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DEPARTMENT OF COMPUTER ENGINEERING AND TECHNOLOGY

CERTIFICATE

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Akshit Singh (1032211401)

of B Tech. (Computer Science & Engineering) have completed their project titled as "**MaanSick:Depression detection using Python & Development**" and have submitted this Capstone Project Report towards fulfillment of the requirement for the Degree Bachelor of Computer Science & Engineering (B Tech- CSE) for the academic year 2024-2025.

22/11/2024
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Project Report

on

Depression detection using python & web development

Submitted by

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Under the Internal Guidance of

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Acknowledgment

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This report is a result of our hard work and commitment to present each part of our project in a clear and complete way. We have tried to include every important detail to make it easy to understand. We would be pleased to hear your feedback and any thoughts on how we can further improve our work.

Abstract

Depression is a serious mental illness that affects more than 300 million people worldwide, making it a leading cause of disability and health problems worldwide. It can negatively impact a person's emotional well-being, physical health, social relationships, and overall quality of life. Early and accurate detection of depression is important for timely intervention, which is important for preventing its development and preventing problems. Despite the urgent need for effective diagnostic procedures, current technologies often face significant limitations, such as limited availability in certain regions, fierce competition to meet increasing demand, and reliance on measurements that may introduce bias. The concept of finding depression aims to solve these problems by combining two methods of detecting depression: psychological assessment and facial analysis. By combining these methods, the system aims to provide a clear and measurable solution for identifying depression and other mental disorders, such as anxiety, depression, post-traumatic stress disorder (PTSD), and bipolar disorder. The system uses Naive Bayes classifier to determine the answers to diagnostic questions and established psychological models. It also uses convolutional neural networks (CNN) to analyze facial expressions, identifying subtle patterns and behavioral patterns often associated with stressful situations. To study the mental and physical aspects of the disease to improve diagnosis. These two methods provide doctors with an objective and multiple perspective on the patient's mental health, reducing the risk of misdiagnosis. In addition, the system's user-friendly design and instant functionality make it ideal for both clinical and non-clinical use-cases.

We follow strict rules to protect users' sensitive information, ensuring privacy and ethical concerns are handled fairly. The system is designed to be widely used in hospitals and mental health clinics to better understand and manage diseases. It offers doctors helpful tools for quick diagnosis, creating personalized treatment plans, and monitoring patients' mental health over time. Its ability to scale means even rural communities with limited resources can benefit, helping to bridge the gap in access to mental health care.

Keywords: Depression Detection, Naive Bayes Classifier, Convolutional Neural Network (CNN), Facial Expression Analysis, Mental Health Diagnosis

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Chapter 1: Introduction

The following chapter introduces our topic and states the problem statement as well as the aim.

1.1 Introduction to topic

Depression is a widespread mental health issue affecting millions of people around the world. It deeply impacts emotional well-being, thinking ability, and overall quality of life. Common symptoms include constant sadness, loss of interest in activities, low energy, and trouble focusing. Depression often leads to serious personal, social, and financial challenges. It is one of the leading causes of disability and early death globally, affecting not just individuals but also their families, workplaces, and healthcare systems. Despite growing awareness, depression is still often untreated in many parts of the world, making its impact even worse.

Traditional individual styles for depression, including clinical interviews and tone-administered questionnaires like the Patient Health Questionnaire-8 (PHQ-8), play an essential part in relating the condition. Still, these styles frequently face challenges similar to reliance on private reporting, which can be told by particular impulses. Furthermore, access to trained internal health professionals is frequently limited, particularly in low-resource settings. These obstacles can delay opinion, hamper timely intervention, and reduce the overall effectiveness of treatment.

To address these challenges, there is increasing interest in using advanced technologies like Artificial Intelligence (AI) and Machine Learning (ML) to improve mental health diagnosis. These technologies provide a promising way to create more accurate and accessible solutions that complement traditional methods. AI-powered systems can analyze large amounts of data, identify complex patterns, and deliver precise insights, making them well-suited for understanding the complex nature of mental health conditions like depression.

This design introduces a slice- edge Depression Discovery System designed to enhance the delicacy and effectiveness of diagnosing depressive diseases. The proposed system integrates cerebral assessments with real- time physiological analysis to produce a robust and multidimensional individual tool. Specifically, it employs a Naive Bayes classifier to estimate responses to a individual quiz, landing cognitive symptoms similar as negative study patterns and emotional torture. contemporaneously, it uses a Convolutional Neural Network(CNN) to dissect facial expressions, which are crucial pointers of emotional countries. Research has found that individuals with depression often show unique facial expression patterns, such as reduced expressiveness, prolonged sadness, and a lack of positive emotions.

By combining these two methodologies, the system addresses both the cognitive and emotional confines of depression, furnishing a comprehensive view of the patient's mental health. This binary approach improves individual delicacy, reduces the eventuality for bias, and enables the identification of colorful types of depressive conditions, including anxiety- related depression and bipolar complaint.

The system also incorporates several practical features that enhance its usability and impact. Real- time data processing ensures timely feedback, while strong sequestration and security measures cover sensitive stoner information. also, the system's scalability allows it to be stationed in different surrounds, from clinical operations to community- grounded internal health programs in under-served areas.

1.2 Problem Statement

Depression is a significant global health concern, impacting millions of individuals and contributing to a substantial burden on healthcare systems. Despite its frequent and serious consequences, depression frequently goes misdiagnosed due to limitations in traditional individual styles. Standard approaches, similar as clinical interviews and tone- reported questionnaires, are innately reliant on private input from cases, which can be told by particular impulses, smirch, or a lack of tone-mindfulness about their internal state. These styles, while precious, also bear trained professionals, making them time- ferocious and less accessible, particularly in low- resource or remote settings.

To tackle these challenges, there is a pressing need for innovative solutions that are unbiased, scalable, and easy to use. Advances in technology, particularly in Artificial Intelligence (AI) and Machine Learning (ML), offer a promising opportunity to address the shortcomings of traditional diagnostic methods. These technologies can process large amounts of data, detect subtle patterns, and provide real-time insights, making them highly suitable for mental health applications. However, most existing AI-based solutions focus only on either psychological assessments or physiological signals, which limits their accuracy and overall effectiveness in diagnosis.

This design aims to bridge this gap by developing a Depression Discovery System that integrates cerebral evaluation with real- time physiological analysis. The system employs a two-rounded approach to produce a further holistic and precise individual tool. First, it incorporates a classifier-grounded model to dissect responses to a individual quiz, which captures cognitive symptoms similar as negative study patterns, emotional torture, and behavioral changes generally associated with depression. Second, it utilizes a Convolutional Neural Network(CNN) to dissect facial expressions in real time, relating crucial emotional cues, similar as reduced expressiveness or sadness, which are explosively linked to depressive countries.

By combining these methodologies, the proposed system aims to address both the cognitive and emotional confines of depression. This integration enhances individual perfection and reduces reliance on private reporting, making the process more objective and dependable. likewise, the system's real- time facial expression analysis introduces a dynamic element that can identify subtle and immediate signs of emotional torture, completing the questionnaire- grounded evaluation.

The Depression Detection System not only seeks to ameliorate individual delicacy but also prioritizes availability and scalability. Its design ensures usability in a variety of surrounds, from clinical settings to remote healthcare surroundings, enabling wide relinquishment. also, the system incorporates robust sequestration and data security measures to cover sensitive stoner information, addressing ethical enterprises related to internal health diagnostics.

1.3 Aim

The end of this design is to develop an innovative and comprehensive Depression Detection System that leverages machine learning techniques to enhance the delicacy, neutrality, and availability of diagnosing depression and related mood diseases. The system seeks to address the limitations of traditional individual approaches by integrating real- time physiological data with cerebral assessments, furnishing a multidimensional view of an patient's internal health.

A key goal of the system is to process real-time data through facial expression analysis, allowing it to immediately detect emotional signals that may indicate depressive states. By analyzing facial expressions dynamically, the system captures subtle emotional patterns often missed in traditional assessments, such as reduced expressiveness or prolonged sadness. Additionally, the system aims to improve the accuracy of emotion detection by using advanced Convolutional Neural Network (CNN) models. CNN excel at identifying complex patterns in visual data, making them well-suited for recognizing emotional states from facial expressions. This ensures the system provides accurate and reliable insights, minimizing the chances of false positives or negatives. Likewise, the system is designed to insure fairness and trustability by combining cerebral data, attained through a individual quiz, with physiological data deduced from facial analysis. This integration provides a more comprehensive individual tool that accounts for both cognitive and emotional confines of depression. By balancing these two perspectives.

Eventually, this design aims to produce a scalable, accessible, and secure platform that empowers healthcare professionals and individuals to identify depressive diseases beforehand, leading to timely intervention and treat mental health issues.

Chapter 2 : Literature Review

2.1 Literature Survey

Research on automatic stress detection has been advanced with various machine learning methods, with each study showing specific challenges and improvements. Donner et al. (2017) reviewed the language model for depression diagnosis, emphasizing that the problem of classroom inequality should be solved through deep learning [1]. Ansari et al. (2023) focused on collaborative models for stress research, suggesting future work to address fairness, bias, and improve accuracy through computation with personal data [2].Barnard-Cocchi et al. (2018) simplified the PHQ-9 to the PHQ-5 and used neural networks for detection, highlighting the importance of physical data for accuracy [3].Chawda and Rakesh (2019) used artificial intelligence and natural language processing (NLP) to analyze social media posts and derive recommendations to improve culture change and flight analysis [4].Salas-Zarat et al. (2022) investigated social media data to identify depression and called for the development of a framework that combines historical and real-time data to increase sensitivity [5]. Yan et al. (2022) used convolutional neural networks (CNN) with EEG data and suggested the use of differential data and continuous treatment models for the diagnosis of major depressive disorder (MDD) [6].Maheshwar et al. (2022) used Support Vector Machine (SVM) model with Mel Frequency Cepstral Coefficients (MFCC) for speech detection and achieved 89% accuracy and stated that differential data is required to support the Mel Frequency Cepstral Coefficients (MFCC) Vector Machine (SVM) model[7]. Hidayatullah and Maharani (2022) developed a decision tree model using the DAIC-WOZ profile, emphasizing the need for available media to increase accuracy and reliability [8].Bastos and Monteiro (2020) proposed a machine learning chatbot for the study of depression, emphasizing the need for psychological knowledge to support moral and development [9].Patil et al. (2020) investigated the role of hyperscanning in the search for depression and proposed the use of noise in speech to enhance thinking [10].

