0.47</td><td>20000</td></tr>
<tr><td>weighted avg</td><td>0.91</td><td>0.88</td><td>0.90</td><td>20000</td></tr>
</table></td>
<td>88.37</td>
<td>
</td>
</tr>
<tr>
<td>Gradient Boosting</td>
<td>
<table>
<tr><th colspan="5">Classification Report for Gradient Boosting:</th></tr>
<tr><th></th><th>precision</th><th>recall</th><th>f1-score</th><th>support</th></tr>
<tr><td>0</td><td>0.96</td><td>0.94</td><td>0.95</td><td>19159</td></tr>
<tr><td>1</td><td>0.00</td><td>0.00</td><td>0.00</td><td>841</td></tr>
<tr><td>accuracy</td><td></td><td></td><td>0.90</td><td>20000</td></tr>
<tr><td>macro avg</td><td>0.48</td><td>0.47</td><td>0.47</td><td>20000</td></tr>
<tr><td>weighted avg</td><td>0.92</td><td>0.90</td><td>0.91</td><td>20000</td></tr>
</table></td>
<td>90.13</td>
<td>
</td>
</tr>
<tr>
<td>SVM</td>
<td>
<table>
<tr><th colspan="5">Classification Report for SVM:</th></tr>
<tr><th></th><th>precision</th><th>recall</th><th>f1-score</th><th>support</th></tr>
<tr><td>0</td><td>0.95</td><td>0.84</td><td>0.89</td><td>19159</td></tr>
<tr><td>1</td><td>0.00</td><td>0.00</td><td>0.00</td><td>841</td></tr>
<tr><td>accuracy</td><td></td><td></td><td>0.80</td><td>20000</td></tr>
<tr><td>macro avg</td><td>0.48</td><td>0.42</td><td>0.45</td><td>20000</td></tr>
<tr><td>weighted avg</td><td>0.91</td><td>0.80</td><td>0.85</td><td>20000</td></tr>
</table></td>
<td>80.20</td>
<td>
</td>
</tr>
<tr>
<td>K-Nearest Neighbors</td>
<td>
<table>
<tr><th colspan="5">Classification Report for K-Nearest Neighbors:</th></tr>
<tr><th></th><th>precision</th><th>recall</th><th>f1-score</th><th>support</th></tr>
<tr><td>0</td><td>0.94</td><td>0.70</td><td>0.81</td><td>19159</td></tr>
<tr><td>1</td><td>0.00</td><td>0.00</td><td>0.00</td><td>841</td></tr>
<tr><td>accuracy</td><td></td><td></td><td>0.67</td><td>20000</td></tr>
<tr><td>macro avg</td><td>0.47</td><td>0.35</td><td>0.40</td><td>20000</td></tr>
<tr><td>weighted avg</td><td>0.90</td><td>0.67</td><td>0.77</td><td>20000</td></tr>
</table></td>
<td>67.48</td>
<td>
</td>
</tr>
</table>

<table>
<tr>
<td>XGBoost</td>
<td><pre>Classification Report for XGBoost:
              precision   recall f1-score   support

           0   0.96   0.95   0.95   19159
           1   0.00   0.00   0.00   841

    accuracy   0.91   20000
   macro avg   0.48   0.48   0.48   20000
weighted avg   0.92   0.91   0.91   20000</pre></td>
<td>0.9155</td>
<td>
</td>
</tr>
</table>

5. Model Optimization and Tuning Phase

Date	09 July 2024
Team ID	SWTID1720017249
Project Title	Panic Disorder Detection
Maximum Marks	10 Marks

The Model Optimization and Tuning Phase involves refining machine learning models for peak performance. It includes optimized model code, fine-tuning hyperparameters, comparing performance metrics, and justifying the final model selection for enhanced predictive accuracy and efficiency.

