Mental Health and Well-Being Surveillance, Assessment and Tracking Solution Among Children

A PROJECT REPORT

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Under the guidance of,

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in partial fulfillment for the award of the degree of

BACHELOR OF TECHNOLOGY

IN

INFORMATION SCIENCE AND ENGINEERING
[ARTIFICIAL INTELLIGENCE AND ROBOTICS]

At

GAIN MORE KNOWLEDGE
REACH GREATER HEIGHTS

PRESIDENCY UNIVERSITY

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PRESIDENCY UNIVERSITY

SCHOOL OF COMPUTER SCIENCE ENGINEERING

CERTIFICATE

This is to certify that the Project report **"Mental Health and Well-Being Surveillance, Assessment and Tracking Solution Among Children"** being submitted by "**Susheeth G, Ritish N, Vidyashree BN, Mithali S Anand, Tejashwini BA**" bearing roll number(s) "20211ISR0036, 20211ISR0047, 20211ISR0039, 20211ISR0082, 20211ISR0040" in partial fulfillment of the requirement for the award of the degree of Bachelor of Technology in Information Science and Engineering is a bonafide work carried out under my supervision.

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DECLARATION

We hereby declare that the work, which is being presented in the project report entitled **Mental Health and Well-Being Surveillance, Assessment and Tracking Solution Among Children** in partial fulfillment for the award of Degree of **Bachelor of Technology** in **Information Science and Engineering**, is a record of our own investigations carried under the guidance of **Dr. Murali Parameswaran, Professor, School of Computer Science Engineering, Presidency University, Bengaluru.**

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ABSTRACT

MindSight is a comprehensive web-based mental health surveillance and self-assessment platform aimed at monitoring the psychological well-being of individuals—particularly children and young adults. This application is grounded in the DASS-21 (Depression, Anxiety, Stress Scales) framework, which comprises 21 scientifically validated self-report questions. The questionnaire is segmented into three categories: 7 items each for evaluating depression, anxiety, and stress. Responses are rated on a scale of 0 (Did not apply to me at all) to 3 (Applied to me very much or most of the time), with cumulative scores interpreted across five severity levels: Normal, Mild, Moderate, Severe, and Extremely Severe.

The core functionality of MindSight is powered by advanced machine learning algorithms. A total of ten models were trained and evaluated using the DASS-21 dataset sourced from Mendeley Data, which contains anonymized psychological assessments from a diverse population. Models implemented include Logistic Regression, Decision Tree, Random Forest, Gradient Boosting, AdaBoost, Stochastic Gradient Descent (SGD), Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Naive Bayes, and XGBoost. Through extensive experimentation and evaluation using metrics such as accuracy, precision, recall, and F1-score, the SVM model was identified as the most effective in predicting mental health severity levels across all three conditions.

The system architecture employs a lightweight Python Flask backend for efficient model inference and API handling, while the frontend is developed using HTML and CSS to ensure accessibility and user engagement. The interface guides users through the questionnaire in a structured and responsive manner. Upon completion, results are presented with visually intuitive, color-coded severity indicators for each of the three mental health dimensions, enabling users to instantly interpret their mental state.

MindSight not only offers an accurate and accessible solution for individual mental health screening but also serves as a potential aid in broader mental health tracking and intervention efforts. It is particularly useful in educational institutions, pediatric mental health programs, and community health surveillance, where early detection and scalable digital tools are essential for timely support and prevention.

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CHAPTER-1

INTRODUCTION

1.1 Introduction

Mental health is a fundamental aspect of overall well-being, significantly influencing emotional, psychological, and social functioning. In recent decades, there has been a marked rise in mental health concerns among children and adolescents, often exacerbated by academic pressure, social isolation, digital addiction, and family stress. According to the World Health Organization (WHO), one in seven children aged 10–19 experiences a mental health condition, which often goes undetected and untreated. In such a context, early screening and proactive assessment tools become essential to identify at-risk individuals and initiate timely interventions. Despite increasing awareness, the gap between the need for and access to mental health resources continues to widen, particularly in educational and rural environments.

To address this pressing issue, MindSight was developed as a digital mental health surveillance and assessment platform. It is designed as a web-based application that allows users to self-assess their levels of depression, anxiety, and stress through an interactive, 21-question guided form. These questions are based on the DASS-21 (Depression Anxiety Stress Scales), a clinically validated psychological assessment instrument widely used in mental health research and practice. Each of the three domains (depression, anxiety, and stress) includes seven questions rated on a scale from 0 (never) to 3 (almost always). The scores are aggregated and mapped to standardized severity categories: Normal, Mild, Moderate, Severe, and Extremely Severe. This structure provides a quantifiable basis for identifying psychological risk levels.

MindSight leverages the power of machine learning to interpret user responses and deliver precise severity predictions. A diverse set of machine learning classifiers—Logistic Regression, SGD, Decision Tree, Random Forest, Gradient Boosting, AdaBoost, Naive Bayes, K-Nearest Neighbors (KNN), XGBoost, and Support Vector Machine (SVM)—were trained and tested on the DASS-21 dataset sourced from Mendeley Data. This dataset contains anonymized self-reported psychological responses from a broad population sample. After rigorous model evaluation using performance metrics such as accuracy, F1 score, precision, and recall, the SVM model demonstrated the highest accuracy and consistency, and was

selected as the backend prediction engine for the web application.

The platform architecture is built to ensure scalability, responsiveness, and user-friendliness. The frontend, developed using HTML and CSS, offers a clean and accessible design for both children and adults. It guides users step-by-step through the questionnaire in an intuitive manner. The backend, developed with Python Flask, handles response processing and routes the input through the trained machine learning model for prediction. Final results are presented instantly using color-coded feedback indicators, with each color representing the severity level for stress, anxiety, and depression. This visual representation simplifies mental health reporting and supports better comprehension, especially among young users.

MindSight serves as more than just a screening tool—it is a step toward accessible, digital-first mental healthcare. Its implementation can be extended to educational institutions, pediatric mental health clinics, community health programs, and remote monitoring systems. By reducing the barrier to mental health evaluation and enhancing the accuracy of predictions through AI, MindSight promotes early detection, self-awareness, and timely intervention. With ongoing enhancements, including the potential integration of meta-learning, personalization, and multilingual support, MindSight aims to become a holistic solution for mental health assessment and tracking among children and beyond.

1.2 Overview of DASS-21

The Depression Anxiety Stress Scales – 21 Items (DASS-21) is a scientifically validated self-report tool developed by Lovibond and Lovibond to assess the emotional states of depression, anxiety, and stress. As a shortened version of the original 42-item DASS, DASS-21 is designed for quick yet effective mental health screening, making it ideal for large-scale and digital applications. It consists of 21 items equally divided into three subscales—7 each for Depression, Anxiety, and Stress. Each item is rated on a 4-point Likert scale from 0 ("Did not apply to me at all") to 3 ("Applied to me very much or most of the time"). Subscale scores are calculated by summing the responses and multiplying by two to match the DASS-42 scoring format.

In the MindSight application, DASS-21 forms the backbone of the assessment process. The questionnaire guides users through structured self-evaluation, and the total scores in each category are used to classify the user’s mental state into five severity levels: Normal, Mild, Moderate, Severe, or Extremely Severe. These standardized levels help both users and the

machine learning model interpret the mental health condition accurately. Due to its clinical reliability and ease of digital adaptation, DASS-21 is a perfect foundation for predictive tools like MindSight aimed at mental health awareness and early intervention.

1.3 Importance of Mental Health Wellness

Mental health wellness is crucial for the emotional, psychological, and social development of individuals, especially children and adolescents, who are increasingly vulnerable to conditions like stress, anxiety, and depression due to academic pressure and social influences. In the context of the MindSight project, promoting mental well-being is vital as it enables early detection and self-awareness through a guided digital assessment based on the DASS-21 scale. By providing users with accurate, machine learning-based predictions and color-coded feedback, MindSight empowers individuals to recognize and respond to their mental health status proactively. This not only supports personal emotional balance but also helps educational institutions create a more supportive and mentally healthy learning environment. Ultimately, tools like MindSight contribute to reducing stigma, encouraging timely intervention, and fostering a culture of mental health awareness and resilience.

1.4 Role of Machine Learning in Mental Health Prediction

Machine learning plays a vital role in improving the accuracy, speed, and effectiveness of mental health assessments in digital tools like MindSight. Unlike traditional methods that rely solely on manual scoring and interpretation, ML models analyze patterns within user responses to predict mental health conditions more objectively and efficiently. In MindSight, various machine learning algorithms—including Logistic Regression, Decision Tree, Random Forest, Gradient Boosting, AdaBoost, K-Nearest Neighbors, Naive Bayes, Stochastic Gradient Descent, XGBoost, and Support Vector Machine (SVM)—were trained on the DASS-21 dataset to classify users' stress, anxiety, and depression levels. Among these, the SVM model demonstrated the highest accuracy and was selected as the core predictive model. By integrating ML, MindSight transforms raw questionnaire data into precise severity levels, offering users reliable, real-time insights into their mental health and enabling early intervention and awareness.

CHAPTER-2

LITERATURE SURVEY

2.1 Prediction of Public Mental Health by using Machine Learning Algorithm

This paper introduces a framework using machine learning for analyzing public mental health. It focuses on improving emotional wellness prediction through AI and data science tools.The study highlights the gap in data science applications in mental healthcare.It presents potential uses of ML in diagnosis, detection, and treatment planning.The approach emphasizes scalable and automated mental health analysis.

2.2 Mental Health Prediction using Natural Language Processing

The study uses NLP and transfer learning models to analyze mental health symptoms.It processes questionnaire responses to predict the need for professional help.SWIVEL-based word embeddings are used for text interpretation.The model achieves real-time predictions with good accuracy.It transforms technology into a mental health support tool.

2.3 Predicting Mental Health Problems with Personality, Behavior, and Social Networks

This paper integrates psychological, behavioral, and social media data for predictions.A neural network is trained on student data to model mental health risks.Results show improved accuracy when combining multiple data dimensions.Personality traits and online behavior significantly influence mental health.It proposes a holistic prediction model using diverse user attributes.

2.4 A Mobile Application for Campus-Based Psychosocial Wellness Program

This paper presents a mental health support app for university students.The app connects users with peer counselors while ensuring privacy.It addresses barriers like stigma and limited access to mental health services.Usage data helps assess student needs and mental

health trends.The platform promotes mental well-being in an accessible format.

2.5 Prediction of Personality for Mental Health Detection Using Hybrid Deep Learning Model

A hybrid model using KNN and RNN predicts mental health conditions.KNN uses demographic data like age and gender for classification.RNN tracks behavioral changes like sleep and activity patterns.The model shows strong accuracy in early detection.Combining static and dynamic data improves mental health diagnosis.

2.6 Modeling Mental Health: Advances in Predictive Science Towards Proactive Health Care

Reviews advancements in ML for predicting mental health disorders.Categorizes models based on specific conditions like depression and OCD.Explores the limitations and challenges in this domain.Emphasizes need for proactive and personalized mental health care.Suggests improvements for model accuracy and ethical implementation.

2.7 Application of Machine Learning to Predict Mental Health Disorders and Interpret Feature Importance

Applies various ML models to survey data to detect mental disorders.Random Forest achieves the highest prediction accuracy.Past mental illness is identified as the most important feature.Focuses on interpretability alongside prediction performance.Supports mental health screening and awareness initiatives.