2.2 Research Gaps

- **Limited Real-Time Data Integration**: Most existing models rely on static data, restricting their ability to adapt to dynamic, real-world situations. This limits their effectiveness in detecting depression in natural environments.

- **Bias and Lack of Fairness**: Many models struggle to generalize across diverse populations due to biased Data-sets, leading to inconsistent accuracy and reduced reliability for different demographic groups.

- **Insufficient Combination of Psychological and Physiological Data**: There is limited research integrating psychological assessments (e.g., quizzes) with physiological markers (e.g., facial expressions), resulting in incomplete analysis and reduced diagnostic reliability.

Chapter 3: Aim & Objectives

This chapter covers the scope of the project along with the assumptions made. The project objectives are also stated.

3.1 Project Scope

This project aims to develop a comprehensive depression detection system that combines psychological assessments with real-time facial expression analysis to improve the accuracy and reliability of diagnosing depressive disorders. The system integrates a Naive Bayes classifier for processing quiz responses and a Convolutional Neural Network (CNN) for real-time emotion detection, providing a multidimensional analysis of mental health. Designed for both clinical and non-clinical use, the system is scalable for deployment in remote areas and tele-health platforms, ensuring accessibility for diverse populations. Strong data security measures, including encryption protocols, protect sensitive information such as quiz responses and facial video recordings. The system will offer real-time analysis with minimal latency and high diagnostic accuracy. Future enhancements include incorporating wearable devices for additional physiological data and expanding the system to address more nuanced emotional states and a broader range of demographic needs.

3.2 Project Assumptions

- **Data Vacuity:** Sufficient and different Data-sets will be available for training both the Convolutional Neural Network(CNN) model and the Naive Bayes classifier. The Data-sets will include a wide range of demographic and artistic backgrounds to insure comprehensive model training and avoid impulses.

- **Tackle and Software coffers:** High- performance GPUs will be available to support effective real- time processing and model training. Quality cameras will be handed for facial videotape recording to insure clear and dependable data for facial recognition tasks. Reliable and effective software tools(e.g., TensorFlow, OpenCV) will be accessible for enforcing machine literacy models and handling real- time videotape processing.

- **Ethical Considerations:** The design will cleave to established ethical norms for internal health diagnostics, icing the protection of stoner sequestration and data confidentiality. Informed concurrence will be attained from druggies previous to participation in any data collection, particularly for the individual quiz and facial videotape recordings.

- **Model delicacy and Scalability:** The Naive Bayes classifier and CNN models will meet respectable delicacy thresholds for both individual assessments and integrated evaluations.

  The system is designed to gauge efficiently for use by multiple concurrent druggies without passing significant declination in performance.

- **Perpetration Constraints:** Real- time facial recognition and quiz processing will serve efficiently under standard environmental conditions. Performance may be impacted in surroundings with poor lighting or when using low- quality cameras, which may challenge

  model delicacy and processing speed. Bayes classifier to reuse individual quiz responses and a Convolutional Neural Network(CNN) for real- time emotion discovery, integrating these results to give a multidimensional analysis of internal health. Designed for both clinical and non-clinical use, the system is scalable for deployment in remote areas and telehealth platforms, icing availability for different populations. Strong data security measures, including encryption protocols, safeguard sensitive stoner information similar as quiz responses and facial videotape recordings. The system aims to deliver real- time analysis with minimum quiescence and high individual delicacy. unborn advancements include the integration of wearable bias for fresh physiological data and the expansion of the system to regard for nuanced emotional countries and broader demographic content.

3.3 Project Objectives

- **Early opinion of Depression:** Develop a system to descry early signs of depression using a combination of individual quizzes and real- time facial expression analysis. separate between
  colorful types of depression (e.g., anxiety, PTSD, bipolar complaint) and give customized recommendations.
- **Real- Time Analysis:** Incorporate real- time data collection via videotape analysis to assess emotional countries effectively. use a Convolutional Neural Network (CNN) for facial expression recognition.
- **Enhanced Availability:** Produce an intuitive and accessible interface for druggies of varying specialized chops. Offer recommendations for treatment installations and give immediate feedback to druggies.
- **Comprehensive opinion:** Integrate cerebral(quiz results) and physiological(facial expressions) data for a holistic approach to depression discovery.

3.4. Project Limitations

- **Data sequestration Challenges:** icing secure storehouse and processing of sensitive stoner data, similar as quiz answers and videotape recordings.
- **Emotion Recognition delicacy**: Challenges in detecting feelings directly under different lighting conditions and camera quality.
- **Bias in Machine Learning Models**: pitfalls of bias in prognostications due to unstable Data-sets or rightly different training data**.**
- **Scalability Constraints:** Implicit performance issues in handling multiple real- time patients.

Chapter 4: Project Requirements

The following chapter specifies the requirement gathering process and various requirements for the project.The objective of the Depression Detection System is to create an accessible tool for early diagnosis of depression using both a diagnostic quiz and real-time facial expression analysis. This system targets users who may be experiencing symptoms of depression by providing an analysis that identifies the most likely type of depression (e.g., anxiety, PTSD, or bipolar disorder) and suggests potential treatment options **.**

4.1 Project Requirements

4.1.1 Stakeholder Analysis

(a) Primary Stakeholders:

- End Users: Individuals experiencing potential symptoms of depression who will interact with the system to assess their mental health status.
- Healthcare Professionals: May refer patients to use the system or use the system's outputs to support diagnosis.
- Development Team: Responsible for creating, testing, and deploying the system.
- Project Mentors: Guide the development team through feedback and oversight.

4.1.2 Functional Requirements

(a) Quiz Module:

- The system must include a diagnostic quiz consisting of multiple-choice questions to assess the user's mental health state.
- The quiz should be processed using a Naive Bayes classifier to determine the type of depression (anxiety, PTSD, bipolar disorder).

- The system should recommend clinics and expert assistance based on quiz results.
- It should generate an interactive map for the user to locate nearby treatment facilities.

(b) Facial Expression Analysis Module:

- Users must be able to record a one-minute video where they talk about themselves.
- A Convolutional Neural Network (CNN) must analyze the user's facial expressions to evaluate emotional states.
- The system should process the data in real-time and refine the diagnosis based on facial analysis.

(c) Front-end & Back-end Integration:

- The front-end, developed using HTML, CSS, and JavaScript, must interface seamlessly with the Python-based back-end.
- User data, including quiz results and facial expression analysis, must be stored in a MongoDB database.

(d) Error Handling:

- The system must handle potential errors in both quiz results and emotion recognition, ensuring reliable outputs.

4.1.3 Non-Functional Requirements

(a) Usability: The system must have an intuitive user interface, making it accessible for users with varying levels of technical expertise.

(b) Performance: Real-time facial expression analysis must be efficient, with results available within seconds after the user’s video is recorded.

(c) Scalability: The system should be scalable to accommodate a large number of users and provide quick responses even under load.

(d) Security: User data, including quiz answers and facial videos, must be securely stored and processed, ensuring privacy and confidentiality.

4.1.4 Hardware and Software Requirements

(a) Hardware Requirements:

- High-Performance GPU: Essential for training the CNN model efficiently, especially when processing large Data-sets. A GPU like the NVIDIA RTX 3090 or equivalent is recommended.
- Microphone and Camera: High-quality microphone and camera for recording facial expressions in real-time and ensuring clear audio/video input for accurate detection.
- High-Capacity Storage: SSD storage for handling large Data-sets, model checkpoints, and logs.
- Ensures faster data retrieval and processing.
- Multi-Core CPU and RAM: A powerful CPU (at least 8 cores) and 32GB RAM to support real-time data processing and model training without delays.

(b) Software Requirements:

- Back-end Processing and Machine Learning: Python with FastAPI for handling back-end tasks, including machine learning processes.
- Web Framework: FastAPI and Node.js for managing API endpoints and web services.
- Database Management: MongoDB for storing user data, quiz results, and real-time facial expression analysis.
- front-end Development: HTML, CSS, JavaScript, and ReactJS for building an interactive and user-friendly interface.
- Machine Learning Libraries/Tools: OpenCV for real-time facial expression recognition. scikit-learn for the Naive Bayes classifier used in the quiz analysis. TensorFlow/Keras for the CNN (Convolutional Neural Network) model to detect emotions from facial expressions.
- Version Control: Git for version control, with GitHub for remote project repository management and team collaboration.

4.2 Risk Management

The project faces several risks including potential inaccuracies in the naive Bayes classifier and CNN models which could lead to incorrect diagnoses to mitigate this regular updates cross-validation and user feedback mechanisms should be implemented real-time performance could be affected by high user volumes so load testing and system optimization are necessary data quality may be compromised by poor video conditions or inaccurate quiz responses which can be addressed through clear instructions and pre-processing techniques privacy concerns require strict adherence to data security standards and informed consent ethical risks of misdiagnosis should be mitigated by clarifying that the system is not a substitute for professional advice additionally environmental factors like lighting and camera quality can impact facial recognition requiring user guidance and adaptive algorithms to improve data collection finally scalability and bias risks can be managed by ensuring the system is built to scale and using diverse Data-sets to avoid model biases.

Table 4.1 Risk-level table

Risk	Description	Risk Level
Model Accuracy	Inaccurate predictions leading to incorrect diagnoses.	High
Real-Time Performance	Slowdowns due to heavy user load impacting real-time processing.	Medium
Data Quality	Poor user input (e.g., bad video quality or inaccurate quiz responses).	Medium
Privacy & Security	Risks of data breaches or misuse of personal data.	High
Ethical Misdiagnosis	Incorrect results may mislead users, particularly in mental health contexts.	High

Environmental Factors	Poor lighting or low-quality cameras affecting facial recognition.	Medium
Scalability	Performance issues as the system scales with more concurrent users.	Medium
Bias & Fairness	Potential bias if training data lacks diversity or representation.	Medium

4.3 Interfaces

1. **User Interface (UI):** Technology mound erected using HTML, CSS, and ReactJS. ReactJS provides dynamic, interactive factors that ameliorate the overall user experience.