5.1 Hyperparameter Tuning Documentation:

Model	Tuned Hyperparameters	Optimal Values
Gradient Boosting	n_estimators, learning_rate, max_depth, min_samples_split, min_samples_leaf, subsample	n_estimators: 200, learning_rate: 0.1, max_depth: 4, min_samples_split: 5, min_samples_leaf: 2, subsample: 0.9
XGBoost	n_estimators, learning_rate, max_depth, subsample, colsample_bytree, gamma	n_estimators: 300, learning_rate: 0.1, max_depth: 4, subsample: 0.8, colsample_bytree: 0.9, gamma: 0.1
Decision Tree	criterion, splitter, max_depth, min_samples_split, min_samples_leaf, max_features	criterion: 'gini', splitter: 'best', max_depth: 30, min_samples_split: 2, min_samples_leaf: 1, max_features: None

5. Model Optimization and Tuning Phase

Date	09 July 2024
Team ID	SWTID1720017249
Project Title	Panic Disorder Detection
Maximum Marks	10 Marks

5.2 Performance Metrics Comparison Report:**Performance Metrics Comparison Report (2 Marks):**

Model	Baseline Metric (Accuracy)	Optimized Metric (Accuracy)
Decision Tree	90.45	90.34
Gradient Boosting	90.13	91.54
XGBoost	91.12	91.51

5. Model Optimization and Tuning Phase

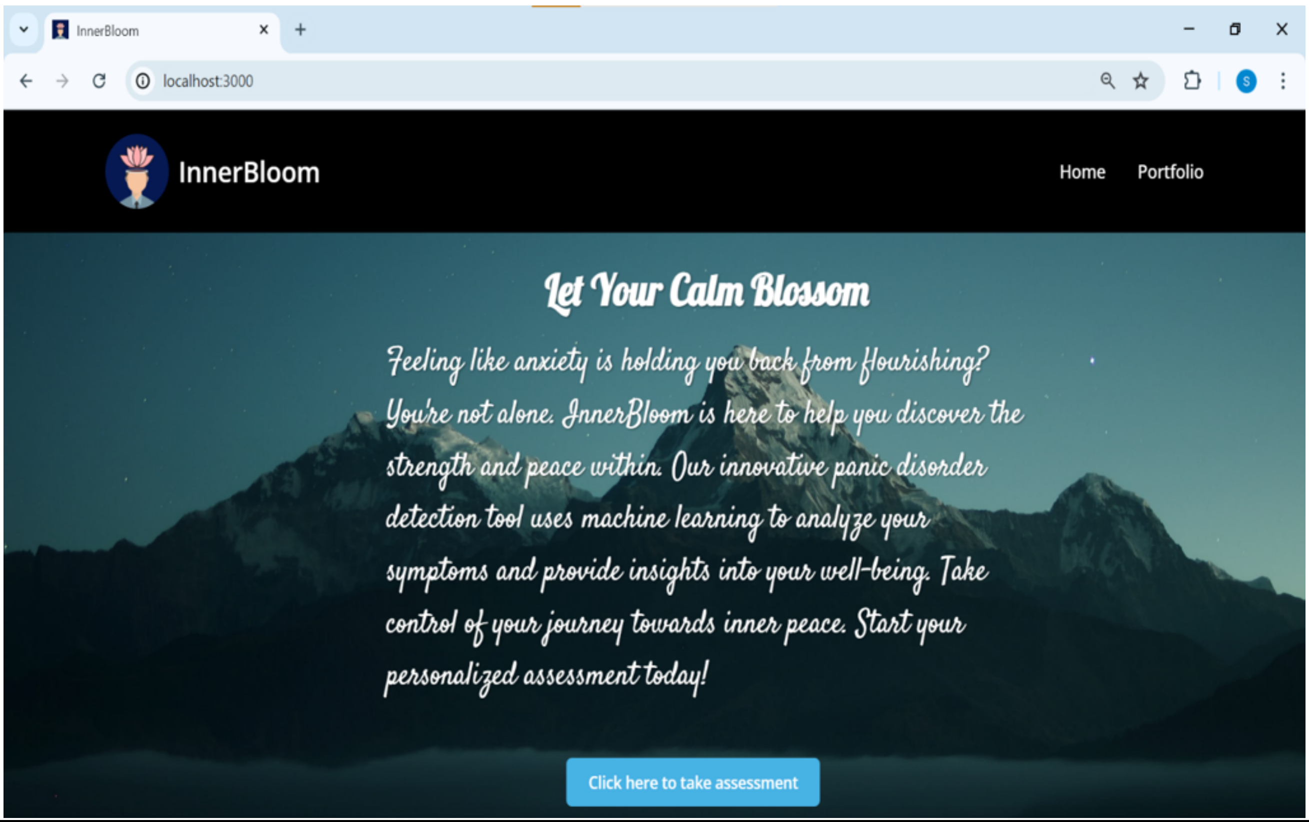
Date	09 July 2024
Team ID	SWTID1720017249
Project Title	Panic Disorder Detection
Maximum Marks	10 Marks