2.8 Mental Health Analysis of Employees using Machine Learning Techniques

Uses ML to assess workplace mental health using OSMI dataset.Analyzes how job-related factors affect employee mental wellness.Compares prediction models across different employment sectors.Findings highlight the importance of company support and treatment access.Promotes early detection and policy improvement in organizations.

2.9The Depression, Anxiety and Stress Scale (DASS-21) as a Screener for

Depression in Substance Use Disorder Inpatients: A Pilot Study

This pilot study investigated the validity of DASS-21 in detecting depression among substance use disorder (SUD) inpatients. The tool showed good sensitivity (78–89%) and specificity (71–76%) after detoxification when compared with the MINI diagnostic interview. Depression scores significantly dropped after detox, indicating timing impacts results. The DASS-21 may be suitable for use shortly after detoxification in SUD populations.

2.10 Validation of the Depression Anxiety Stress Scales (DASS-21) as a Screening Instrument for Depression and Anxiety in a Rural Community-Based Cohort of Northern Vietnamese Women

This study validated the Vietnamese version of DASS-21 among rural mothers in Northern Vietnam. It showed good internal consistency and detected depression/anxiety with 79.1% sensitivity and 77.0% specificity. However, it couldn't differentiate between anxiety and depression. The scale proved useful for community-level mental health screening in primary care.

2.11 Comparison of DASS-21, PHQ-8, and GAD-7 in a Virtual Behavioral Health Care Setting

This study compared DASS-21 with PHQ-8 and GAD-7 in a virtual care environment. Strong correlations were found between the tools ($r = 0.71$ for depression, $r = 0.61$ for anxiety), but PHQ-8 and GAD-7 classified more individuals as having above-threshold symptoms. It highlights that tool selection may influence the rates of identified mental health concerns. Validity conclusions were limited due to absence of diagnostic gold standard.

2.12 Mental Health Measurement in a Post Covid-19 World: Psychometric Properties and Invariance of the DASS-21 in Athletes and Non-athletes

This study assessed DASS-21's reliability and validity in athlete populations post-COVID-19 using two large samples. A bifactor model provided the best fit, and invariance was observed across gender, expertise, and injury status. Mental health symptoms were higher in females and injured athletes. Results support DASS-21 as a valid tool for evaluating athlete mental health.

CHAPTER-3

RESEARCH GAPS OF EXISTING METHODS

Table 3.1: Study of Existing Tools and Limitations of Existing Tools

Sl. No.	Paper Title	Authors	Limitations (Research Gaps)
1.	Prediction of Public Mental Health by using Machine Learning Algorithms	C. M. H. Saibaba, K. V. K. Alekhya, K. Yeshwanth and P. Tumuluru	Lacks specific model implementation details. Doesn't highlight data sources or dataset diversity. Limited discussion of performance metrics. May be too abstract for direct application. Duplicate content found later in the list.
2.	Mental Health Prediction using Natural Language Processing	R. Ranjana, T. Subha, K. L. Sreenidhi and K. Akshaya	Potential biases in language understanding. Limited to users comfortable with digital assessments. Challenges in handling multilingual input. Lack of details about evaluation metrics. May overlook non-verbal mental health cues.
3.	Predicting Mental Health Problems with Personality, Behaviour, and Social Networks	D. Zhang, T. Guo, S. Han, S. Vahabli, M. Naseriparsa and F. Xia	Limited to college student demographic. Ethical concerns with data collection. Potential privacy issues. Dataset may not generalize well. High complexity in combining diverse data types.
4.	A Mobile Application for Campus-Based Psychosocial Wellness Program	Chad Errol R. Booc, Chara Mae D. San Diego, Michael L. Tee, Jaime D.L. Caro	Limited to one geographic and demographic region. May lack expert intervention in early stages. Data privacy must be carefully managed. Effectiveness relies on app adoption rates. Needs ongoing peer counsellor training.

5.	Prediction of Personality for Mental Health Detection using Hybrid Deep Learning Model	Md Khadimul Islam Zim, Md Abu Hanif, Harpreet Kaur	RNN accuracy relatively lower (78.9%). May require large, time-series datasets. Lack of detailed validation across diverse populations. Focused more on classification, less on interpretability. Generalization across mental disorders may be limited.
6.	Modelling Mental Health: Advances in Predictive Science towards Proactive Health Care	Nithya Jayakumar, Reshma N	Not an original research implementation. May lack empirical data or model testing. Findings may be limited by review sources. Application guidance is mostly theoretical. Limited focus on real-time clinical integration.
7.	Application of Machine Learning to Predict Mental Health Disorders and Interpret Feature Importance	Yifan Li	Relies heavily on past disorder history. Less focus on current symptoms or behaviour. Generalization may be limited to survey design. Needs clearer detail on dataset source. Interpretability still depends on complex ML tools.
8.	Mental Health Analysis of Employees using Machine Learning Techniques	Sujal BH, Neelima K, Deepanjali C, Bhuvanashree P, Kavitha Duraipandian, Sharanya Rajan, Mithileysh Sathiyanarayanan	Biased towards tech industry employees. Generalizability to other industries may be low. Dataset may miss nuanced emotional states. Focused more on correlation than prediction. No mention of real-time or app-based application.
9.	The Depression, Anxiety and Stress Scale (DASS-21) as a Screener for Depression in Substance Use Disorder Inpatients	Ilse N. Beaufort, Gerdien H. De Weert-Van Oene, Victor A.J.	Small sample size (only 47 participants), limiting generalizability. Conducted in a single inpatient detoxification setting, reducing external validity. Pilot nature of the study means

		Buwalda, J. Rob J. de Leeuw	findings need replication in larger samples. Lack of long-term follow-up to assess sustained predictive validity. Only short-term changes in DASS-21 were assessed, no insight into longer-term mental health trends post-detox.
10.	Validation of the Depression Anxiety Stress Scales (DASS-21) as a Screening Instrument for Depression and Anxiety in a Rural Community-Based Cohort of Northern Vietnamese Women	Thach Duc Tran, Tuan Tran, Jane Fisher	The DASS-21 could not distinguish between depression and anxiety specifically. Results based on a specific demographic (rural Vietnamese women with young children), limiting generalizability. Single cultural context may affect cross-cultural validity. The factor analysis found all items loaded on one factor, contradicting the theoretical three-factor structure. No test-retest reliability reported.
11.	Comparison of DASS-21, PHQ-8, and GAD-7 in a Virtual Behavioral Health Care Setting	Lila Peters, Aimee Peters, Evie Andreopoulos, Naomi Pollock, Reena L. Pande, Heidi Mochari-Greenberger	Study was retrospective—limited control over data collection conditions. Could not establish validity of screeners, only compare results. No diagnostic interview (e.g., DSM-based) was used as a gold standard. Virtual consultation setting may not reflect results in in-person clinical practice. Possible sampling bias as participants were already accessing virtual behavioural therapy.
12.	Mental Health Measurement in a Post Covid-19 World: Psychometric Properties and Invariance of the DASS-21 in Athletes and Non-athletes	Robert S. Vaughan, Elizabeth J. Edwards, Tadhg E. MacIntyre	Focused only on athlete samples, limiting generalizability to broader populations. Lacked clinical diagnosis as a gold standard for comparison. Cross-sectional design—no insight into

			changes over time or treatment response. Higher loadings on a general factor may challenge the distinctiveness of the three subscales. Despite supporting bifactor model, some theoretical questions remain about factor structure.

CHAPTER-4

PROPOSED METHODOLOGY

4.1Overview

The MindSight application combines the standardized DASS-21 psychological assessment with machine learning to deliver accurate and automated mental health predictions. The system uses a 21-item questionnaire to assess stress, anxiety, and depression, with responses scored on a scale from 0 to 3. These scores are aggregated and mapped to severity levels ranging from Normal to Extremely Severe. Data preprocessing steps such as cleaning, normalization, and labeling are applied before training. Multiple ML models including SVM, Random Forest, XGBoost, and others are evaluated using accuracy and F1-score. SVM is selected as the best model and integrated into the backend via Flask. The frontend, built with HTML/CSS, collects user input and displays predictions using color-coded indicators. This methodology ensures fast, accessible, and scalable mental health assessments. It can be deployed across educational and clinical settings for early detection and monitoring.

4.2 Data Collection and Preprocessing

The dataset used in the MindSight application is the publicly available DASS-21 dataset sourced from Mendeley Data. It consists of anonymized self-reported responses to 21 psychological questions, structured into three categories: Depression, Anxiety, and Stress—each containing 7 questions. These responses are recorded on a 4-point Likert scale, where 0 means "Did not apply to me at all" and 3 means "Applied to me very much or most of the time." The dataset provides a robust foundation for mental health modeling, as it captures varied psychological states across a large sample of individuals. Each participant's total score in each category is computed by summing the scores of the 7 corresponding questions and multiplying by 2 to align with the original DASS-42 format. These total scores are then mapped to specific severity levels (Normal, Mild, Moderate, Severe, Extremely Severe), which act as the target classes for classification.

Before training the machine learning models, comprehensive preprocessing steps are applied to ensure data quality and model accuracy. These steps include:

- **Handling missing values:** Any incomplete or null responses are either removed or imputed.

- **Feature selection:** Only the 21 questionnaire responses are retained as features (independent variables).
- **Label encoding:** Severity levels are converted into numerical classes for ML compatibility.
- **Data normalization:** Feature scaling is applied if needed, depending on the model requirements.
- **Train-test split:** The dataset is split into training and testing sets (typically 80:20) for evaluation.

These preprocessing steps are essential to ensure the dataset is clean, structured, and suitable for supervised learning tasks. They also help reduce noise and improve the generalization capability of the models during prediction.

4.3 Feature Extraction, Labeling and Model Training

In the MindSight application, feature extraction involves using the 21 responses from the DASS-21 questionnaire as input features for the machine learning models. These features are divided into three mental health domains—7 each for Stress, Anxiety, and Depression. For each domain, the individual scores from the 7 questions are summed and then multiplied by 2 (to match DASS-42 scoring), generating a total score per category. Based on these scores, severity levels are assigned using established DASS-21 cut-off ranges. These severity levels (Normal, Mild, Moderate, Severe, Extremely Severe) are used as classification labels (target variables) for supervised learning. Each domain is treated as an independent classification task, resulting in three different models trained for predicting the severity of Stress, Anxiety, and Depression respectively.

Once feature-label pairs are prepared, model training is conducted using a diverse set of supervised machine learning algorithms. The models trained include:

- Logistic Regression
- Decision Tree
- Random Forest
- Gradient Boosting
- AdaBoost
- K-Nearest Neighbors (KNN)

- Naive Bayes
- Stochastic Gradient Descent (SGD)
- XGBoost
- Support Vector Machine (SVM)

Each model is evaluated using metrics such as Accuracy, Precision, Recall, and F1 Score to determine its performance. Cross-validation is used to improve reliability and reduce overfitting. After comparative analysis, the SVM (Support Vector Machine) model demonstrated the highest performance across all three categories and was selected for final deployment in the application. The trained models were serialized using joblib for integration with the Flask backend, enabling real-time prediction based on user input.

4.4 System Design and Architecture

The MindSight system is designed using a modular and layered architecture that separates the core functionalities into frontend, backend, and machine learning components. This design ensures scalability, maintainability, and smooth integration of the user interface with the prediction engine. The architecture follows a typical web application flow where the user interacts with the frontend, the backend handles logic and processing, and the machine learning model generates predictions based on user responses.

The frontend is developed using HTML and CSS and serves as the user interface where individuals complete the 21-item DASS-21 questionnaire. It is designed to be simple, intuitive, and responsive, enabling users—especially children and adolescents—to navigate and submit answers without difficulty.