   Features

   - Quiz Module Displays - A user-friendly individual quiz conforming of multiple-choice questions. tutor users step- by- step through the quiz process to assess their internal health.
   - Video Recording Module - Allows users to record a one- nanosecond videotape through an bedded camera interface. Ensures ease of access with clear instructions and a real- time videotape exercise.
   - Results Display - Provides a summary of the quiz and videotape analysis results, along with recommendations for farther backing.

2. **Back-end Interface :** Technology Stack Developed using FastAPI, a Python- grounded frame optimized for erecting API's**.**
   - Receives user inputs from the front-end(quiz responses and videotape recordings).
   - Interacts with machine literacy models to reuse the data
   - Quiz responses are anatomized by a Naive Bayes Classifier.
   - Facial expressions in videos are reused by a Convolutional Neural Network(CNN).
   - Generates and sends the results back to the front-end for user display**.**

3. **Database Interface**
   - Uses MongoDB for effective storehouse and reclamation of user data.
   - Liabilities Stores quiz results, videotape analysis labors, and user biographies in a structured format. Maintains logs of user relations for future reference or analysis.
   - Ensures the security of sensitive data with encryption mechanisms and access controls.

4.4 Interactions

(a) System and User Interaction:

Flow: The user starts by interacting with the interface to complete the diagnostic test. Once the test is completed, the video is recorded via the built-in camera interface. The test and video analysis results are displayed in real time on the interface. Conclusion: The system provides a detailed report including the type of depression detected (if any) and recommendations for nearby clinics or specialists.

Interaction between the front-end and back-end: Process: The front-end collects data (test answers and videos) from the user and sends them to the back-end via an API endpoint. FastAPI on the back-end processes the input data, interacts with the machine learning model, and prepares the results. Result delivery: Processed data, such as analysis results and recommendations, are sent back to the front-end for display. System and database interaction: Data storage: The back-end stores test answers, video analysis results, and user profiles in a MongoDB database.

Data extraction: If necessary, the back-end retrieves the stored data for further processing or analysis. For example: Past user data can be used for follow-up actions or to improve the machine learning model. Interaction between system and model: Completion: The back-end combines the test analysis results (Naive Bayes classifier) with the facial expression analysis (CNN model). The combined data improves the accuracy of the diagnosis. Processing: The real-time video data is processed frame by frame by CNN model to detect emotions. The responses to the test are statistically evaluated by Naive Bayes classifier to predict the possible type of depression.

Feedback loop: Input-based learning: Capture and analyze user input (test data and video recordings) to improve the performance of the machine learning model. Continuous Improvement: Over time, with more data, the model adapts to a wider range of user behaviors and emotional expressions, improving predictions and accuracy.

Chapter 5: System Architecture design

5.1 Design Considerations

Here are some key design considerations to guide the proposed architecture:

1. **Real- Time Processing**

   - The system must dissect the user's videotape and quiz inputs in * real- time * to insure instant feedback.
   - Technologies like TensorFlow/ Keras(for CNN) and OpenCV(for facial analysis) are used to optimize processing speed without compromising delicacy.
   - Effective use of multithreading and GPU acceleration ensures quick data processing, indeed under cargo.

2. **Scalable Architecture**

   - The back-end system should be designed to scale horizontally, allowing it to handle increased activity, such as more users uploading videos simultaneously.
   - Platforms like AWS or Azure should enable dynamic resource scaling to ensure consistent performance during high demand.
   - Implementing asynchronous processing in FastAPI will allow it to manage multiple requests at the same time, ensuring high efficiency and throughput.

3. **Integration of Machine Learning Models**

   - A Naive Bayes Classifier processes quiz responses to identify depression types grounded on textual data.

- A Convolutional Neural Network(CNN) interprets facial expressions for emotional countries(e.g., sadness, joy, anxiety).
- Both models are integrated into the back-end to insure flawless data inflow and unified individual affair.

4. Usability

- The user interface is designed with simplicity in mind, employing ReactJS for a dynamic and responsive experience.
- Users should be suitable to navigate through the quiz and videotape recording process effortlessly.
- Interactive feedback ensures users feel engaged and informed during the process.

5. Security and sequestration

- All data, including quiz results and videotape recordings, must be translated using TLS during transmission.
- User data stored in the database is secured with encryption at rest and access control mechanisms like part- Grounded Access Control(RBAC).
- Secure authentication mechanisms help unauthorized access to sensitive user data.

6. Data- Driven Advancements

- User commerce logs are stored and anatomized periodically to identify areas for enhancement in both the interface and the machine literacy models.

- Feedback from real- world operation helps in retraining models for better performance and delicacy.

7. Error Handling

- o Error dispatches are displayed easily for issues similar as Failed videotape uploads.
- o Missing quiz responses.
- o Deficient data processing due to system or network issues.
- o The system should also retry failed operations where possible, minimizing user frustration

5.2 Assumptions and Dependencies

When conducting a system analysis and proposing an architecture or high-level design for the **Depression detection system using Machine Learning & web Technology** system, it is essential to consider the assumptions and dependencies that may impact the design and implementation. Here are some key aspects to address:

(a) Assumptions:

- o Device Availability: users will have bias with functional cameras and microphones togive videotape and audio inputs.
- o Stable Internet: Real- time data processing assumes users have a stable and sufficient internet connection for videotape uploads and commerce with the back-end.
- o User Honesty :Quiz responses are assumed to be genuine, as incorrect or deceiving inputs may affect the delicacy of the opinion.
- o Model delicacy :The trained CNN and Naive Bayes models are assumed to give highdelicacy within the compass of their training Data-sets

(b) Dependencies:

- oHardware: GPUs (e.g., NVIDIA RTX 3090) are essential for efficient training and real-time inference of CNN models. High-quality cameras and microphones ensure accurate data capture for facial expression analysis

- oSoftware Libraries: TensorFlow/Keras for building and deploying the CNN model. OpenCV For real-time video frame processing and facial recognition. scikit-learn For quiz result classification using the Naive Bayes algorithm.

- oBack-end Framework Fast API provides robust API endpoints for front-end-back-end communication.

- oDatabase: MongoDB handles data storage for quiz results, user profiles, and video outputs. cloud Platforms Platforms like AWS or Heroku are used for hosting, scaling, and deploying the application.

5.3 General Constraints:

1. Data Privacy Regulations: Compliance with GDPR or HIPAA to ensure the protection of user data. Implement secure encryption protocols for both data at rest and in transit.

2. Real-Time Requirements: The system must process quiz responses and video recordings within a few seconds to provide a seamless user experience. Latency caused by high server load should not exceed acceptable limits (e.g., <3 seconds per user interaction).

3.Lighting and Camera Quality: Poor lighting or low-resolution cameras may reduce the accuracy of facial expression recognition. Users may need to ensure proper environmental conditions for optimal results.

4. Data-set Limitations: The system's models are limited by the quality and diversity of the training Data-sets, which might not fully represent all demographics or emotional expressions.

5.Hardware Limitations: Real-time performance may degrade for users on low-powered devices or those with outdated hardware.

6.Bias in Models: Training Data-sets should include diverse examples to minimize biases in detecting emotions and predicting depression types