5.3 Final Model Selection Justification:

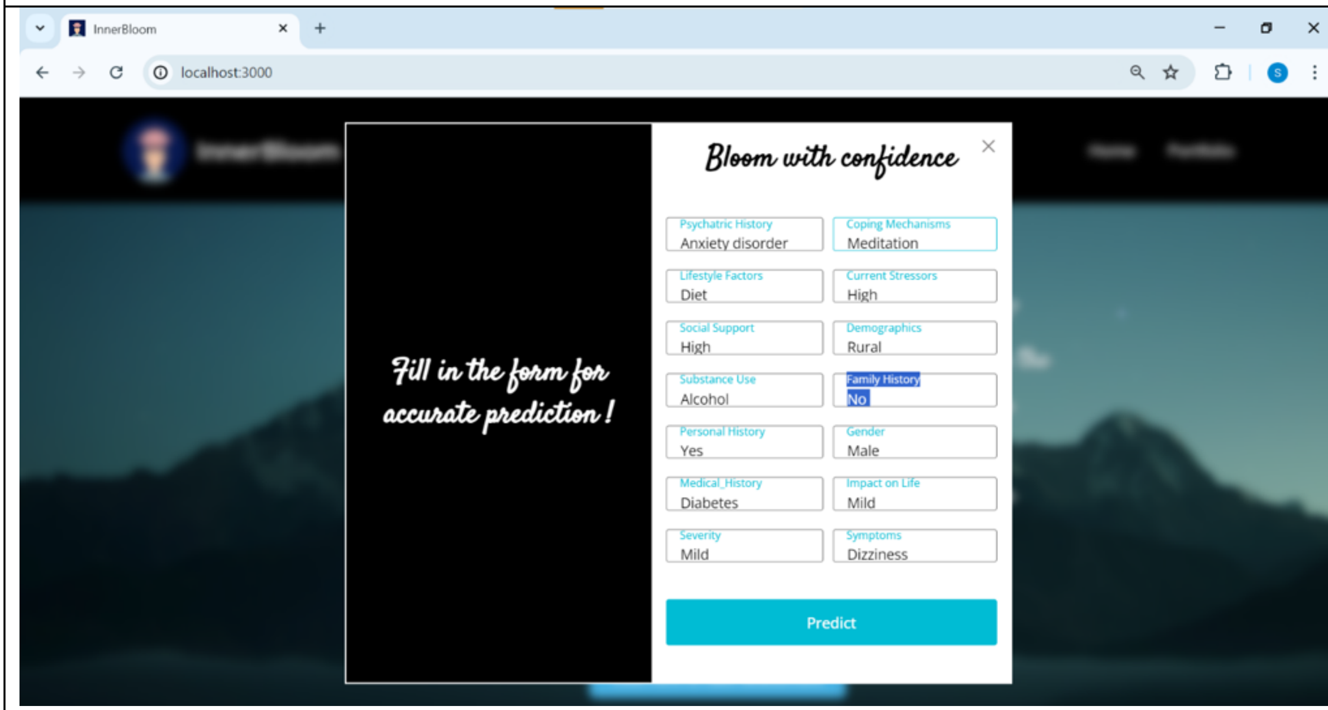
Final Model	Reasoning
Gradient Boosting	Gradient Boosting achieved the highest optimized accuracy of 91.54%, showing a significant improvement over its baseline accuracy of 90.13%. This indicates that the model benefits greatly from hyperparameter tuning. Although XGBoost also performed well with an optimized accuracy of 91.51%, the slight edge in accuracy and the stability of Gradient Boosting make it the preferred choice. Furthermore, Gradient Boosting has shown to be less prone to overfitting in this context compared to Decision Tree, whose optimized accuracy decreased. Therefore, Gradient Boosting is selected for its superior performance and robustness after optimization.