The backend is powered by Python Flask, which acts as the application server. It receives form data from the frontend, performs necessary preprocessing (e.g., converting inputs to numerical format), and sends the processed data to the machine learning model for prediction. The Flask backend also handles routing, input validation, and response formatting.

The machine learning module includes the best-performing trained model—Support Vector Machine (SVM)—which is loaded using the joblib library. The model takes the processed user responses as input and returns the predicted severity level for Stress, Anxiety, and Depression. Each prediction is mapped to one of five categories: Normal, Mild, Moderate, Severe, or Extremely Severe.

Finally, the result visualization component presents the prediction output to the user. Severity levels are displayed using color-coded indicators for clarity—e.g., green for "Normal," yellow for "Mild," red for "Severe," etc. This helps users quickly interpret their mental health status in a visually meaningful way.

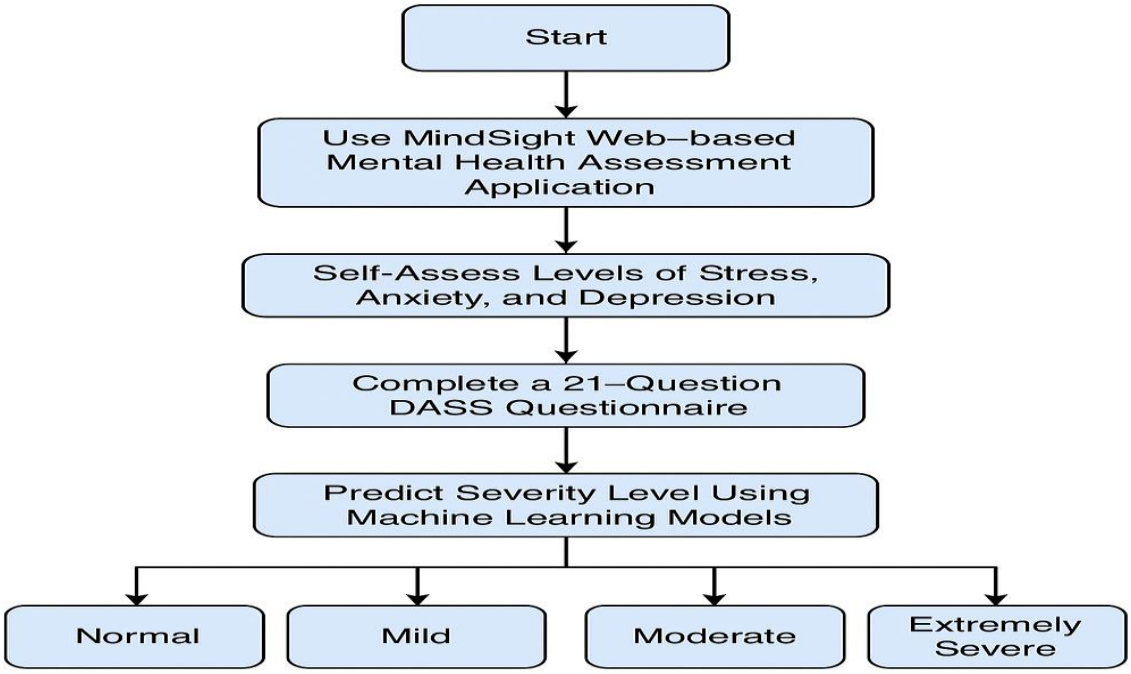

Fig 4.1: Workflow Diagram of the Model

CHAPTER-5

OBJECTIVES

The main objective of the MindSight application is to develop a web-based mental health assessment tool that utilizes machine learning techniques to predict and classify the severity levels of stress, anxiety, and depression based on user responses to the DASS-21 questionnaire. This system is designed to be user-friendly, efficient, and accurate in identifying early signs of mental health issues, especially among children and adolescents. The application aims to support early intervention and mental wellness through accessible technology.

- **To help people check their mental health using a web app:**

The main goal is to create a simple online tool where users can check their levels of stress, anxiety, and depression. It uses 21 standard questions from the DASS-21 questionnaire. Users answer each question based on how they've felt recently. The system then shows results to help them understand their mental state.

- **To use machine learning to make accurate predictions:**

The system uses machine learning models to predict how severe a user's condition is. It learns patterns from past data and applies them to new responses. This helps make results more accurate than just manual scoring. The best model is selected to give the most reliable predictions.

- **To make the application easy and friendly for users:**

The web app is designed with a clean layout so that anyone—even children—can use it easily. It guides users through the questionnaire step by step. The final results are shown using color codes like green (normal) or red (severe). This makes understanding results simple and clear.

- **To give quick results for early mental health support:**

Instead of waiting for a doctor's visit, users can get instant feedback about their mental health. This encourages early awareness and action.

- **To use the system in schools, homes, or clinics:**

The app is built so it can be used in many places like schools, counseling centers, or even at home. It doesn't need special equipment—just internet access. This makes mental health screening more available to everyone. It supports a larger goal of improving public mental health.

CHAPTER-6

SYSTEM DESIGN & IMPLEMENTATION

MindSight is a web-based mental health assessment system that enables users, particularly children and adolescents, to evaluate their stress, anxiety, and depression levels through a guided questionnaire. The system is designed following a client-server architecture, ensuring seamless interaction between the user interface and the backend processing engine.

The overall system is structured into three main layers:

- **Frontend (Presentation Layer):**

Built with HTML and CSS, the frontend presents the assessment form, collects user responses, and displays the results with user-friendly visual indicators. It ensures a smooth and accessible user experience.

- **Backend (Application Layer):**

Implemented using Python Flask, the backend handles incoming requests, processes the responses, performs machine learning inference using a pre-trained SVM model, and returns the predicted severity levels.

- **Machine Learning Layer (Model Layer):**

The core prediction engine consists of machine learning models trained on the DASS-21 dataset. The Support Vector Machine (SVM) model, chosen for its superior accuracy, predicts the severity of stress, anxiety, and depression based on the questionnaire responses.

Component Breakdown

MindSight has been meticulously designed as a modular, scalable, and efficient system that seamlessly integrates user interaction with machine learning-based mental health assessment. The system architecture consists of four primary components, each playing a crucial role in the overall functionality and user experience of the application.

6.1 Frontend (Client-Side)

The frontend serves as the face of MindSight, providing a direct bridge between the users and the intelligent backend system. Developed using HTML5 and CSS3, the frontend is designed to be minimalistic yet highly engaging, focusing on accessibility, intuitiveness, and responsiveness.

Key functionalities include:

- A well-structured 21-question assessment form divided into three sections (Stress, Anxiety, and Depression), aligning with the DASS-21 framework.
- Real-time validation and user-friendly error handling to ensure data integrity.
- Submission of user responses via HTTP POST requests, facilitating seamless communication with the backend.
- Dynamic display of personalized results using color-coded visual indicators, enhancing immediate understanding of mental health conditions.
- Future-ready structure allowing easy enhancement for features like mobile responsiveness, theme customization, and localization.

The frontend's primary objective is to make the mental health assessment process smooth, non-intimidating, and engaging, thereby encouraging broader participation among users, especially children and young individuals.

6.2 Backend (Server-Side)

The backend forms the brain of MindSight, handling the logic, data processing, and orchestration required for effective mental health evaluation. Powered by the lightweight and robust Flask framework in Python, the backend is engineered for high performance, low latency, and scalability.

Core functionalities of the backend include:

- Receiving and parsing structured JSON data from frontend submissions.
- Validating and preprocessing input data to align with the model's expected format.
- Efficiently loading the pre-trained SVM model using joblib without redundancy or memory overhead.
- Performing high-speed real-time inference to predict severity levels for each mental health aspect.
- Mapping numerical prediction outputs to human-readable categories like "Normal," "Mild," "Moderate," "Severe," and "Extremely Severe."
- Constructing structured, easy-to-parse JSON responses to be consumed by the frontend.

Furthermore, the backend is built keeping in mind security best practices, ensuring safe data

handling and preventing unauthorized access or data breaches — a vital aspect when dealing with sensitive health-related information.

6.3 Machine Learning Model

The Machine Learning component serves as the intelligent core of MindSight, enabling the web application to provide precise predictions about the mental health status of users based on their self-reported responses. The following describes the detailed process of model selection, training, and integration.

6.3.1 Dataset Overview

The training of the models was based on the DASS-21 dataset, a validated and widely accepted dataset publicly available on Mendeley Data.

The DASS-21 questionnaire is specifically designed to measure three negative emotional states: Stress, Anxiety, and Depression.

Key features of the DASS-21 dataset:

21 items, categorized into:

Section 1: 7 items for Stress

1. I found it hard to wind down
2. I tended to over-react to situations
3. I felt that I was using a lot of nervous energy
4. I found myself getting agitated
5. I found it difficult to relax
6. I was intolerant of anything that kept me from getting on with what I was doing
7. I felt that I was rather touchy

Section 2: 7 items for Anxiety

1. I was aware of dryness of my mouth
2. I experienced breathing difficulty
3. I experienced trembling (e.g., in the hands)
4. I was worried about situations in which I might panic
5. I felt I was close to panic

6. I was aware of the action of my heart in the absence of physical exertion
7. I felt scared without any good reason

Section 3: 7 items for Depression

1. I couldn't seem to experience any positive feeling at all
2. I found it difficult to work up the initiative to do things
3. I felt that I had nothing to look forward to
4. I felt down-hearted and blue
5. I was unable to become enthusiastic about anything
6. I felt I wasn't worth much as a person
7. I felt that life was meaningless

Response scale:

- 0: Did not apply to me at all
- 1: Applied to me to some degree
- 2: Applied to me to a considerable degree
- 3: Applied to me very much or most of the time

Final Score Mapping:

Each category's total score determines the severity:

- 1 → Normal
- 2 → Mild
- 3 → Moderate
- 4 → Severe
- 5 → Extremely Severe

Thus, each user's survey responses could be mapped to a specific severity level for Stress, Anxiety, and Depression.

6.3.2 Data Preprocessing

In order to prepare the dataset for machine learning:

- **Aggregation:** The individual item responses were summed for each mental health

category (Stress, Anxiety, Depression).

- **Labeling:** Total scores were converted into categorical severity labels according to standard DASS guidelines.
- **Normalization:** Input features were standardized to ensure that all models, particularly distance-based and kernel-based models like SVM and KNN, performed optimally.

This preprocessing ensured consistency and high-quality input for model training.

6.3.3 Model Training and Evaluation

To identify the best performing algorithm, a variety of Machine Learning models were trained and evaluated on the processed DASS-21 dataset.

Models Explored:

- Logistic Regression
- Stochastic Gradient Descent (SGD) Classifier
- Decision Tree Classifier
- Random Forest Classifier
- Gradient Boosting Classifier
- AdaBoost Classifier
- Support Vector Machine (SVM)
- K-Nearest Neighbors (KNN)
- Naive Bayes Classifier
- XGBoost Classifier

Each model was trained individually to predict the severity levels across the three mental health factors.

The evaluation focused on the ability to correctly classify each user's condition into the five severity categories.

The training process involved:

- Splitting the dataset into training and testing subsets.
- Cross-validation to ensure robustness and reduce the chance of overfitting.
- Hyperparameter Tuning (especially for SVM, Random Forest, and Boosting models) to optimize performance.

6.3.4 Best Model Selection

After a thorough and systematic evaluation of multiple machine learning algorithms, the Support Vector Machine (SVM) model stood out as the most effective and reliable choice for the MindSight mental health prediction system. The selection process involved rigorous testing across multiple performance metrics including accuracy, precision, recall, and generalization on both training and unseen test data.