5.4 System Architecture

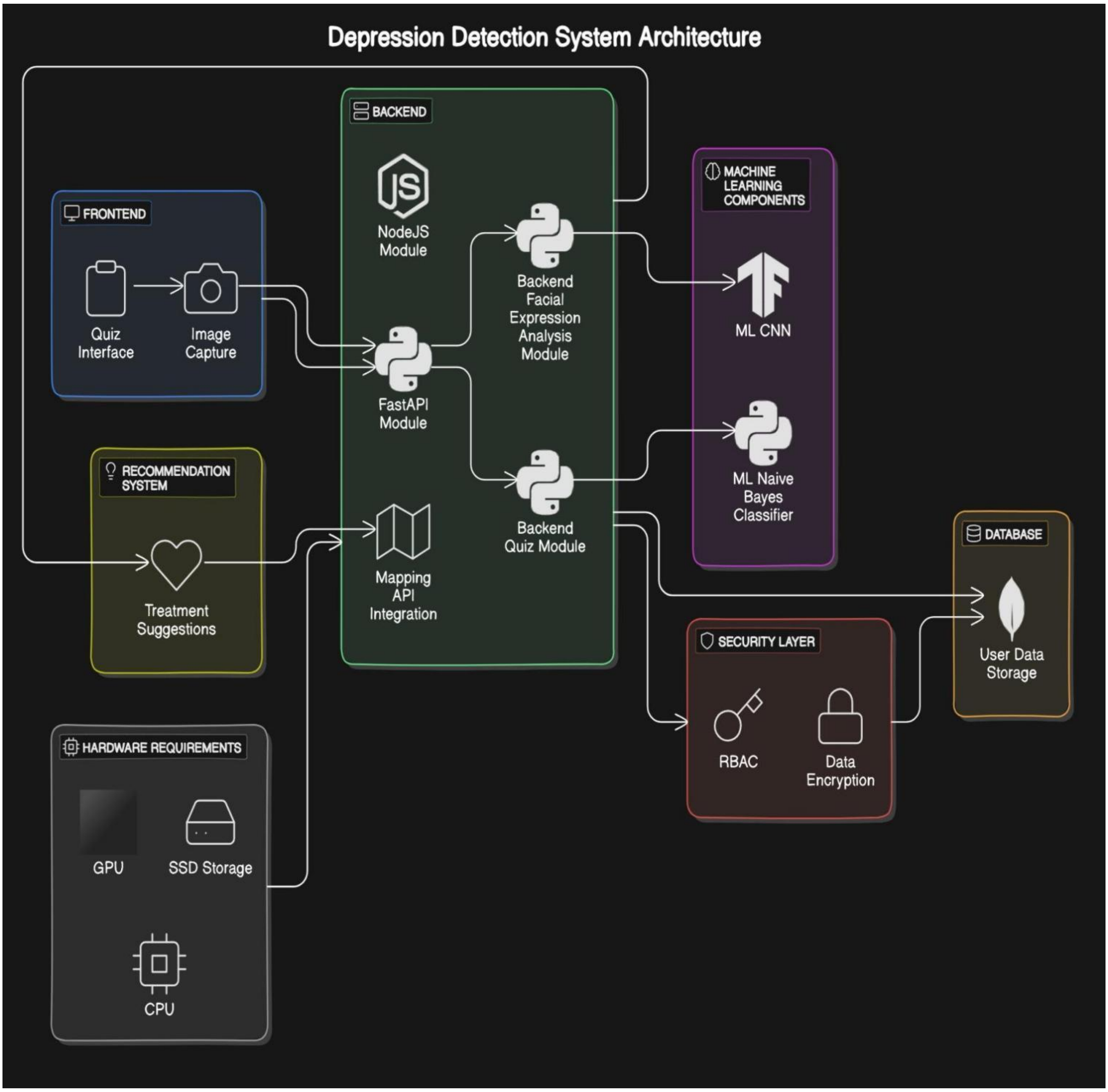

Fig.5.1 System Architecture Diagram

5.5 UML Diagrams

- **Use Case Diagram**

In UML, use-case diagrams model the behavior of a system and help to capture the requirements of the system. Use-case diagrams describe the high-level functions and scope of a system. These diagrams also identify the interactions between the system and its actors. The use cases and actors in use-case diagrams describe what the system does and how the actors use it.Use-case diagrams illustrate and define the context and requirements of either an entire system or the important parts of the system.

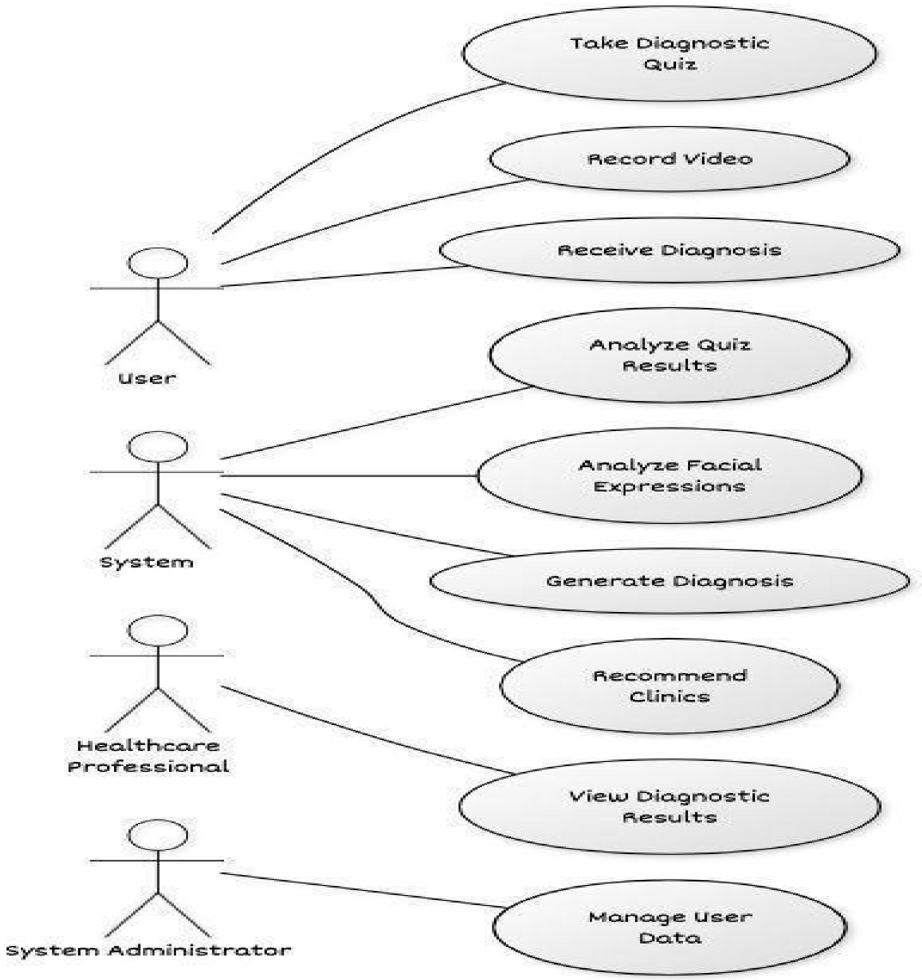

Figure 5.2:Use Case Diagram

- **Class Diagram**

Class diagram is a static diagram. It represents the static view of an application. Class diagram is not only used for visualizing, describing, and documenting different aspects of a system but also for constructing executable code of the software application. Class diagram describes the attributes and operations of a class and also the constraint imposed on the system. The class diagrams are widely used in the modeling of object- oriented systems because they are the only UML diagrams which can be mapped directly with object-oriented languages. Class diagram shows a collection of classes, interfaces, associations, collaborations, and constraints. It is also known as a structural diagram.

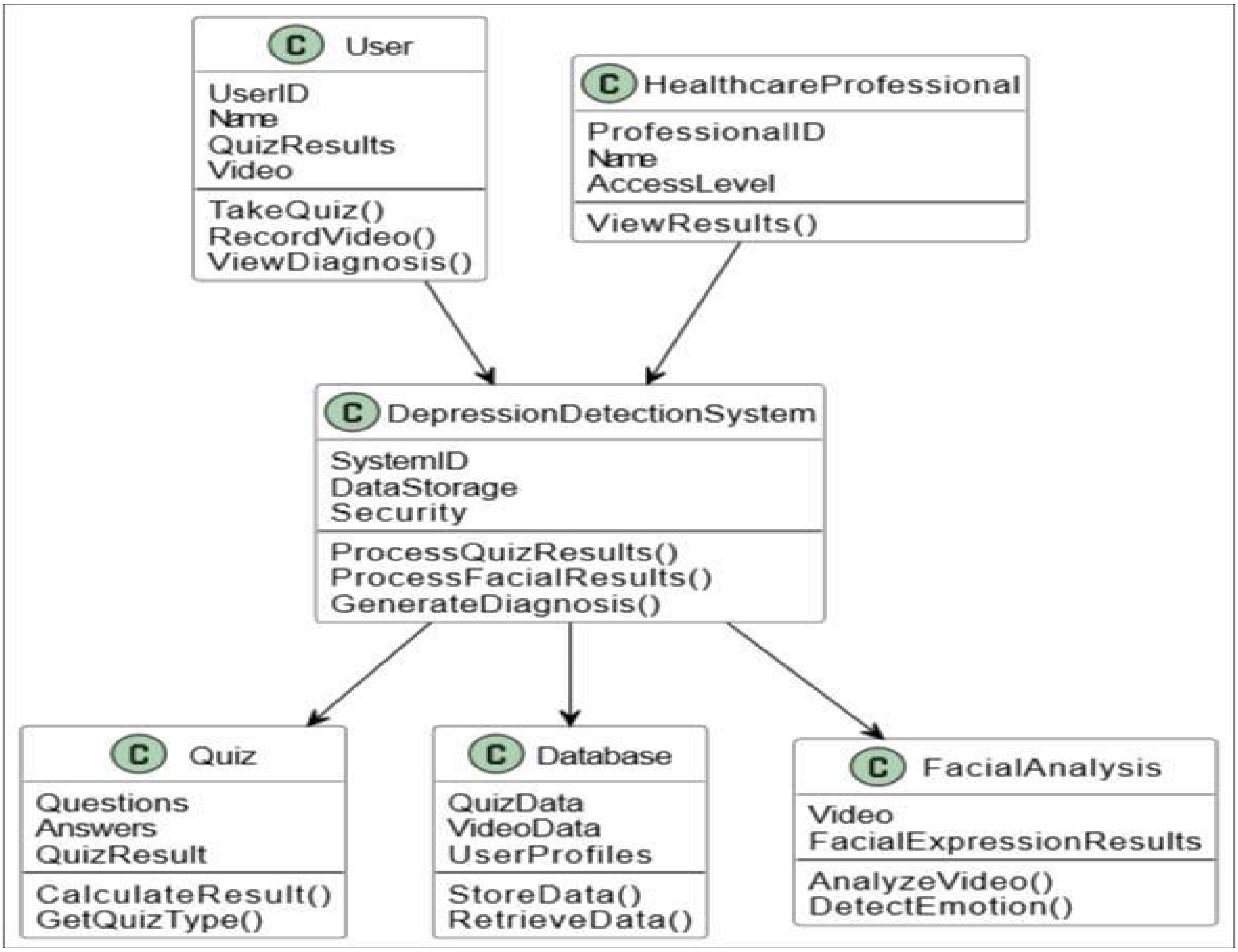

Figure 5.3 : Class Diagram

- **Activity Diagram**

Activity diagram is another important diagram in UML to describe the dynamic aspects of the system. Activity diagram is basically a flowchart to represent the flow from one activity to another activity. The activity can be described as an operation of the system.The control flow is drawn from one operation to another. This flow can be sequential, branched, or concurrent. Activity diagrams deal with all types of flow control by using different elements such as fork, join, etc.