6. Results

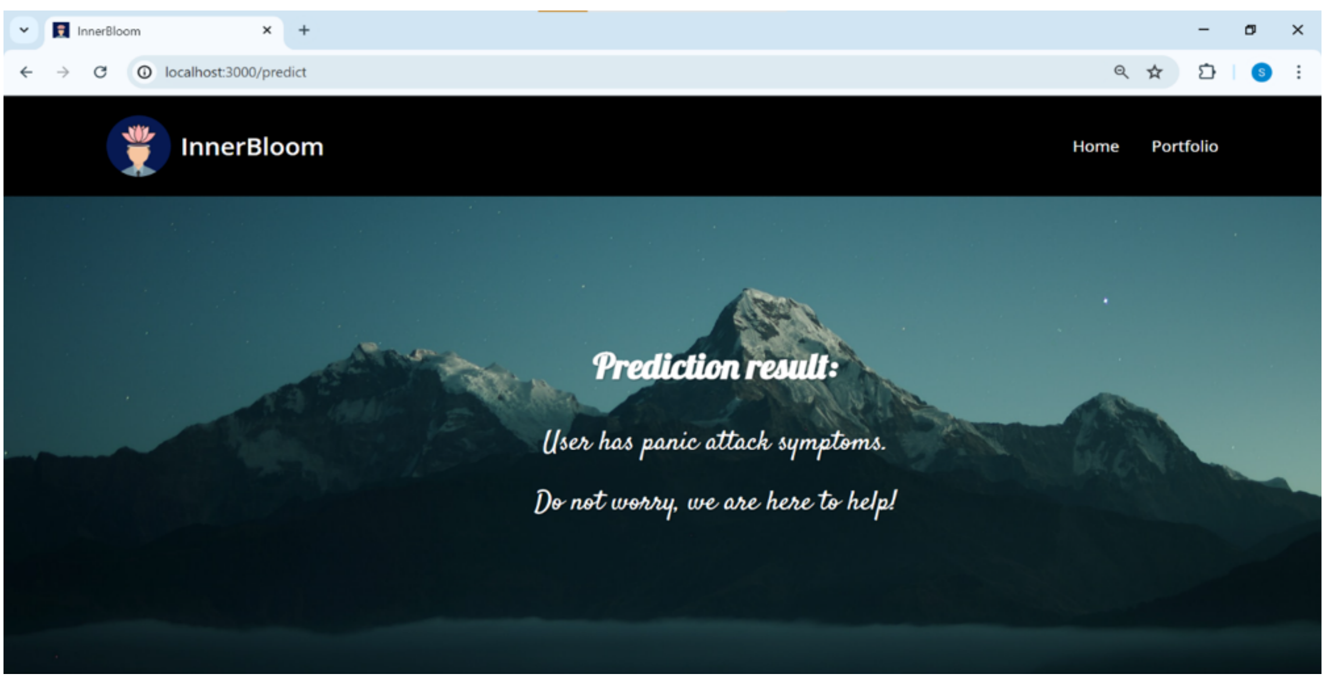
6.1. Output Screenshots

Home Screen


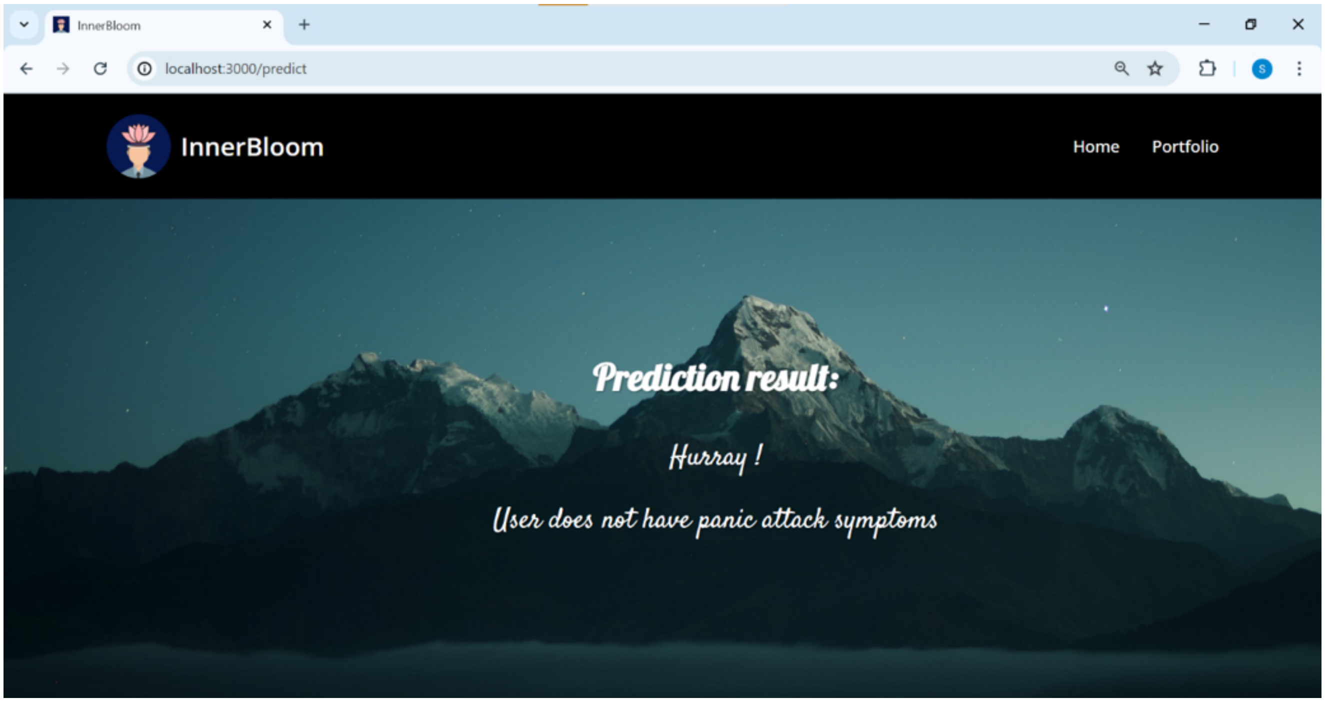
Assessment form



Prediction Page (User has panic attack symptoms)



Prediction Page (User does not have panic attack symptoms)



7. Advantages & Disadvantages

Advantages

1. **Improved Diagnosis Accuracy:**
   - Utilizing a machine learning model such as Gradient Boosting can enhance the accuracy of panic disorder detection by identifying complex patterns in patient data that might be missed by traditional methods.
2. **Early Detection:**
   - Early detection of panic disorder through this system can lead to timely intervention, potentially reducing the severity and impact of the disorder on individuals' lives.
3. **Accessibility:**
   - The web-based application allows for widespread accessibility, enabling individuals in remote or underserved areas to receive assessments and recommendations.
4. **Efficiency:**
   - Automating the diagnostic process can save time for mental health professionals, allowing them to focus more on patient care rather than data analysis.
5. **Consistent Evaluations:**
   - The system provides consistent and objective evaluations, reducing the risk of subjective biases that can occur in manual assessments.
6. **Scalability:**
   - The system can handle large volumes of data and accommodate a growing number of users, making it scalable for widespread adoption.

Disadvantages

1. **Data Dependency:**
   - The accuracy and reliability of the model heavily depend on the quality and comprehensiveness of the data collected. Poor data quality can lead to incorrect predictions.
2. **Integration Challenges:**
   - Integrating the system with existing Electronic Health Record (EHR) systems and other mental health management software can be complex and require significant resources.
3. **User Training:**
   - Mental health professionals will need to be trained to use the system effectively, which can take time and resources.
4. **Potential for Over-Reliance:**
   - There is a risk that mental health professionals might over-rely on the system's predictions, potentially overlooking their clinical judgment and expertise.