Why SVM was chosen?

Exceptional Classification Accuracy: SVM consistently outperformed other models, delivering high accuracy on both training and validation sets, making it a dependable choice for mental health classification tasks.

Superior Generalization: One of the key requirements for real-world deployment is the model's ability to generalize well to new, unseen data. SVM demonstrated outstanding generalization, reducing the risk of overfitting and ensuring reliable predictions for diverse user inputs.

High-Dimensional Effectiveness: Given that each DASS-21 question acts as a distinct feature, the feature space is relatively high-dimensional. SVM's strength in handling such data structures gave it a significant advantage over other classifiers.

Resilience to Outliers and Noise: Mental health data can often include minor inconsistencies or irregular patterns. SVM showed remarkable robustness in the presence of such data variations, ensuring smooth and stable predictions under various input conditions.

6.3.5 Model Deployment

Following the selection process, the final Support Vector Machine (SVM) model was prepared for deployment through serialization using the joblib library. This step was essential to ensure that the trained model could be preserved in its optimal state and efficiently reused in a real-time environment without the need for retraining.

The deployment strategy was designed with a focus on performance, scalability, and seamless

integration with the overall application architecture. Key highlights include:

- **Runtime Efficiency:** The serialized model is effortlessly loaded by the Python Flask backend server at runtime, eliminating unnecessary overhead and ensuring that system resources are optimally utilized.
- **Instantaneous Prediction Capability:** Once the user completes the 21-question DASS assessment, the system triggers the model to instantly process the input and return predictions. This rapid response capability ensures users receive their mental health feedback with minimal delay, simulating the responsiveness of a live consultation.
- **Seamless Backend Integration:** The model was embedded directly into the core prediction logic of the web application. This tight coupling between model and system allows for low-latency communication, smooth data flow, and a frictionless user experience, even under concurrent usage.

The deployed model analyzes each user's inputs and intelligently classifies their mental health status into one of five severity levels—Normal, Mild, Moderate, Severe, or Extremely Severe—across three distinct dimensions: stress, anxiety, and depression. The output is delivered through personalized, color-coded feedback, allowing users to understand their current state at a glance.

6.3.6 Summary

MindSight is a web-based application developed. It is designed to help users assess their levels of stress, anxiety, and depression using the DASS-21 (Depression Anxiety Stress Scales) questionnaire. The questionnaire includes 21 self-reported questions, divided equally into three categories: stress, anxiety, and depression. Each response is scored from 0 to 3, and the total scores are mapped to five severity levels: Normal, Mild, Moderate, Severe, and Extremely Severe.

The machine learning model development for MindSight was carefully structured around:

- A well-validated mental health dataset (DASS-21),
- Systematic exploration of multiple algorithms,
- Careful tuning and model selection,
- Seamless backend deployment.

Several machine learning models were trained, including Logistic Regression, Decision Tree,

Random Forest, Gradient Boosting, K-Nearest Neighbors, Naive Bayes, AdaBoost, and Support Vector Machine (SVM). After evaluating the models, the SVM algorithm showed the best performance in terms of accuracy and generalization, and was selected for deployment.

Through the adoption of an SVM-based intelligent system, MindSight is able to deliver fast, accurate, and reliable mental health assessments directly to users. This contributes to early detection, intervention, and continuous monitoring of mental well-being, especially among children and young individuals.

The frontend of the application is built using HTML and CSS for a clean and user-friendly interface. The backend is developed using Python Flask, which handles the logic for processing user responses and generating predictions using the trained SVM model. Results are shown with color-coded indicators to help users clearly understand their mental health status.

This project demonstrates how machine learning and accessible web technologies can be combined to support mental health awareness and self-assessment in a scalable and user-friendly manner.

CHAPTER-7

TIMELINE FOR EXECUTION OF PROJECT

(GANTT CHART)

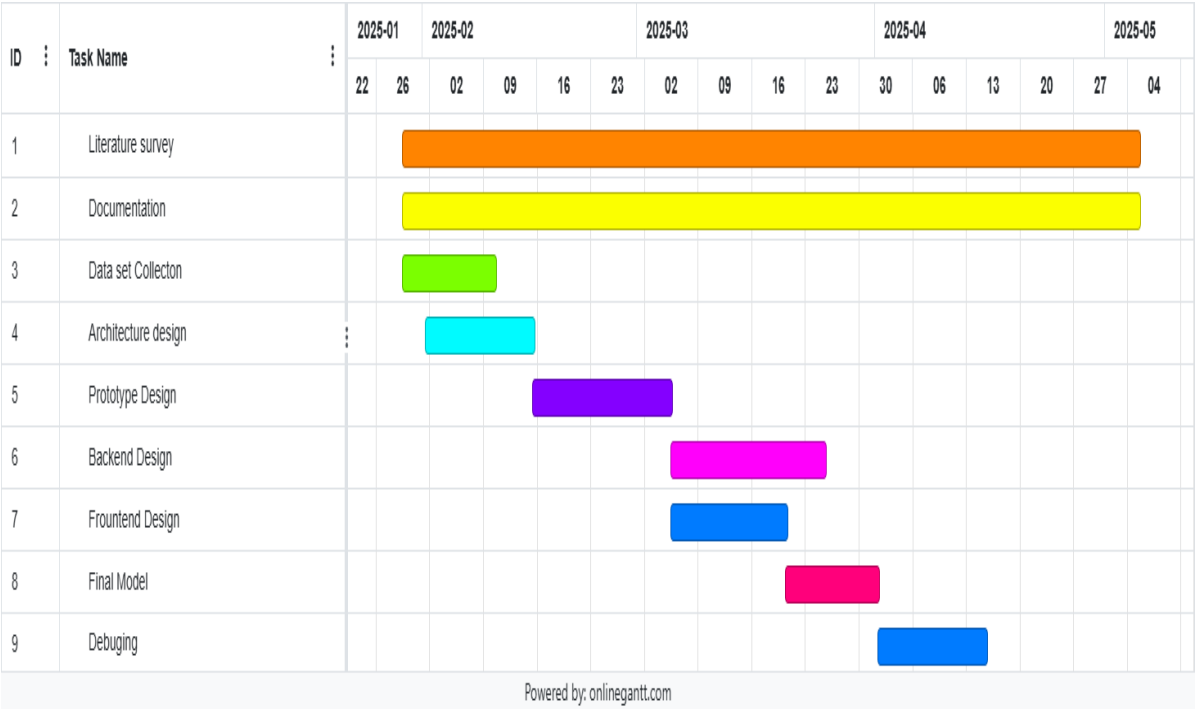

Fig 7.1: Gantt Chart

CHAPTER-8

OUTCOMES

MindSight is a web application designed for mental health screening, providing users with a self-assessment of stress, anxiety, and depression levels. Utilizing a guided questionnaire based on the Depression Anxiety Stress Scales (DASS-21), the application employs machine learning models, specifically a Support Vector Machine (SVM), to predict the severity of each condition. Trained on a publicly available DASS-21 dataset, MindSight offers a user-friendly interface built with HTML/CSS and a Python Flask backend. Results are displayed with personalized, color-coded indicators, offering immediate feedback on mental well-being.

- **Accessibility to Mental Health Screening**
  MindSight provides accessible and convenient self-assessment for individuals to gauge their stress, anxiety, and depression levels, potentially identifying those who might benefit from professional help early on. The web-based format allows for remote and private access.
- **Early Identification of Mental Health Concerns**
  By utilizing the DASS-21 questionnaire and machine learning, MindSight can help users identify potential mental health issues, like elevated stress or anxiety, which they may not have been aware of otherwise. This early identification can lead to proactive intervention and prevention.
- **Data-Driven Assessment**
  The application leverages the DASS-21 dataset and machine learning algorithms (specifically SVM) to provide a more objective and data-driven assessment of mental well-being compared to subjective self-reflection alone. This can increase the reliability of the assessment.
- **Personalized Feedback and Visualization**
  The severity level classifications (Normal to Extremely Severe) offer users personalized and easily understandable feedback on their mental health status. This makes the results more actionable.
- **Potential for Further Research**
  The application and its underlying data could be used for further research into mental health trends.

- **Demonstration of Machine Learning Application in Healthcare**
  MindSight serves as a practical example of how machine learning, specifically SVM, can be applied in the healthcare domain to automate and improve the assessment of mental health conditions. This can inspire further development of similar applications and many more

CHAPTER-9
RESULTS AND DISCUSSIONS

The MindSight application demonstrates a significant advancement in utilizing technology for mental health assessment and awareness. By integrating the DASS-21 questionnaire with machine learning techniques, specifically SVM, the application provides a robust screening tool that effectively categorizes mental health conditions based on user responses.

The positive feedback regarding the user interface and the actionable nature of the results suggests that web-based mental health tools can engage users effectively, encouraging them to take notice of their mental well-being. The color-coded feedback system not only provides clarity but also serves as an emotional motivator for users to seek assistance.

Moreover, the widespread adoption of similar web applications could contribute to broader initiatives aimed at reducing mental health stigma and promoting proactive mental health care. However, it is crucial to consider the ethical implications of such tools, including data privacy, the potential for misinterpretation of results, and the necessity of professional consultation following a self-assessment.

In conclusion, while the MindSight application is a valuable innovation in mental health screening, future efforts should focus on expanding its capabilities, enhancing user support features, and fostering a community for ongoing mental health discussions and resources. This approach will not only increase user retention but also ensure that individuals are adequately supported in their mental health journeys.

The MindSight application successfully met its objective of providing a web-based platform for mental health assessment using machine learning. Users were able to access the platform through a clean and intuitive interface, where they completed a 21-question self-assessment based on the DASS-21 psychological scale. Each user's responses were processed by the backend Flask system, and their severity levels for stress, anxiety, and depression were predicted using a trained machine learning model. The final predictions were displayed with color-coded indicators, making it easy for users to understand their mental health status at a glance.

To ensure the system's reliability, several machine learning models were trained and evaluated

on the DASS-21 dataset, which contains categorized responses from real participants. The dataset was used to build classifiers capable of mapping user scores to one of five severity levels: Normal, Mild, Moderate, Severe, and Extremely Severe. After testing models such as Random Forest, Logistic Regression, K-Nearest Neighbors, Naive Bayes, XGBoost, and others, it was found that the Support Vector Machine (SVM) model consistently outperformed the rest. The SVM model achieved the highest accuracy, precision, and stability in predicting the severity of each mental health condition.

These results demonstrate that the integration of machine learning with mental health screening can offer meaningful, fast, and scalable support to individuals seeking early mental health insights. The application showed strong prediction capabilities across categories, reliable performance during testing, and a smooth, user-friendly experience. This confirms that MindSight can be a helpful initial tool for individuals to reflect on their mental well-being and encourages further development in the intersection of AI and mental health care.