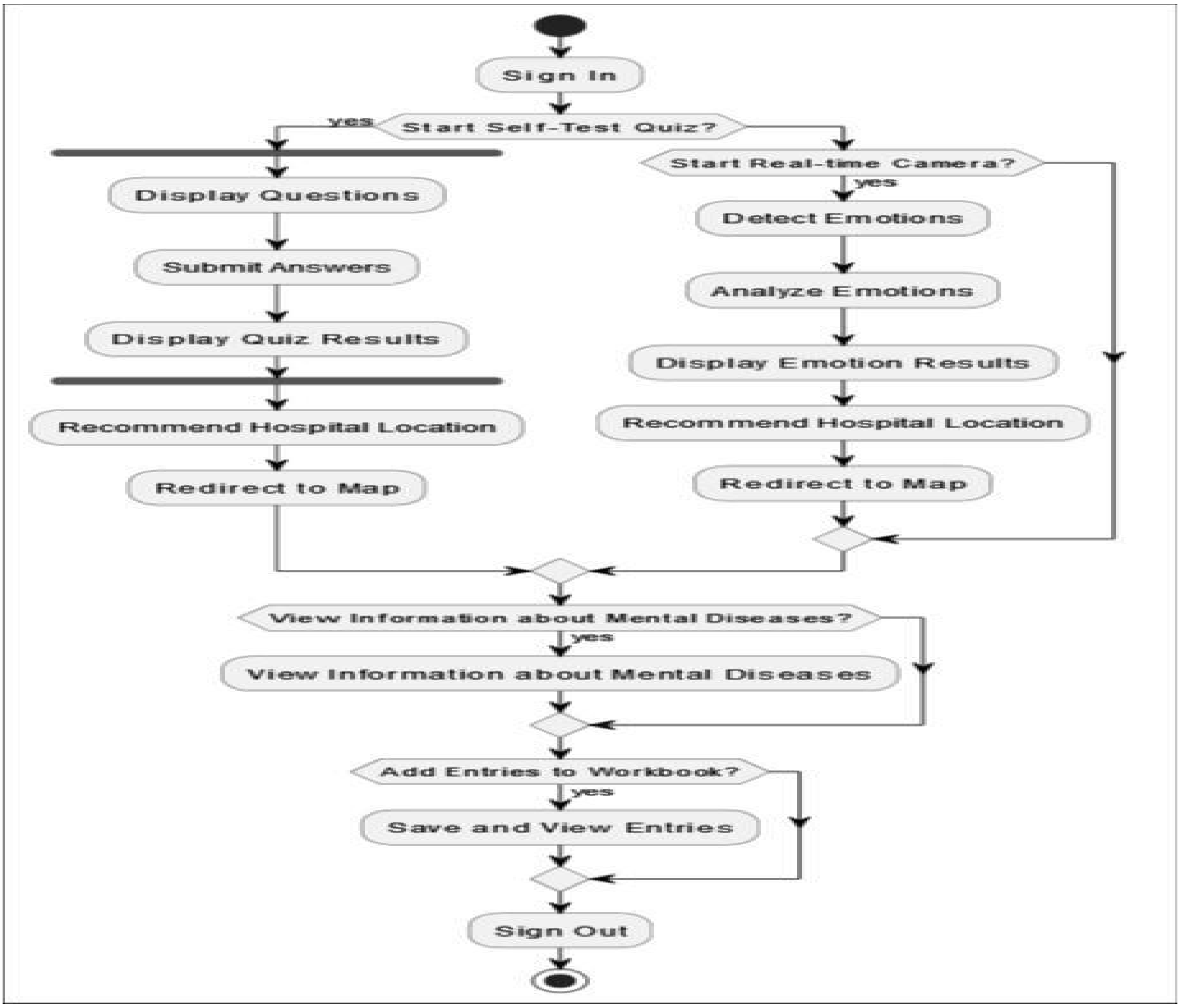

Figure 5.4: Activity Diagram

Chapter 6: Project Plan

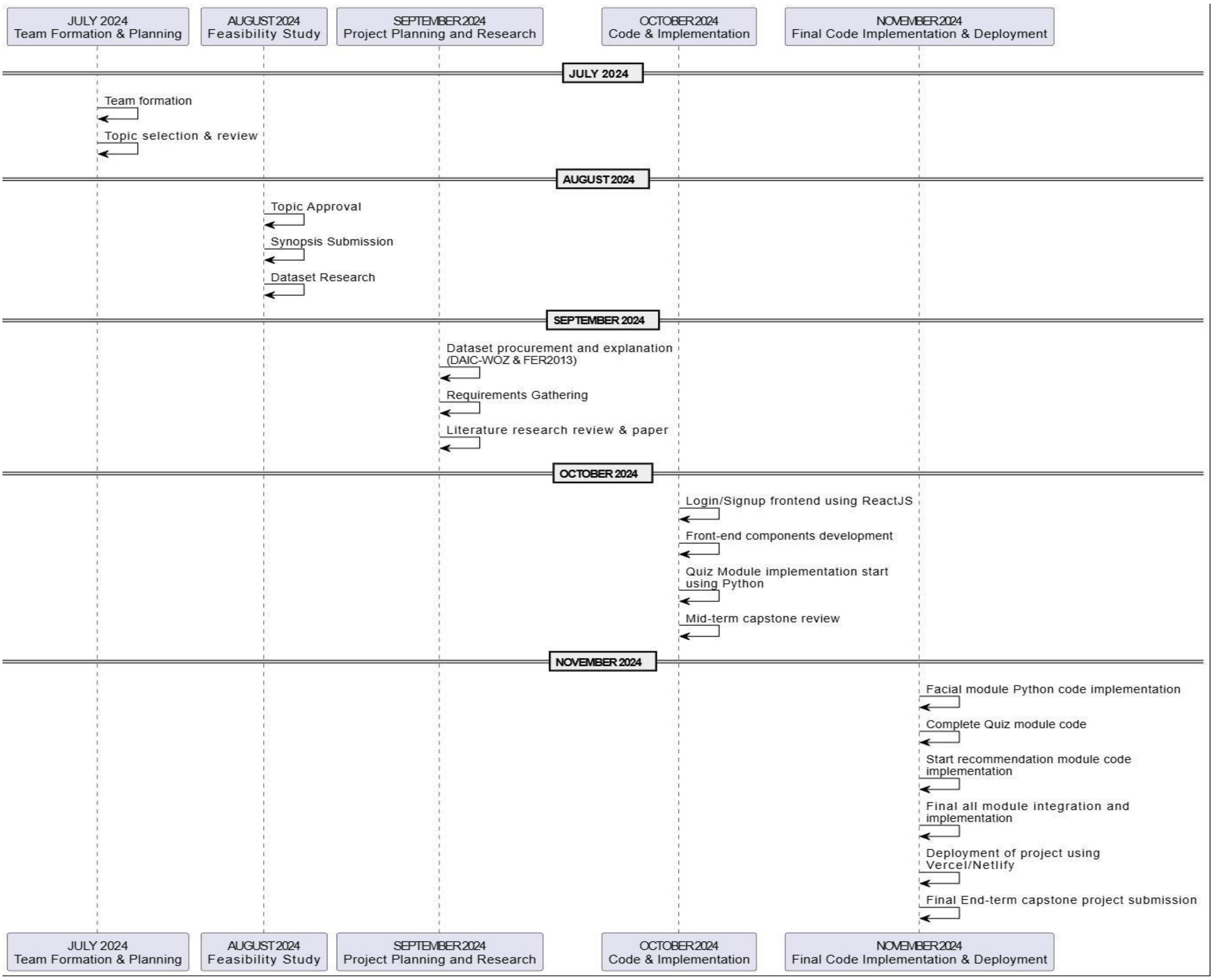

Figure 6.1: Project Plan

Chapter 7: Implementation

7.1 Methodology

1. Naive Bayes Classifier: The Naive Bayes classifier is a probabilistic model employed to dissect quiz responses and classify the liability of colorful depression- related conditions similar as anxiety, PTSD, or bipolar complaint. By calculating the tentative chances of each outgrowth, the model identifies the most likely order grounded on stoner inputs. Its simplicity and effectiveness make it particularly suitable for recycling categorical quiz data, and it performs robustly indeed with lower Data-sets. This enables accurate and nippy prognostications, icing a dependable original individual process.

2. CNN: A Convolutional Neural Network(CNN) is used to dissect facial expressions in videotape frames, enabling the discovery of emotional patterns reflective of depression. The CNN processes input videotape data frame by frame, using convolutional layers to prize facial features and completely connected layers to classify emotional countries similar as sadness, frustration, or anxiety. This deep literacy fashion is largely effective in image and videotape processing tasks, allowing the system to capture subtle emotional shifts that may gesture underpinning internal health enterprises.

3. Real- Time Processing: Thesystem is designed to give immediate feedback by recycling both quiz results and facial expression data in real time. OpenCV is employed for live videotape prisoner and facial discovery, while TensorFlow and Keras fabrics grease rapid-fire prosecution of the CNN model. This ensures that users admit instant and practicable perceptivity, maintaining the system's responsiveness and engagement. The focus on real- time processing enhances usability and aligns with the thing of furnishing timely internal health evaluations.

4.Management and Storage: The system leverages MySQL for secure storehouse and effective reclamation of quiz responses, videotape data, and analysis labors. user data is translated to insure confidentiality and compliance with data sequestration regulations. The database design supports rapid-fire queries for real- time analysis while maintaining scalability to handle growing Data-sets. This robust data operation frame underpins the system's capability to deliver quick and secure access to critical stoner information.