8. Conclusion

The development and implementation of a panic disorder detection system using a Gradient Boosting model mark a significant step forward in the field of mental health care. This innovative approach leverages machine learning to provide a more accurate, efficient, and accessible means of diagnosing panic disorder, addressing many of the limitations of traditional diagnostic methods.

Enhanced Accuracy and Early Detection

One of the key benefits of utilizing a Gradient Boosting model is its ability to enhance diagnostic accuracy. Traditional methods of diagnosing panic disorder often rely on subjective evaluations by mental health professionals, which can vary significantly and lead to inconsistent results. In contrast, the Gradient Boosting model analyses a vast array of patient data, identifying subtle patterns and correlations that are indicative of panic disorder. This data-driven approach minimizes the risk of misdiagnosis, ensuring that patients receive the correct diagnosis more quickly and reliably.

User-Friendly and Accessible

The integration of the Gradient Boosting model into a user-friendly web application ensures that the system is accessible to a wide range of users. The intuitive interface is designed to facilitate easy input of patient data and seamless access to diagnostic reports. This accessibility is particularly important in reaching underserved populations and individuals in remote areas who may not have easy access to traditional mental health services. By making diagnostic tools available online, the system democratizes access to mental health care, ensuring that more people can receive the help they need.

Efficiency and Consistency

Automating the diagnostic process not only improves accuracy but also enhances efficiency. Mental health professionals can save valuable time that would otherwise be spent on manual data analysis, allowing them to focus more on direct patient care and treatment planning. The system provides consistent evaluations, reducing the variability that can occur with human assessors and ensuring that all patients receive a uniform standard of care.