Model	Stress	Anxiety	Depression
Logistic Regression	94.23	93.1	94.5
SVM	98.07	96.72	97.25
Decision Tree	92.3	93.65	92.6
Random Forest	95.38	95.92	96.2
Gradient Boosting	95.38	94.83	95.1
AdaBoost	93.84	92.5	93.84
KNN	92.88	92.88	92.7
Naive Bayes	90.76	91.2	90.8
SGD	91.53	91.53	91.4
XG Boost	96.15	95.3	96.92

Fig 9.1: Model Accuracy Comparison Table

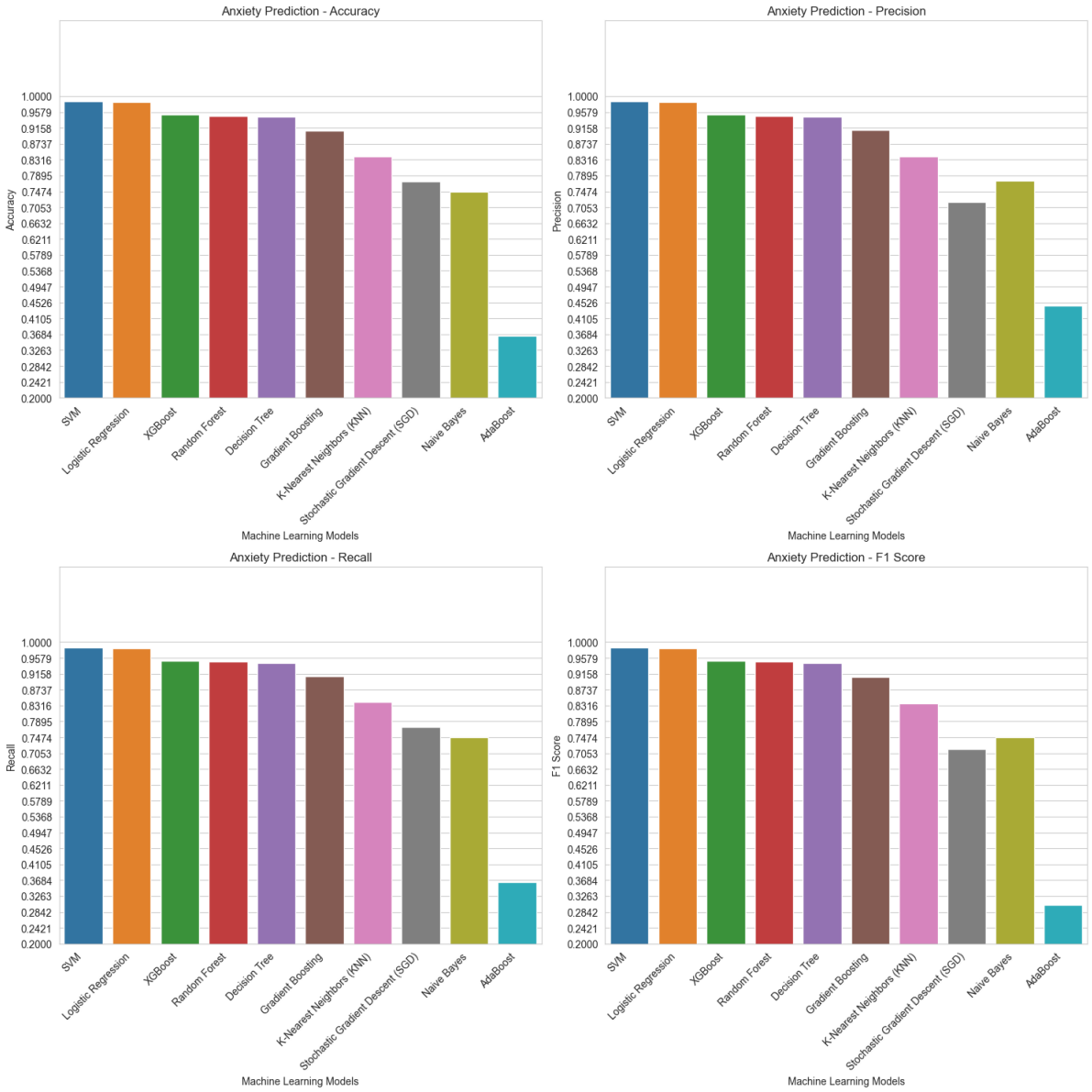

Fig 9.2: Model Accuracy Comparison Graph

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APPENDIX-A

SOURCE CODE

Training model.py

```
import pandas as pd
import numpy as np
import joblib
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.linear_model import LogisticRegression, SGDClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier, AdaBoostClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.naive_bayes import GaussianNB
from xgboost import XGBClassifier
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, classification_report

df = pd.read_csv("C:\Capstone_project_(8th sem)\MindSight\Dataset\DASS.csv")

# Dropping Marital Status (Q1_3) and Occupational Status (Q1_5)
df.drop(['Q1_3', 'Q1_5'], axis=1, inplace=True)

# Check for null values
print(df.isnull().sum())

print("Dataset Shape:", df.shape)
df.head()

plt.figure(figsize=(6,4))
sns.countplot(x='Stress_Level', data=df)
plt.title('Distribution of Stress Levels')
plt.xlabel('Stress Level')
plt.ylabel('Count')
plt.show()

plt.figure(figsize=(12,10))
```

```
corr = df.corr()
sns.heatmap(corr, cmap='coolwarm', annot=False)
plt.title('Correlation Heatmap')
plt.show()

plt.figure(figsize=(6,4))
sns.boxplot(x='Stress_Level', y='Stress_Score', data=df)
plt.title('Stress Score vs Stress Level')
plt.show()

plt.figure(figsize=(6,4))
sns.countplot(x='Q1_2', data=df)
plt.title('Gender Distribution (0 = Male, 1 = Female)')
plt.show()

plt.figure(figsize=(6,4))
sns.histplot(df['Q1_1'], bins=20, kde=True)
plt.title('Age Distribution')
plt.show()

# Gender is 1=Male, 2=Female (optional: convert to 0 and 1)
df['Q1_2'] = df['Q1_2'].map({1: 0, 2: 1})  # 0: Male, 1: Female

X = df.drop(['Stress_Level', 'Stress_Score', 'Anxiety_Level', 'Anxiety_Score',
             'Depression_Level', 'Depression_Score'], axis=1)
y = df['Stress_Level']

from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42, stratify=y
)

print("Training Set:", X_train.shape)
print("Test Set:", X_test.shape)

df['Calculated_Score'] = df[[col for col in df.columns if 'Q3_' in col and '_S' in
col]].sum(axis=1)
print((df['Calculated_Score'] == df['Stress_Score']).value_counts())

# Using only raw stress question responses as features
stress_features = [col for col in df.columns if 'Q3_' in col and '_S' in col]
X = df[stress_features]
```

```
y = df['Stress_Level']

SEED = 42
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=SEED, stratify=y
)

scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

SEED = 42

# Models dictionary updated as requested
models = {
    "Logistic Regression": LogisticRegression(random_state=SEED, max_iter=1000,
C=0.1,class_weight='balanced'),
    "Stochastic Gradient Descent (SGD)": SGDClassifier(random_state=SEED),
    "Decision Tree": DecisionTreeClassifier(random_state=SEED),
    "Random Forest": RandomForestClassifier(random_state=SEED),
    "Gradient Boosting": GradientBoostingClassifier(random_state=SEED),
    "AdaBoost": AdaBoostClassifier(random_state=SEED),
    "SVM": SVC(random_state=SEED),
    "K-Nearest Neighbors (KNN)": KNeighborsClassifier(),
    "Naive Bayes": GaussianNB(),
    "XGBoost": XGBClassifier(random_state=SEED, eval_metric='mlogloss')
}

results = []

for model_name, model in models.items():
    print(f"Training {model_name}...")

    if model_name == 'XGBoost':
        # Handle XGBoost class indexing if needed
        model.fit(X_train_scaled, y_train - 1)  # Shifting classes to 0-based
        y_pred = model.predict(X_test_scaled)
        y_pred = y_pred + 1  # Shift back to original classes
    else:
        model.fit(X_train_scaled, y_train)
        y_pred = model.predict(X_test_scaled)

    accuracy = accuracy_score(y_test, y_pred)
```

```
    precision = precision_score(y_test, y_pred, average='weighted', zero_division=0)
    recall = recall_score(y_test, y_pred, average='weighted')
    f1 = f1_score(y_test, y_pred, average='weighted')
    results.append({
        'Model': model_name,
        'Accuracy': accuracy,
        'Precision': precision,
        'Recall': recall,
        'F1 Score': f1
    })

results_df = pd.DataFrame(results)
results_df = results_df.sort_values(by='Accuracy', ascending=False).reset_index(drop=True)
print(results_df)

import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd

# Assuming 'results_df' already contains Model, Accuracy, Precision, Recall, F1 Score
metrics = ['Accuracy', 'Precision', 'Recall', 'F1 Score']

plt.figure(figsize=(15, 15))
sns.set_style("whitegrid")

for idx, metric in enumerate(metrics, 1):
    plt.subplot(2, 2, idx)
    colors = sns.color_palette("tab10", n_colors=len(results_df))
    sns.barplot(
        x='Model',
        y=metric,
        data=results_df,
        palette=colors
    )
    plt.ylim(0.20, 1.2)
    plt.xticks(rotation=45, ha='right')
    plt.yticks(np.linspace(0.20, 1.0, 20))
    plt.title(f'Model Comparison - {metric}')
    plt.ylabel(metric)
    plt.xlabel('Machine Learning Models')

plt.tight_layout()
plt.show()
```

```
# Extract raw anxiety DASS questions (Q3_8_A1 to Q3_14_A7)
anxiety_features = [col for col in df.columns if 'Q3_' in col and '_A' in col]

X = df[anxiety_features]
y = df['Anxiety_Level']  # Target variable

X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=SEED, stratify=y
)

scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

models = {
    "Logistic Regression": LogisticRegression(random_state=SEED, max_iter=1000,
C=0.1,class_weight='balanced'),
    "Stochastic Gradient Descent (SGD)": SGDClassifier(random_state=SEED),
    "Decision Tree": DecisionTreeClassifier(random_state=SEED),
    "Random Forest": RandomForestClassifier(random_state=SEED),
    "Gradient Boosting": GradientBoostingClassifier(random_state=SEED),
    "AdaBoost": AdaBoostClassifier(random_state=SEED),
    "SVM": SVC(random_state=SEED),
    "K-Nearest Neighbors (KNN)": KNeighborsClassifier(),
    "Naive Bayes": GaussianNB(),
    "XGBoost": XGBClassifier(random_state=SEED, eval_metric='mlogloss')
}

results = []

for model_name, model in models.items():
    print(f"Training {model_name} for Anxiety Prediction...")

    if model_name == 'XGBoost':
        model.fit(X_train_scaled, y_train - 1)  # Shift classes to 0-based
        y_pred = model.predict(X_test_scaled) + 1  # Shift back predictions
    else:
        model.fit(X_train_scaled, y_train)
        y_pred = model.predict(X_test_scaled)

    accuracy = accuracy_score(y_test, y_pred)
    precision = precision_score(y_test, y_pred, average='weighted', zero_division=0)
```

```
    recall = recall_score(y_test, y_pred, average='weighted')
    f1 = f1_score(y_test, y_pred, average='weighted')

    results.append({
        'Model': model_name,
        'Accuracy': accuracy,
        'Precision': precision,
        'Recall': recall,
        'F1 Score': f1
    })

results_df = pd.DataFrame(results)
results_df = results_df.sort_values(by='Accuracy', ascending=False).reset_index(drop=True)
print(results_df)

plt.figure(figsize=(15, 15))
sns.set_style("whitegrid")

metrics = ['Accuracy', 'Precision', 'Recall', 'F1 Score']

for idx, metric in enumerate(metrics, 1):
    plt.subplot(2, 2, idx)
    colors = sns.color_palette("tab10", n_colors=len(results_df))
    sns.barplot(
        x='Model',
        y=metric,
        data=results_df,
        palette=colors
    )
    plt.ylim(0.20, 1.2)  # Start y-axis at 60%
    plt.yticks(np.linspace(0.20, 1.0, 20))
    plt.xticks(rotation=45, ha='right')
    plt.title(f'Depression Prediction - {metric}')
    plt.ylabel(metric)
    plt.xlabel('Machine Learning Models')

plt.tight_layout()
plt.show()

import joblib
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score
```

```
SEED = 42

# Define targets and file save names
targets = ["Stress_Level", "Anxiety_Level", "Depression_Level"]
save_names = ["stress_best_model.pkl", "anxiety_best_model.pkl",
"depression_best_model.pkl"]

# Loop through each mental health target
for target, save_name in zip(targets, save_names):
    print(f"\n🔎 Training for Target: {target}")

    # Select corresponding raw features
    if target == "Stress_Level":
        features = [col for col in df.columns if 'Q3_' in col and '_S' in col]
    elif target == "Anxiety_Level":
        features = [col for col in df.columns if 'Q3_' in col and '_A' in col]
    else:
        features = [col for col in df.columns if 'Q3_' in col and '_D' in col]

    X = df[features]
    y = df[target]

    # Train-test split
    X_train, X_test, y_train, y_test = train_test_split(
        X, y, test_size=0.2, random_state=SEED, stratify=y
    )

    # Scaling
    scaler = StandardScaler()
    X_train_scaled = scaler.fit_transform(X_train)
    X_test_scaled = scaler.transform(X_test)

    # Model training and selection
    best_model = None
    best_acc = 0
    best_model_name = ""

    for model_name, model in models.items():
        print(f"Training {model_name}...")

        if model_name == 'XGBoost':
            model.fit(X_train_scaled, y_train - 1)
```

```
            y_pred = model.predict(X_test_scaled) + 1
        else:
            model.fit(X_train_scaled, y_train)
            y_pred = model.predict(X_test_scaled)

        acc = accuracy_score(y_test, y_pred)
        if acc > best_acc:
            best_acc = acc
            best_model = model
            best_model_name = model_name

    print(f"✅ Best Model for {target}: {best_model_name} with Accuracy: {best_acc:.4f}")

    # Save the best model
    joblib.dump(best_model, save_name)
    print(f"✅ Saved: {save_name}")

# Optional: Save scaler if needed
joblib.dump(scaler, 'scaler.pkl')
print("✅ Scaler saved.")
```