5. Evaluation and Verification: Comprehensive testing ensures the system's delicacy and trustability. element testing validates individual modules, similar as the Naive Bayes classifier and CNN, while integration testing confirms flawless communication between the front-end, back-end, and database. Performance testing assesses the system under colorful cargo conditions, and user feedback is gathered to upgrade usability and ameliorate overall performance. These measures insure that the system meets high norms of functionality and user experience

6. Implementation project Screenshots

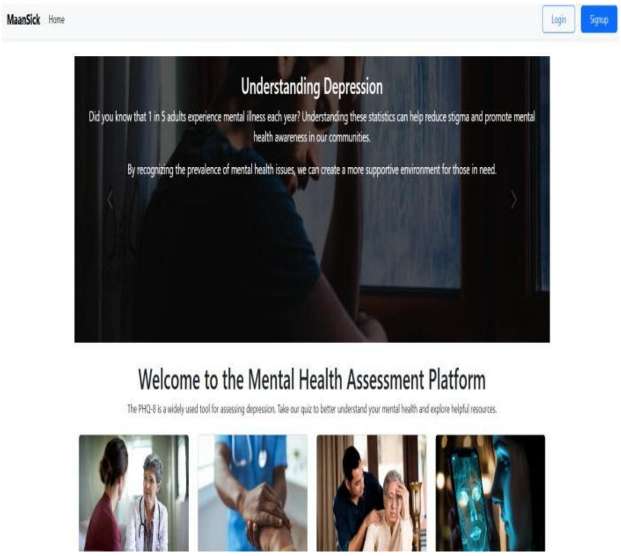

Fig 7.1 HomePage

Fig 7.2 HomePage

Fig 7.3 Login Page

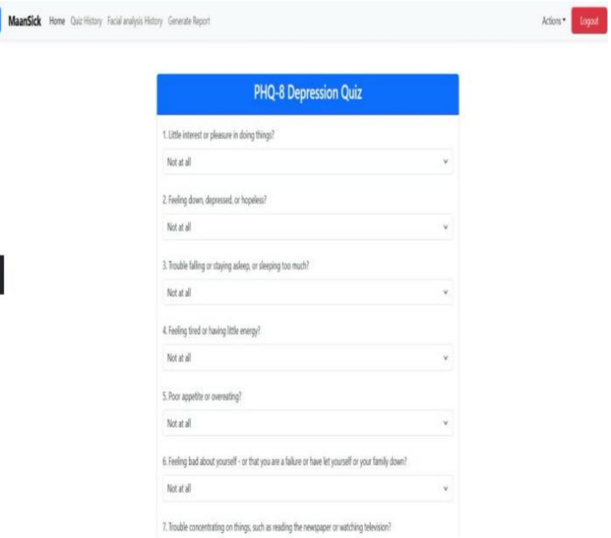

Fig 7.4 PHQ-8 Quiz

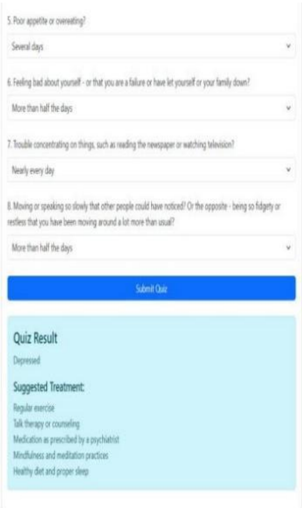

Fig 7.5 Quiz Results

Fig 7.6 Facial expression module

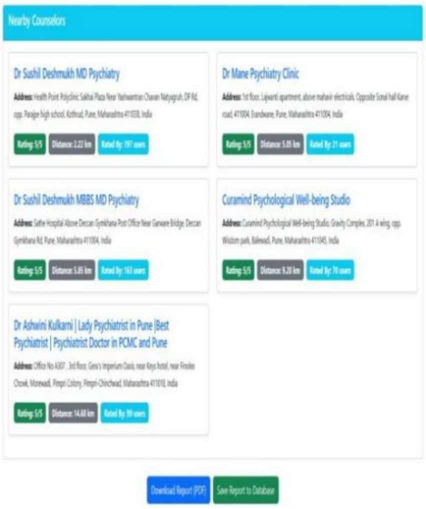

Fig 7.7 Counsellor Recommendation

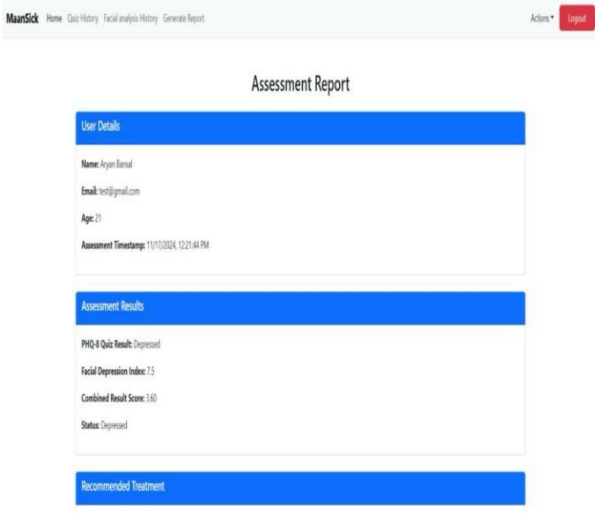

Fig 7.8 Assessment report

7. Libraries and Tools Used

- o Front-end: Html, css,Bootstrap,ReactJS
- o Back-end: FastAPI(Python),NodeJS(Javascript),ExpressJS(API servers)
- o Database: MongoDB
- o Algorithms:
  - • Naive-Bayes classifier for Quiz module
  - • CNN/Deepface for Facial module
- o External API's services used:
  - • Google Places API: for nearby psychiatrist recommendation
  - • EmailJS API: for email services integration
  - • Cloudinary API: for storing profile images and image assets
- oPython modules used:
  - • sci-kit sklearn
  - • tensorflow
  - • pandas
  - • joblib
  - • OpenCV
  - • Keras
  - • Matplotlib

oCI/CD: Git/Github

oAPI testing: Postman, ThunderClient

oDeployment: Vercel/Netlify/AWS.

7.2 Data-set

1. DAIC-WOZ Data-set (Quiz Module): The DAIC-WOZ Data-set is designed for mental health assessment research, containing audio, video, and transcripts of clinical interviews with a virtual agent. It includes participant demographics and clinical diagnostic scores, making it ideal for training models to analyze user responses for mental health diagnostics.

2.FER2013 Data-set (Facial Module): The FER2013 Data-set is a benchmark for facial expression recognition, containing over 35,000 grayscale images (48x48 pixels) labeled with seven emotions: anger, disgust, fear, happiness, sadness, surprise, and neutral. It is widely used to train CNN models for emotion detection in facial data.

	A	B	
1	emotion	pixels	Usage
2	0	70 80 82 72 58 58 60 63 54 58 60 48 89 115 121 119 115 110 98 91 84 84 90 99 110 126 143 153 158 171 169 172 169 165 129 110 113 107 95 79 66 62 56 57 61 52 43 4	Training
3	0	151 150 147 155 148 133 111 140 170 174 182 154 153 164 173 178 185 185 189 187 186 193 194 185 183 186 180 173 166 161 147 133 172 151 114 161 161 146 131	Training
4	2	231 212 156 164 174 138 161 173 182 200 106 38 39 74 138 161 164 179 190 201 210 216 220 224 222 218 216 213 217 220 220 218 217 212 174 160 162 160 139 135	Training
5	4	24 32 36 30 32 23 19 20 30 41 21 22 32 34 21 19 43 52 13 26 40 59 65 12 20 63 99 98 98 111 75 62 41 73 118 140 192 186 187 188 190 190 187 182 176 173 172 173 25	Training
6	6	4 0 0 0 0 0 0 0 0 0 0 0 3 15 23 28 48 50 58 84 115 127 137 142 151 156 155 149 153 152 157 160 162 159 145 121 83 58 48 38 21 17 7 5 25 27 24 25 1 0 0 0 0 0 0 0 0 0 0	Training
7	2	55 55 55 55 55 54 60 68 54 85 151 163 170 179 181 185 188 188 191 196 189 194 198 197 195 194 190 193 195 184 175 172 161 159 158 159 147 136 137 136 146 120	Training
8	4	20 17 19 21 25 38 42 42 46 54 56 62 63 66 82 108 118 130 139 134 132 126 113 97 126 148 157 161 155 154 154 164 189 204 194 168 180 188 214 214 214 216 208 22	Training
9	3	77 78 79 79 78 75 60 55 47 48 58 73 77 79 57 50 37 44 56 70 80 82 87 91 86 80 73 66 54 57 68 69 68 68 49 46 75 71 69 70 70 72 72 71 72 74 77 76 83 84 82 81 81 69 60	Training
10	3	85 84 90 121 101 102 133 153 153 169 177 189 195 199 205 207 209 216 221 225 221 220 218 222 223 217 220 217 211 196 188 173 170 133 117 131 121 88 73 73 50	Training
11	2	255 254 255 254 254 179 122 107 95 124 149 150 169 178 179 179 181 181 184 190 191 191 193 190 190 195 194 192 193 196 193 192 188 182 173 162 152 144 129 1	Training
12	0	30 24 21 23 25 25 49 67 84 103 120 125 130 139 140 139 148 171 178 175 176 174 180 180 178 178 182 185 183 186 186 178 180 172 175 171 155 152 141 136 132 13	Training
13	6	39 75 78 58 58 45 49 48 103 156 81 45 41 38 49 56 60 49 32 31 28 52 83 81 78 75 62 31 18 19 19 20 17 20 16 15 12 10 11 10 23 36 65 59 9 3 5 7 93 69 86 90 84 75 51 12	Training
14	6	219 213 206 202 209 217 216 215 219 218 223 230 227 227 233 235 234 236 237 238 234 226 219 212 208 201 190 183 176 161 74 15 24 22 22 22 21 19 19 20 20 23 7	Training
15	6	148 144 130 129 119 122 129 131 139 153 140 128 139 144 146 143 132 133 134 130 140 142 150 152 150 134 128 149 142 138 156 155 140 136 143 143 139 144 160	Training
16	3	4 2 13 41 56 62 67 87 95 62 65 70 80 107 127 149 153 150 165 168 177 187 176 167 152 128 130 149 149 146 130 139 139 143 134 105 78 56 36 50 69 82 64 35 10 11 1	Training
17	5	107 107 109 109 109 109 110 101 123 140 144 144 149 153 160 161 161 167 168 169 172 172 173 175 176 171 170 166 165 162 162 157 150 149 145 140 136 132 128	Training
18	3	14 14 18 28 27 22 21 30 42 61 77 86 88 95 100 99 101 99 98 99 99 96 101 102 96 95 94 88 78 72 65 55 40 25 20 20 42 64 74 129 133 125 144 151 153 154 154 155 16 14	Training
19	2	255 255 255 255 255 255 255 255 255 255 255 255 255 255 255 255 255 255 255 255 255 255 255 255 255 255 255 255 255 255 255 255 255 255 255 255 255 255 255	Training
20	6	134 124 167 180 197 194 203 210 204 203 209 204 206 211 211 216 219 224 228 230 230 226 222 220 217 217 210 207 213 210 199 191 190 188 177 172 148 142 90 4	Training
21	4	219 192 179 148 208 254 192 98 121 103 145 185 83 58 114 227 225 220 203 202 168 154 157 164 182 211 164 94 122 155 176 238 240 242 192 87 43 39 60 85 34 57 8	Training
22	4	1 1 1 1 1 1 1 1 1 1 1 1 1 2 2 2 2 7 12 23 45 38 35 14 43 27 31 24 18 20 29 18 6 2 4 2 0 1 1 1 1 0 5 13 16 16 16 15 14 1 1 1 1 1 1 1 1 1 1 1 1 1 0 0 3 7 9 27 44 43 42 26 28 60 76 61	Training
23	2	174 51 37 37 38 41 22 25 22 24 35 51 70 83 98 113 119 127 136 149 149 141 125 107 77 50 30 21 9 38 96 79 72 87 60 23 25 43 29 24 33 51 36 33 26 20 136 255 107 46	Training
24	0	123 125 124 142 209 226 234 236 231 232 235 223 211 196 184 181 182 186 185 193 208 211 208 201 196 192 191 192 194 201 207 216 225 225 223 220 219 220 172	Training
25	0	8 9 14 21 26 32 37 46 52 62 72 70 71 73 76 83 98 92 80 90 110 148 158 149 166 172 166 166 164 179 196 197 189 185 194 189 174 173 177 179 186 197 192 191 185 17	Training
26	3	252 250 246 229 182 140 98 72 53 44 67 95 95 89 89 90 90 93 94 89 88 88 83 82 81 73 74 69 69 64 58 49 46 49 35 32 27 25 24 21 13 9 11 15 15 15 21 24 254 246 221 17	Training
27	3	224 227 219 217 215 210 187 177 189 200 206 212 210 208 204 207 206 207 205 203 203 206 206 201 204 199 196 189 187 187 186 185 184 186 183 182 182 173 161	Training
28	5	162 200 187 180 197 198 196 192 176 152 136 114 109 117 124 133 162 182 195 200 202 203 204 200 201 202 200 200 200 200 198 195 192 189 185 183 168 152 130	Training
29	0	236 230 225 226 228 209 199 193 196 211 199 198 194 199 214 209 202 207 179 156 154 152 157 156 151 144 136 138 140 148 183 209 192 177 158 179 232 255 254	Training
30	3	210 210 210 210 211 207 147 103 68 60 47 70 124 118 119 123 124 131 136 138 146 144 147 152 157 159 162 165 165 164 163 161 159 159 159 162 159 159 156 151 1	Training
31	5	50 44 74 141 187 187 169 113 80 128 181 172 76 62 37 41 40 37 55 44 37 36 48 45 40 48 82 82 78 69 56 60 50 42 52 69 125 154 128 68 57 46 50 51 46 40 37 38 48 76 11	Training
32	3	234 233 228 231 234 233 236 230 236 196 112 85 100 114 129 133 132 132 147 164 180 156 161 156 151 150 137 117 139 157 138 145 137 132 114 94 80 70 65 88 88	Training
33	6	244 214 198 187 105 89 47 38 40 28 26 29 42 39 33 48 35 22 28 31 42 46 42 58 61 54 42 46 54 43 38 49 50 86 100 101 93 65 69 71 61 114 161 211 237 242 248 250 222	Training
34	3	88 116 108 66 61 52 56 74 80 70 55 57 61 68 57 44 62 69 65 61 60 61 68 55 51 65 66 71 60 79 95 94 86 113 112 99 113 108 116 118 88 72 68 25 46 135 102 99 125 123	Training
35	2	59 63 70 67 67 72 69 80 95 105 125 141 149 155 164 168 168 174 180 181 184 187 190 194 194 196 200 201 201 200 200 196 193 191 186 181 179 168 153 197 244 23	Training
36	3	66 63 76 65 49 44 52 43 47 95 121 51 41 49 145 231 230 231 233 235 235 235 236 236 236 235 234 235 244 254 254 254 254 254 254 254 254 254 254 254 254 254	Training
37	6	81 106 91 100 90 85 108 130 147 84 46 81 156 206 222 229 233 235 236 238 240 240 241 240 240 240 240 239 239 238 236 231 226 221 213 198 166 110 43 27 15 13 2	Training
38	6	185 179 183 191 204 150 35 27 25 59 114 134 145 145 145 145 146 149 154 157 158 159 158 160 160 161 162 162 159 159 159 155 148 145 131 90 35 15 19 118 187 1	Training