Challenges and Considerations

While the advantages of the panic disorder detection system are substantial, it is important to acknowledge and address the associated challenges. Ensuring the privacy and security of sensitive patient data is paramount. The system must incorporate robust encryption, access controls, and regular security audits to protect against data breaches and comply with regulations such as HIPAA and GDPR.

Integrating the system with existing Electronic Health Record (EHR) systems and other mental health management software can be complex and resource-intensive. However, seamless integration is essential for providing comprehensive patient records and facilitating holistic treatment planning. Proper planning and resource allocation are necessary to overcome these integration challenges.

Social Impacts:

1. **Improved Mental Health Diagnosis:**
    a. The panic disorder detection system can contribute to improved mental health diagnosis by providing accurate and timely identification of panic disorder. This can lead to early intervention and appropriate treatment, resulting in better outcomes for individuals suffering from panic disorder.

2. **Increased Accessibility to Diagnosis:**
    a. By leveraging technology, the panic disorder detection system can potentially increase accessibility to diagnosis. It can be deployed in various healthcare settings, including remote or underserved areas, making it easier for individuals to access mental health assessments and receive appropriate care.

3. **Reduced Stigma and Misdiagnosis:**
    a. Implementing an objective and reliable panic disorder detection system can help reduce stigma associated with mental health conditions. It can also minimize the risk of misdiagnosis, as the system relies on data-driven analysis rather than subjective judgment alone, promoting more accurate understanding and treatment of panic disorder.

Business Impacts:

1. **Enhanced Diagnostic Efficiency:**
    - The panic disorder detection system can improve the efficiency of mental health diagnosis within healthcare organizations. It can automate data collection and analysis processes, enabling mental health professionals to streamline their workflow and allocate more time for personalized patient care.

2. **Cost Savings:**
    - By facilitating early and accurate detection of panic disorder, the system can potentially lead to cost savings for healthcare providers and payers. Timely diagnosis and intervention can prevent prolonged treatments, unnecessary hospitalizations, and complications, thereby reducing overall healthcare expenses.

3. **Improved Treatment Planning:**
    - The panic disorder detection system's insights and reports can aid mental health professionals in developing personalized treatment plans for individuals diagnosed with panic disorder. This can enhance treatment effectiveness, patient adherence, and long-term outcomes, ultimately benefiting the business by building a reputation for quality care.

9. Future Scope

Looking ahead, the future scope of the panic disorder detection project includes several areas for enhancement and expansion. Incorporating more advanced machine learning techniques, such as deep learning, can further improve the model's accuracy and robustness. Expanding data collection to include more diverse sources, such as wearable devices and social media activity, can provide a more comprehensive assessment of an individual’s mental health.

Developing features for real-time monitoring and assessment can enable immediate intervention during panic attacks, potentially through mobile applications or wearable technology. Integrating the system with telehealth platforms can facilitate remote consultations and continuous support for patients, enhancing accessibility and convenience.

10. Appendix

10.1. References

- Supervised learning: https://www.javatpoint.com/supervised-machine-learning
- Unsupervised learning: https://www.javatpoint.com/unsupervised-machine-learning
- Decision tree: https://www.javatpoint.com/machine-learning-decision-tree-classificationalgorithm
- Random forest: https://www.javatpoint.com/machine-learning-random-forest-algorithm
- Gradient Boost: https://www.analyticsvidhya.com/blog/2021/09/gradient-boosting-algorithm-a-complete-guide-for-beginners/
- KNN: https://www.javatpoint.com/k-nearest-neighbor-algorithm-for-machine-learning
- Xgboost: https://www.analyticsvidhya.com/blog/2018/09/an-end-to-end-guide-tounderstand-the-math-behind-xgboost/
- Evaluation metrics: https://www.analyticsvidhya.com/blog/2019/08/11-important-modelevaluation-error-metrics/
- Flask Basics : https://www.youtube.com/watch?v=lj4I_CvBnt0

10.2. Source Code

Source Code Link -
https://colab.research.google.com/drive/1xZdAZugdwqZPe1gK8IElE079KD8YoG3E?usp
=sharing

10.3. GitHub & Project Demo Link

GitHub link - **https://github.com/kvidisha/panic_disorder_detection**
Project Demo Link - https://drive.google.com/file/d/1PLr
hscrQc2XytP657LTSP2Sgaj_oaJs/view