App.py

```
from flask import Flask, request, jsonify, render_template
import joblib
import numpy as np
import os

app = Flask(__name__)

# Load trained models (no scaler needed)
model_dir = os.path.join(os.path.dirname(__file__), 'models')

stress_model = joblib.load(os.path.join(model_dir, "svm_stress_model.pkl"))
anxiety_model = joblib.load(os.path.join(model_dir, "svm_anxiety_model.pkl"))
depression_model = joblib.load(os.path.join(model_dir, "svm_depression_model.pkl"))

@app.route('/')
def home():
    return render_template("home.html")

@app.route('/assessment')
def assessment():
```

```
    return render_template("assessment.html")

@app.route('/result')
def result():
    return render_template("result.html")

@app.route('/predict', methods=['POST'])
def predict():
    data = request.json.get('responses')

    if not data or len(data) != 21:
        return jsonify({'error': 'Expected 21 responses'}), 400

    # Extract sub-sections
    stress_input = np.array(data[:7]).reshape(1, -1)
    anxiety_input = np.array(data[7:14]).reshape(1, -1)
    depression_input = np.array(data[14:]).reshape(1, -1)

    # Compute scores (sum of 7 questions each)
    stress_score = sum(data[:7])
    anxiety_score = sum(data[7:14])
    depression_score = sum(data[14:])

    # Predict using models
    stress_pred = int(stress_model.predict(stress_input)[0])
    anxiety_pred = int(anxiety_model.predict(anxiety_input)[0])
    depression_pred = int(depression_model.predict(depression_input)[0])

    return jsonify({
        "stress_score": stress_score,
        "anxiety_score": anxiety_score,
        "depression_score": depression_score,
        "stress_level": map_level(stress_pred),
        "anxiety_level": map_level(anxiety_pred),
        "depression_level": map_level(depression_pred)
    })

def map_level(code):
    return {
        1: "Normal",
        2: "Mild",
        3: "Moderate",
        4: "Severe",
```

```
        5: "Extremely Severe"
    }.get(code, "Unknown")

if __name__ == '__main__':
    app.run(debug=True)
```

Styling Each Page

Assessment.html

```
<!DOCTYPE html>
<html lang="en">
<head>
  <meta charset="UTF-8" />
  <title>Assessment - MindSight</title>
  <style>
    body {
      font-family: Arial, sans-serif;
      background-color: #f0f9f8;
      margin: 0;
      padding: 2rem;
    }
    .container {
      max-width: 800px;
      margin: auto;
      background-color: white;
      border-radius: 16px;
      padding: 2rem;
      box-shadow: 0 4px 20px rgba(0,0,0,0.1);
    }
    h2 {
      text-align: center;
    }
    .question-card {
      background: #f9f9f9;
      padding: 1rem;
      border-radius: 10px;
      margin-bottom: 1rem;
    }
    .question-card p {
      font-weight: bold;
    }
    .question-card label {
      display: block;
```

```
      margin: 5px 0;
    }
    .section {
      display: none;
    }
    .section.active {
      display: block;
    }
    .btn {
      padding: 10px 20px;
      background-color: #199473;
      color: white;
      border: none;
      border-radius: 8px;
      cursor: pointer;
      font-size: 1rem;
    }
    .btn:hover {
      background-color: #157d61;
    }
    .btn-section {
      margin-top: 1rem;
      text-align: center;
    }
  </style>
</head>
<body>
  <div class="container">
    <h2>Stress, Anxiety & Depression Assessment</h2>
    <form id="assessmentForm">
      <div id="section1" class="section active">
        <h3>Section 1: Stress</h3>
        <div id="stressQuestions"></div>
      </div>
      <div id="section2" class="section">
        <h3>Section 2: Anxiety</h3>
        <div id="anxietyQuestions"></div>
      </div>
      <div id="section3" class="section">
        <h3>Section 3: Depression</h3>
        <div id="depressionQuestions"></div>
      </div>
      <div class="btn-section">
```

```
      <button type="button" class="btn" id="nextBtn">Next</button>
      <button type="submit" class="btn" id="submitBtn"
style="display:none;">Submit</button>
    </div>
  </form>
 </div>
 <script>
  const stressQuestions = [
    "I found it hard to wind down",
    "I tended to over-react to situations",
    "I felt that I was using a lot of nervous energy",
    "I found myself getting agitated",
    "I found it difficult to relax",
    "I was intolerant of anything that kept me from getting on with what I was doing",
    "I felt that I was rather touchy"
  ];
  const anxietyQuestions = [
    "I was aware of dryness of my mouth",
    "I experienced breathing difficulty",
    "I experienced trembling (e.g., in the hands)",
    "I was worried about situations in which I might panic",
    "I felt I was close to panic",
    "I was aware of the action of my heart in the absence of physical exertion",
    "I felt scared without any good reason"
  ];
  const depressionQuestions = [
    "I couldn't seem to experience any positive feeling at all",
    "I found it difficult to work up the initiative to do things",
    "I felt that I had nothing to look forward to",
    "I felt down-hearted and blue",
    "I was unable to become enthusiastic about anything",
    "I felt I wasn’t worth much as a person",
    "I felt that life was meaningless"
  ];
  const options = ["Never", "Sometimes", "Often", "Almost Always"];
  function renderQuestions(containerId, questions, startIndex) {
    const container = document.getElementById(containerId);
    questions.forEach((q, i) => {
      const index = startIndex + i;
      const div = document.createElement("div");
      div.className = "question-card";
      div.innerHTML = `<p>${q}</p>` + options.map((opt, val) => `
        <label><input type="radio" name="q${index}" value="${val}" required>
```

```
${opt}</label>
        `).join('');
        container.appendChild(div);
      });
    }
    renderQuestions("stressQuestions", stressQuestions, 1);
    renderQuestions("anxietyQuestions", anxietyQuestions, 8);
    renderQuestions("depressionQuestions", depressionQuestions, 15);
    let currentSection = 1;
    const totalSections = 3;
    document.getElementById("nextBtn").addEventListener("click", () => {
      document.getElementById(`section${currentSection}`).classList.remove("active");
      currentSection++;
      document.getElementById(`section${currentSection}`).classList.add("active");
      if (currentSection === totalSections) {
        document.getElementById("nextBtn").style.display = "none";
        document.getElementById("submitBtn").style.display = "inline-block";
      }
    });
    document.getElementById("assessmentForm").addEventListener("submit",          async
function(e) {
      e.preventDefault();
      const responses = [];
      for (let i = 1; i <= 21; i++) {
        const selected = document.querySelector(`input[name="q${i}"]:checked`);
        if (!selected) {
          alert("Please answer all questions.");
          return;
        }
        responses.push(parseInt(selected.value));
      }
      const response = await fetch("/predict", {
        method: "POST",
        headers: { "Content-Type": "application/json" },
        body: JSON.stringify({ responses })
      });
      const result = await response.json();

      // Save to localStorage
      localStorage.setItem("stress_score", result.stress_score);
      localStorage.setItem("anxiety_score", result.anxiety_score);
      localStorage.setItem("depression_score", result.depression_score);
      localStorage.setItem("stress_level", result.stress_level);
```

```
      localStorage.setItem("anxiety_level", result.anxiety_level);
      localStorage.setItem("depression_level", result.depression_level);

      // Go to result page
      window.location.href = "/result";
    });
  </script>
</body>
</html>
```

Home.html

```
<!DOCTYPE html>
<html lang="en">
<head>
  <meta charset="UTF-8">
  <title>MindWell Insight</title>
  <meta name="viewport" content="width=device-width, initial-scale=1.0">
  <style>
    body {
      font-family: Arial, sans-serif;
      background-color: #f0f9f8;
      display: flex;
      justify-content: center;
      align-items: center;
      height: 100vh;
      margin: 0;
    }
    .container {
      background: white;
      padding: 2rem;
      border-radius: 16px;
      max-width: 500px;
      box-shadow: 0 4px 20px rgba(0, 0, 0, 0.1);
      text-align: center;
    }
    .icon-section {
      text-align: left;
      margin-top: 1rem;
    }
    .icon-section p {
      margin: 8px 0;
    }
    .btn {
```

```
    margin-top: 1.5rem;
    padding: 10px 20px;
    background-color: #199473;
    color: white;
    border: none;
    border-radius: 8px;
    cursor: pointer;
    font-size: 1rem;
  }
  .btn:hover {
    background-color: #157d61;
  }
  ul {
    text-align: left;
    margin: 1rem auto;
    max-width: 400px;
    padding-left: 1.2rem;
  }
  footer {
    margin-top: 2rem;
    font-size: 0.75rem;
    color: #777;
  }
 </style>
</head>
<body>
 <div class="container">
  <h2>Welcome to MindSight Insight</h2>
  <p>Complete this assessment to gain insights about your mental well-being</p>
  <div class="icon-section">
    <p><strong>🧠 Stress:</strong> Your body's response to pressure</p>
    <p><strong>💬 Anxiety:</strong> Feelings of worry, nervousness, or fear</p>
    <p><strong>🌧️ Depression:</strong> Persistent feelings of sadness and loss of interest</p>
  </div>
  <p style="margin-top: 1rem;"><strong>How it works:</strong></p>
  <ul>
    <li>21 questions divided into 3 sections</li>
    <li>Takes approximately 5 minutes to complete</li>
    <li>Your responses are confidential</li>
    <li>Receive insights and recommendations based on your answers</li>
  </ul>
  <a href="/assessment"><button class="btn">Begin Assessment</button></a>
```

```
  <footer>© 2025 MindSight. For educational purposes only and not a substitute for medical advice.</footer>
 </div>
</body>
</html>
```