Fig 7.9 FER-2013 dataset csv file

Chapter 8 : Performance and Evaluation Testing

Performance and evaluation testing is a process used to assess how a system operates under specific conditions, focusing on its speed, responsiveness, stability, and resource usage. It involves testing the system's ability to handle varying loads (load testing), extreme stress (stress testing), and its scalability to adapt to changing workloads. Evaluation testing goes further to measure the system's functionality, usability, and adherence to requirements, ensuring it meets expected standards and performs effectively in real-world scenarios. These tests identify bottlenecks, verify reliability, and improve the overall user experience.

8.1 Test Plans

Table 8.1: Test Plan

Testing Description	Status
User cannot log in with a valid username and invalid password.	Pass
Verify the message for invalid login.	Pass
If the password field is either visible as an asterisk or bullet.	Pass
Verify the login page when the field is blank, and the submit button is clicked.	Pass
The user is able to upload the image of ingredients as well as the nutrition table.	Pass
The user is able to update user information.	Pass
The user is able to edit/add allergens.	Pass
The application shows the user "Safe to use" & "Not safe to use" prompts after processing the input image.	Pass
The user should get logged out after clicking the Logout button.	Pass

The quiz results are displayed correctly based on the user's responses.	Pass
The system processes real-time facial expressions for emotion detection.	Pass
The recommendation module suggests nearby counselors based on the user's location.	Pass
The map displays the correct location of the recommended counselors.	Pass

These were the test plans and their results when the system is actually being tested on basis of plans.

Chapter-09: Results and Analysis

The Depression Detection System, as proposed, is a major step forward in detecting depression early by uniting psychological evaluation with real-time analysis of physiological data. Combining a Naive Bayes classifier for quiz-based mental health assessment with a CNN for analyzing facial expressions, the system provides a thorough and easy-to-use diagnostic tool. The Naive-Bayes classifier and the SVM classifier resulted in the accuracy of 95.45% whereas the CNN used for Facial expression recognition gave an accuracy of 66.04% . We used weighted sum technique to combine the results of both assessments to return the combined results to increase accuracy in depression detection. Comprehensive testing shows how the system has the potential to enhance both the accuracy and speed of diagnosing depression. Upcoming tasks will concentrate on improving the system's ability to expand, maintain privacy, and increase accuracy, specifically in the areas of emotion detection and combining multiple types of data.

- **Facial Expression Module:**
  - CNN facial expression recognition model Accuracy: 68.09%
  - F1 Score: 0.67
- **Quiz Module:**
  - Classifier Comparison Results:

Table 9.1 Classifier comparison

Classifier	Accuracy	Precision	Recall	F1 Score
Naive Bayes	94%	0.96	0.95	0.96
SVM	85%	0.84	0.83	0.83
Random Forest	88%	0.87	0.86	0.87

- **Psychiatrist Recommendations:**
  - Response Time: ~500ms
  - Top 5 recommended psychiatrists displayed with ratings and distances.

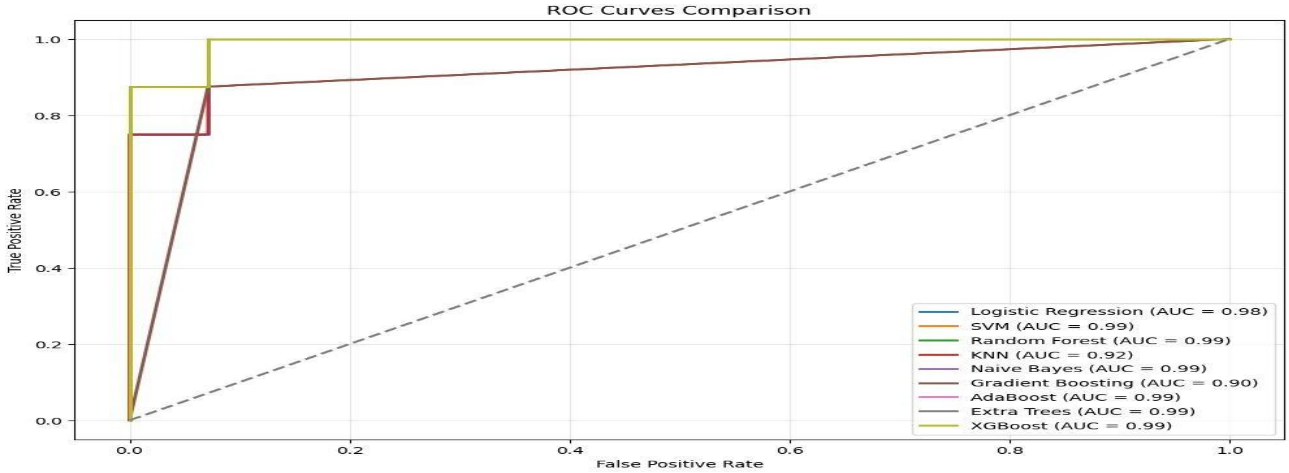

Fig 9.1 Classifier comparison grap

Chapter-10: Conclusion

- **Innovative Diagnostic Solution**: The Depression Detection System merges machine learning technologies with a user-friendly interface, offering an advanced method for early detection of depression through self-assessments and real-time emotional analysis.
- **Efficient Mental health assessment:** Combining both quiz module and facial module results in efficient mental condition/health assessment and help in providing better results.
- **Thorough Testing and Accuracy**: Comprehensive evaluations of system components including Naive Bayes Classifier, CNN, to ensure precise results and effective operation in real world scenerios.
- **Transforming Mental Health Care:** Integrating AI with practical design empowers individuals to understand their mental health proactively while offering healthcare professionals valuable insights to complement traditional diagnostics.

The Depression Detection System demonstrates how AI-powered solutions can revolutionize mentalhealth diagnostics, offering reliable, accessible, and impactful tools for both users and professionals.

Chapter 11: Future Scope

- **Integration of Additional Data Sources**:

  (a) Speech patterns, EEG signals, and wearable device data to complement quiz and facial expression analysis.
  (b) Improved diagnostic precision for detecting subtle mental health signs.