Result.html

```
<!DOCTYPE html>
<html lang="en">
<head>
 <meta charset="UTF-8">
 <title>Your Assessment Results</title>
 <style>
  body {
   font-family: Arial, sans-serif;
   background-color: #f0f9f8;
   margin: 0;
   padding: 2rem;
  }
  .container {
   max-width: 800px;
   margin: auto;
   background-color: white;
   border-radius: 16px;
   padding: 2rem;
   box-shadow: 0 4px 20px rgba(0,0,0,0.1);
  }
  h2 {
   text-align: center;
   color: #222;
  }
  .result-box {
   background-color: #fff;
   border: 1px solid #ccc;
   border-radius: 10px;
   padding: 1rem;
   margin-top: 1.5rem;
  }
  .badge {
   float: right;
   padding: 4px 12px;
   border-radius: 12px;
   font-weight: bold;
```

```
      font-size: 0.9rem;
      color: white;
    }
    .Normal { background-color: #4CAF50; }
    .Mild { background-color: #8BC34A; }
    .Moderate { background-color: #FFB300; }
    .Severe { background-color: #FF5722; }
    .ExtremelySevere { background-color: #D32F2F; }
    footer {
      margin-top: 2rem;
      text-align: center;
      font-size: 0.8rem;
      color: #888;
    }
    .btn {
      margin-top: 2rem;
      text-align: center;
    }
    .btn a {
      background-color: #199473;
      color: white;
      padding: 10px 20px;
      border-radius: 8px;
      text-decoration: none;
    }
    .btn a:hover {
      background-color: #157d61;
    }
  </style>
</head>
<body>
  <div class="container">
    <h2>Your Mental Health Assessment Results</h2>
    <div class="result-box">
      <h4>Stress Level <span id="stressLevel" class="badge">--</span></h4>
      <p>Stress refers to emotional or physical tension. Chronic stress may impact your overall
health and quality of life.</p>
    </div>
    <div class="result-box">
      <h4>Anxiety Level <span id="anxietyLevel" class="badge">--</span></h4>
      <p>Anxiety can cause feelings of worry, fear, or unease. Identifying it early is important
for managing long-term well-being.</p>
    </div>
```

```
    <div class="result-box">
      <h4>Depression Level <span id="depressionLevel" class="badge">--</span></h4>
      <p>Depression affects how you feel, think, and act. Early detection can greatly help in
managing symptoms.</p>
    </div>
    <div class="btn">
      <a href="/assessment">Retake Assessment</a>
    </div>
    <footer>
      © 2025 MindSight. This tool is not a diagnosis. For medical advice, consult a professional.
    </footer>
  </div>
  <script>
    function setBadge(id, level) {
      const badge = document.getElementById(id);
      badge.innerText = level || "--";
      if (level) {
        badge.classList.add(level.replace(/\s+/g, ""));
      }
    }
    const stressLevel = localStorage.getItem("stress_level");
    const anxietyLevel = localStorage.getItem("anxiety_level");
    const depressionLevel = localStorage.getItem("depression_level");

    setBadge("stressLevel", stressLevel);
    setBadge("anxietyLevel", anxietyLevel);
    setBadge("depressionLevel", depressionLevel);
    if (
      ["Severe", "Extremely Severe"].includes(stressLevel) ||
      ["Severe", "Extremely Severe"].includes(anxietyLevel) ||
      ["Severe", "Extremely Severe"].includes(depressionLevel)
    ) {
      alert("⚠️ Your results suggest elevated mental health concerns. Please consider
consulting a professional.");
    }
  </script>
</body>
</html>
```