- **Enhanced CNN Model**:

  (a) Use larger, diverse datasets and transfer learning.
  (b) Address variables like lighting, cultural differences, and demographics for better emotion detection.

- **Scalability and Accessibility**:

  (a) Utilize cloud platforms (AWS, Google Cloud) for performance, scalability, and data storage.
  (b) Expand to mobile apps and browser extensions for broader accessibility.

- **AI-Driven Personalization**:

  (a) Tailor recommendations based on age, gender, and cultural background for greater relevance.

- **Interactive Tools**:

  (a) Introduce AI-powered chatbots for emotional support and user guidance.

Chapter 12: Individual Contribution

Name of the Student: Sai Venktesh Dubey

Module Title: Quiz Module for Depression Detection

Project's Module Objectives:

The objective is to develop a quiz module in Python using libraries like NumPy, Pandas, Matplotlib, and Scikit-learn, alongside classifier models such as Naive Bayes, Random Forest, SVM, and others. This module will utilize the DAIC-WOZ data-set to train multiple classifiers, identify the best-performing model, and create a robust prediction system.

Project's Module Scope:

This module is responsible for cleaning and handling data, importing and initializing classifiers, evaluating their performance, and exporting the best model for integration into the back-end.

Project's Module(s):

1. Module Interfaces:

- user-friendly interface for quiz input and result display.
- Integration with back-end services to utilize the trained model for real-time predictions.
- Integration with External Modules:
- Connection to back-end services to export the trained model for use in the application.

2. Module Dependencies:

- Libraries: NumPy, Pandas, Matplotlib, Scikit-learn
- Classifiers: GaussianNB, SVC, Random-Forest, AdaBoost, XGBoost

3.Module Design:

- Data cleaning and prep-rocessing steps to transform the DAIC-WOZ Data-set into a usable format.
- Implementation of multiple classifiers (Naive Bayes, Random Forest, SVM, etc.) with modular comparison features.
- Evaluation metrics include accuracy, precision, recall, and F1 score for robust model comparison.

4. Module Implementation:

- Code for data pre-processing and cleaning.
- Initialization of classifiers and training on the data-set.
- Comparison of all trained models to select the best-performing classifier.
- Exporting the selected model using Joblib for integration into the Python back-end server.

5. Module Testing Strategies:

- Unit Tests: Verify data pre-processing, model training, and evaluation functionality.
- Integration Tests: Ensure seamless compatibility between the exported model and the back-end system.

6. Module Deployment:

- The module will be deployed as part of the larger depression detection system and integrated into the Python back-end server.

Name of the Student: Aryan Bansal

Module Title: Facial Expression-Based Depression Detection

Project's Module Objectives:

1. Develop a module for facial expression-based depression detection using Python and JavaScript, leveraging CNN (convolutional neural networks) for facial expression recognition.
2. Build and integrate a Python back-end using FastAPI for machine learning model handling and a Node.js back-end for user operations and API handling.

Project's Module Scope:

This module involves constructing a CNN-based facial expression detection system trained on the FER2013 data-set, developing a back-end to handle ML requests and user operations, and integrating both components for seamless functionality in a web application.

Project's Module(s):

1. Module Interfaces:

- Front-end integration for live video feed capture and display of predictions.
- API s for transferring data between the front-end, Python back-end, and Node.js back-end.

2. Integration with External Modules:

- Connection to Python back-end for ML model inference.
- Communication with Node.js back-end for user data operations and combined result analysis.

3. Module Dependencies:

- Libraries: OpenCV, TensorFlow/Keras for CNN model, FastAPI for back-end, Node.js, MongoDB for database.
- Data-set: FER2013 for facial expression recognition.

4. Module Design:

(a) Facial Expression Module:

- Perform exploratory data analysis (EDA) to understand the FER2013 Data-set.
- Design and construct a 5-layer CNN for feature extraction and expression recognition.
- Train the CNN model for 30 epochs on the FER2013 Data-set and evaluate its performance on live video feeds.
- Export the trained model for integration with the back-end.

(b) back-end Design:

- Implement a Python back-end using FastAPI to handle ML model requests and perform combined analysis with the quiz module.
- Develop a Node.js back-end for managing user operations and connecting the web app to the database.

5. Module Implementation:

(a) Facial Expression Module:

- Load and preprocess the FER2013 Data-set.
- Train the CNN model and evaluate it using OpenCV on real-time video feeds.
- Save and export the trained model for back-end integration.

(b) back-end:

- Develop API endpoints in FastAPI for processing facial module results and combining them with quiz module outputs.
- Set up the Node.js back-end for user data handling and MongoDB integration.

6. Module Deployment:

- The module will be deployed as a critical part of the depression detection web application.

Name of the Student: Akshit Singh

Module Title: Counsellor Recommendation and User Authentication

Project's Module Objectives:

1. Develop a counsellor recommendation module using JavaScript, Google Places API, and Geo-location API to assist patients in finding psychiatrists or doctors nearby.
2. Implement basic login/sign-up authentication for patients/users with secure storage and authorization mechanisms.

Project's Module Scope:

This module facilitates user authentication and authorization while providing recommendations for the top-rated and nearby psychiatrists or doctors based on the user's current location.

Project's Module(s):

- **Module Interfaces:**
  - User-friendly interface to fetch and display counsellor recommendations based on location.
  - Login/Sign-up forms for user authentication and access to the application.
- **Integration with External Modules:**
  - Integration with Google Places API for fetching data on psychiatrists and doctors.
  - Use of JWT tokens and Bcrypt.js for secure authentication processes.
- **Module Dependencies:**
  - API: Google Places API, Geo-location API
  - Libraries: JSON Web Token (JWT), Bcrypt.js for authentication and password security
- **Module Design:**
  - **Counsellor Recommendation Module:**
    - Use the geolocation API to fetch the user's current coordinates.
    - Query the Google Places API using the user's coordinates to retrieve data on nearby psychiatrists or doctors.
    - Process the API results to filter and recommend the top 5 best-rated and nearby doctors.

    - **Authentication Module:**
        - Implement secure user login/signup functionality using hashed passwords stored securely with Bcrypt.js.
        - Use JWT tokens to handle user authentication and authorization.
- **Module Implementation:**
    - **Counsellor Recommendation Module:**
        - Fetch the user's location from the front-end using the Geo-location API.
        - Write and execute a query to the Google Places API using the user's coordinates.
        - Process the retrieved data and display the top 5 recommendations.
    - **Authentication Module:**
        - Create routes for user registration and login.
        - Hash passwords with Bcrypt.js before saving them to the database.
        - Generate and validate JWT tokens for secure user sessions.
- **Module Testing Strategies:**
    - **Unit Tests:**
        - Validate Geo-location API responses and Google Places API queries.
        - Test password hashing and JWT generation/validation.
    - **Integration Tests:**
        - Ensure smooth interaction between the counsellor recommendation module and the API.
        - Test end-to-end user authentication and authorization processes.
- **Module Deployment:**
    - Deploy the module as an integrated feature of the application, ensuring secure user authentication

Name of the Student: Aerth Saraogi

Module Title: User Interface and Front-End Development

Project's Module Objectives:

The objective is to design and implement a user-friendly and interactive front-end for the web application using HTML, CSS, Bootstrap, and ReactJS. The module will focus on creating an engaging user experience while ensuring efficient handling and representation of data retrieved from the back-end.

Project's Module Scope:

This module covers the front-end development of the web application, including user interface design, seamless data exchange with back-ends, and email service integration for support components.

Project's Module(s):

- **Module Interfaces:**
  - Interactive and visually appealing user interface using ReactJS.
  - Seamless communication with Python and Node.js back-ends using Axios.
- **Integration with External Modules:**
  - Integration with back-ends for data retrieval and submission.
  - Integration of EmailJS for email service functionality.
- **Module Dependencies:**
  - Technologies: ReactJS, HTML, CSS, Bootstrap
  - Libraries: Axios, EmailJS
- **Module Design:**
  - Design an intuitive and interactive user interface for a smooth user experience.
  - Develop components to efficiently render and handle back-end data.
  - Integrate email service functionality for support features using EmailJS.
- **Module Implementation:**
  - Create ReactJS components for key features and ensure responsive design using Bootstrap.
  - Use Axios for API calls to send and receive data between the front-end and back-ends.
  - Implement EmailJS in the support component for user email services.

- **Module Testing Strategies:**
    - **Unit Tests:**
        - Validate ReactJS components for correct rendering and interactivity.
        - Test API calls made through Axios for data exchange with the back-end.
    - **Integration Tests:**
        - Ensure seamless integration of front-end components with Python and Node.js back-ends.
        - Verify the functionality of email services using EmailJS.
- **Module Deployment:**
    - Deploy the front-end module as part of the complete web application.

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Project to Outcome Mapping

Objectives:

1. Develop a user-friendly and interactive user interface using ReactJS, HTML, CSS, and Bootstrap.
   Train and evaluate the depression detection quiz module using the DAIC-WOZ Data-set and implement model comparisons using classifiers like Naive Bayes and SVM.
2. Implement emotion recognition using the CNN model to detect depression based on facial expressions from real-time video feeds and efficiently retrieve, process, and display data from Python and NodeJS back-ends.
3. Recommend psychiatrists/doctors using Google Places API based on user location andprovide a secure user authentication mechanism.

Sr. No.	PRN No.	Student Name	Individual Project Student Specific Objective	Learning Outcomes Mapped (To be filled by Guide)
1	1032211329	Aryan Bansal	Develop and train a CNN model for facial expression recognition to detect depression and integrate results into the application back-end.	
2	1032211208	Aerth Saraogi	Design an interactive user interface using ReactJS and efficiently handle data exchange with back-ends using Axios and EmailJS.	
3	1032211401	Akshit Singh	Implement Google Places API and Geo-location API for recommending nearby psychiatrists, and develop secure authentication using JWT andBcrypt.js.	
4	1032211476	Sai Venktesh dubey	Train and evaluate the depression detection quiz module using the DAIC-WOZ Data-set and implement model comparisons using classifiers like Naive Bayes , SVM.	