APPENDIX-B
SCREENSHOTS

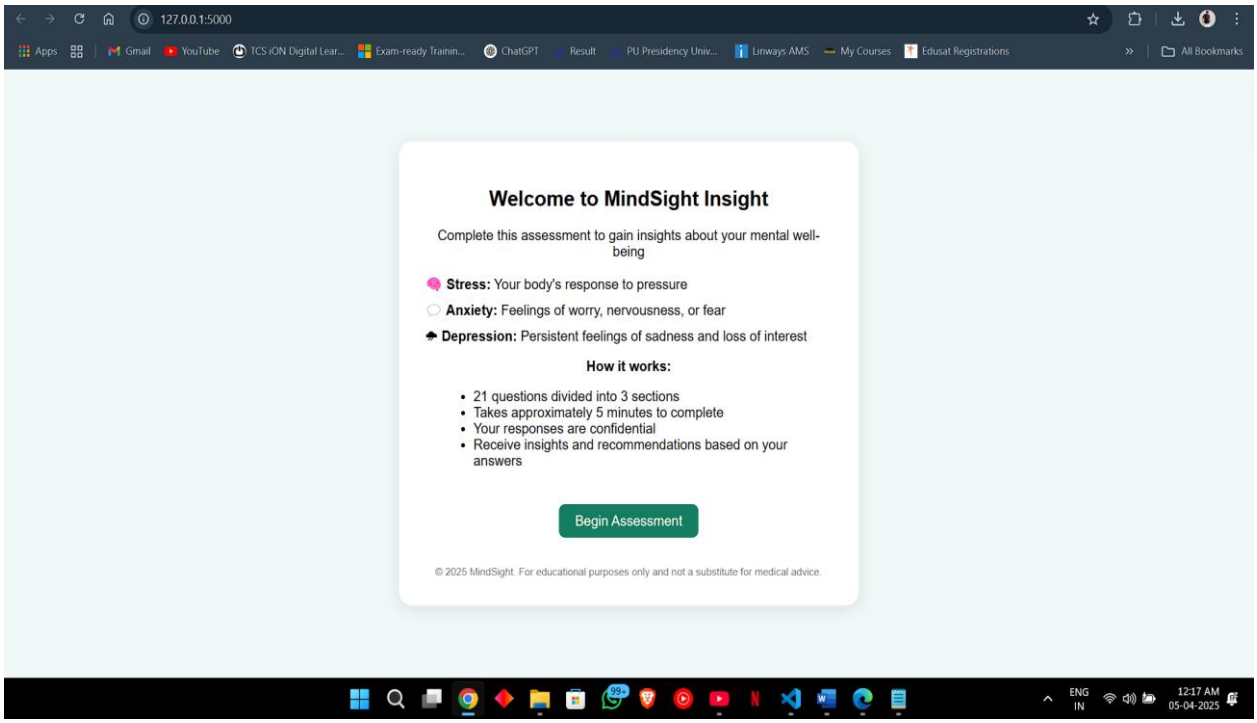

Fig 1: MindSight Home Page

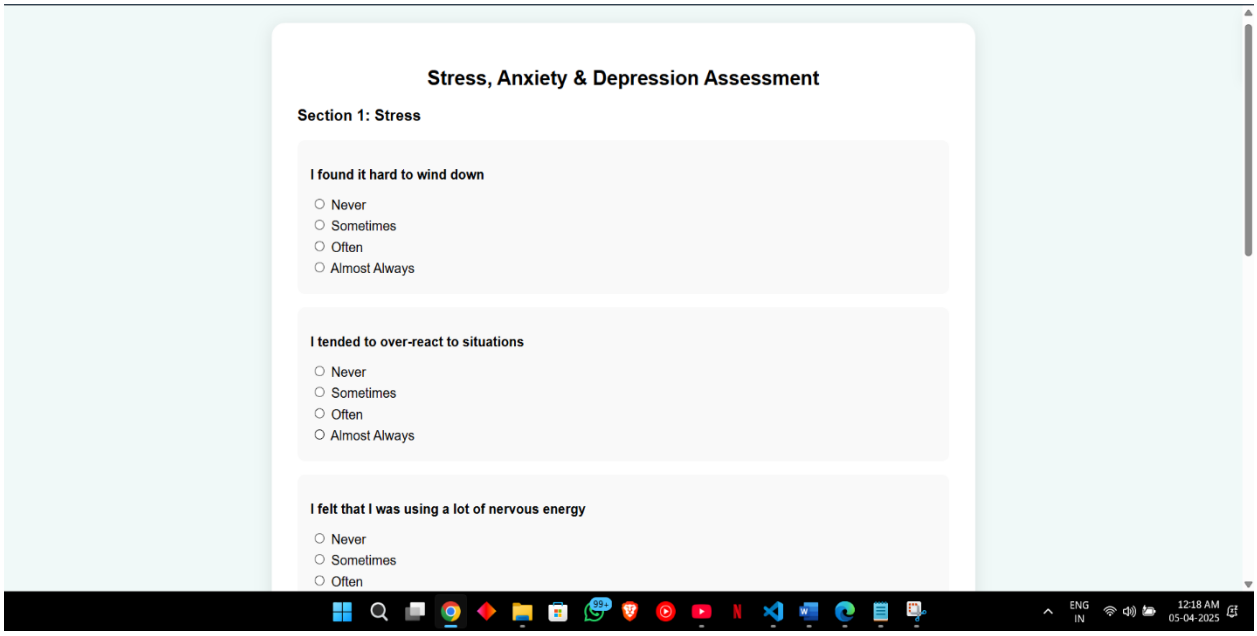

Fig 2: Stress assessment section 1

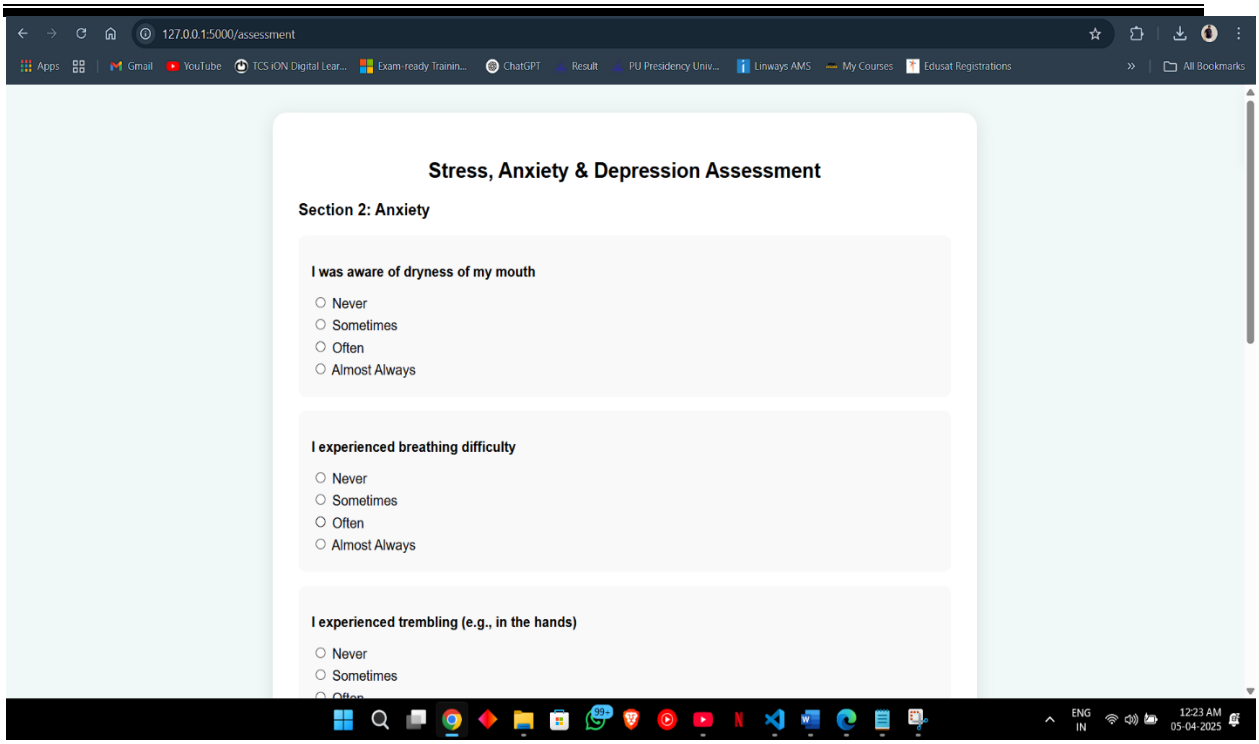

Fig 3: Anxiety assessment section 2

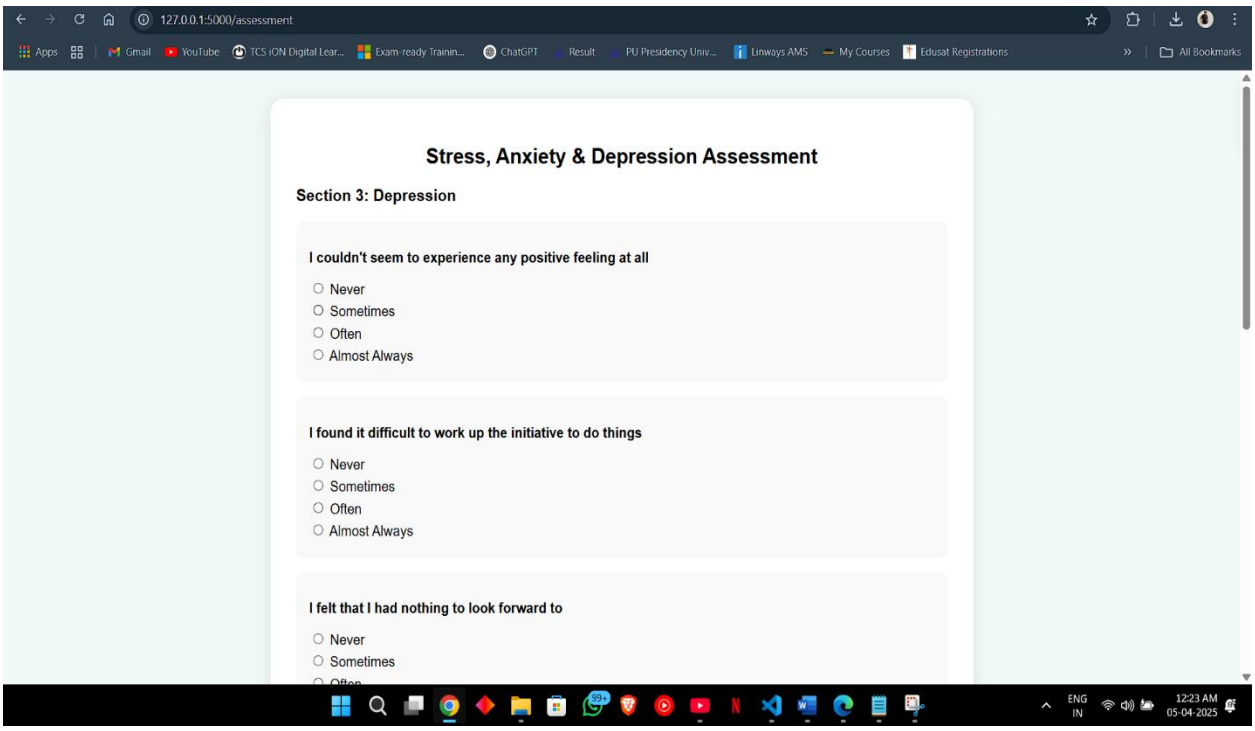

Fig 4: Depression assessment section 3

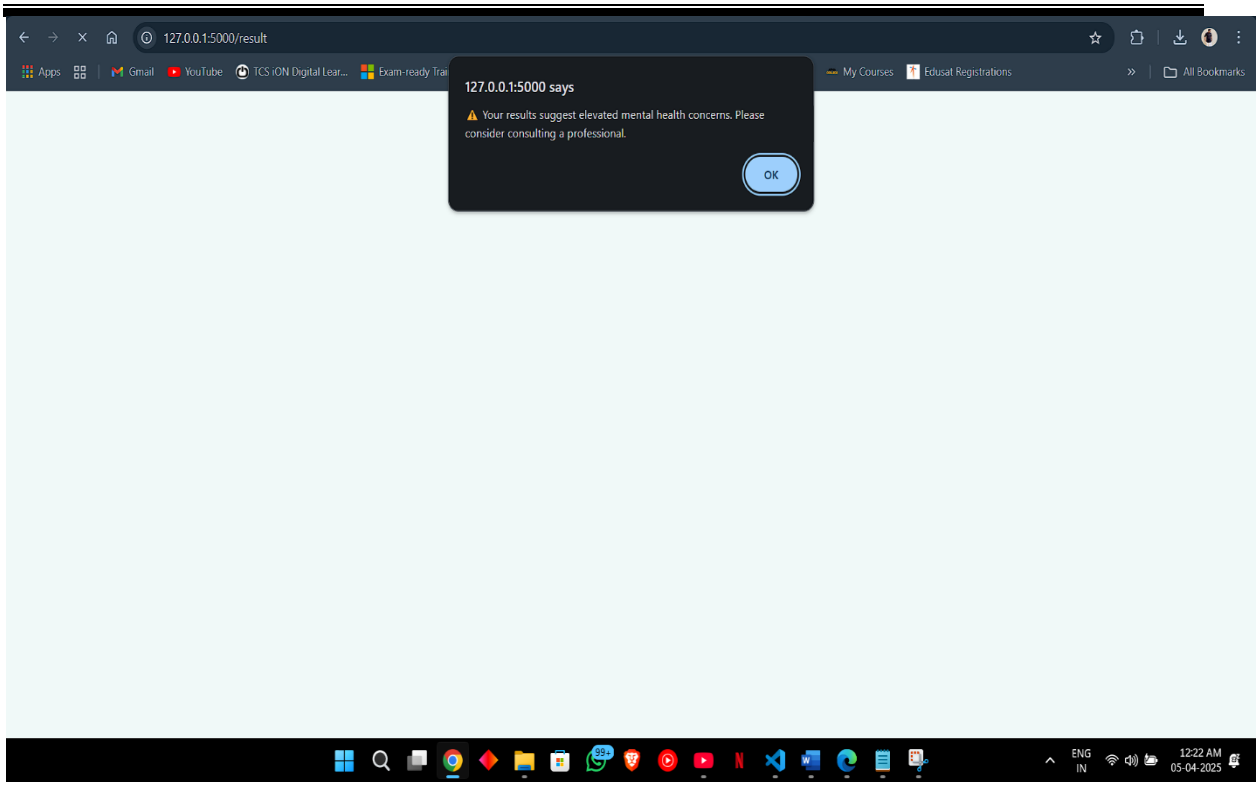

Fig 5: Result tab

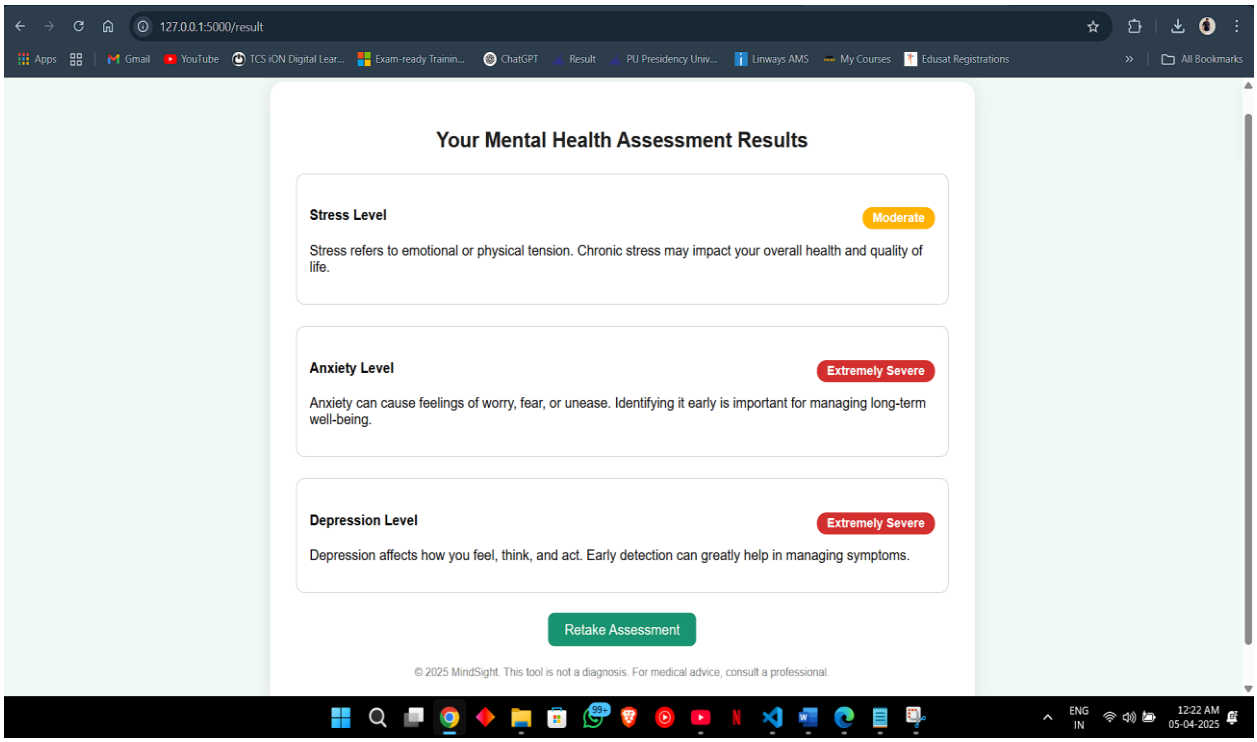

Fig 6: Mental Health Assessment results

APPENDIX-C

ENCLOSURES

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Sustainable Development Goals (SDGs)

Fig 8: SDG [12]

SDG 3: Good Health and Well-Being

MindSight directly addresses mental health issues by enabling early self-assessment of stress, anxiety, and depression levels.

It promotes overall psychological well-being by encouraging timely intervention and self-awareness.

SDG 4: Quality Education

By promoting emotional resilience and reducing psychological barriers, MindSight helps students focus better on their education.

Good mental health directly enhances learning outcomes, attendance, and academic performance.

SDG 9: Industry, Innovation and Infrastructure

By leveraging cutting-edge technologies like Machine Learning, MindSight represents an innovative digital health solution.

It demonstrates how modern infrastructure can be used to create accessible, efficient public health services.

SDG 10: Reduced Inequalities

MindSight provides free, anonymous access to mental health evaluation tools, breaking barriers related to socio-economic status, geography, or stigma.

It ensures equitable mental health support for underserved and marginalized populations.

SDG 16: Peace, Justice and Institutions

MindSight indirectly supports social peace by helping individuals achieve mental balance and emotional stability.

Promoting inner peace and resilience strengthens societal harmony and community well-being over time.

SDG 17: Partnerships for The Goal

MindSight opens possibilities for collaborations with educational institutions, NGOs, healthcare providers, and governments.

These partnerships can expand mental health outreach programs and integrate well-being initiatives across wider communities.