DEPRESSION DETECTION AND SUPPORT SYSTEM

PROJECT REPORT

21AD1513- INNOVATION PRACTICES LAB

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BONAFIDE CERTIFICATE

Certified that this project report titled "**DEPRESSION DETECTION AND SUPPORT SYSTEM**" is the bonafide work of **VARSHA R (211422243349), SAVITHRI D (211422243297), TAMILSELVI V (211422243332).** who carried out the project work under my supervision. Certified further, that to the best of my knowledge the work reported herein does not form part of any other project report or dissertation on the basis of which a degree or award was conferred on an earlier occasion on this or any other candidate.

INTERNAL GUIDE

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INTERNAL EXAMINER **EXTERNAL EXAMINER**

ABSTRACT

This project presents the design and implementation of an AI-powered Depression Detection and Support System, aimed at providing timely mental health assistance through machine learning and conversational AI. The system utilizes a Random Forest algorithm to assess depression severity based on user responses to a structured online questionnaire. Each question offers four selectable options, and the responses are analyzed to categorize the severity of depression into mild, moderate, or severe levels. The Random Forest model was trained on extensive mental health data, employing data preprocessing and feature selection techniques to ensure accurate and reliable classification of depression severity.

Additionally, for users identified with higher levels of depression, the system integrates a chatbot powered by the Gemini API to deliver real-time support and empathy-driven responses. The chatbot is designed to guide users through challenging moments and offer strategies that foster emotional resilience. This dual approach of automated assessment and interactive support positions the system as a valuable tool in digital mental health. Future enhancements include refining the model for real-time monitoring and enhancing chatbot responses to provide even more personalized support. This project underscores the potential of AI in mental health, paving the way for scalable, accessible solutions that can positively impact human well-being.

Keywords *: Artificial Intelligence (AI), Depression Detection, Mental Health Support, Random Forest Algorithm, Conversational AI, Chatbot, Gemini API, Machine Learning, Depression Severity Classification, Online Questionnaire, Data Preprocessing, Feature Selection, Real-time Assistance, Human-Computer Interaction, Emotional Resilience, Mental Health Monitoring*

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LIST OF ABBREVIATIONS

ABBREVIATION	MEANING
AI	Artificial Intelligence
DNN	Deep Neural Network
RF	Random Forest
API	Application Programming Interface
UI	User Interface
ML	Machine Learning
Chatbot	Conversational Agent
KNN	K-Nearest Neighbors
CV	Cross Validation
TP	True Positive
TN	True Negative
FP	False Positive
FN	False Negative
JSON	JavaScript Object Notation
NLP	Natural Language Processing

CHAPTER 1

INTRODUCTION

1.1 Background

In the field of mental health, the integration of artificial intelligence (AI) is proving to be a transformative approach to supporting individuals experiencing depression. This project centers on the development of an AI-powered chatbot, utilizing the Gemini API, designed to assist individuals during times of emotional distress. The implementation of a user-friendly website enhances this initiative by allowing users to engage in a self-assessment process through a series of targeted questions. Each question is accompanied by four response options, enabling the system to accurately evaluate the user's emotional state.

To determine the severity of depression, the project employs a Random Forest algorithm, a robust machine learning technique known for its efficacy in classification tasks. By analyzing user responses, the system assigns a depression severity level, facilitating personalized interactions with the chatbot for users identified as experiencing high levels of depression. This real-time support mechanism not only provides immediate assistance but also encourages individuals to engage in meaningful conversations aimed at fostering emotional recovery. Through this innovative approach, the project aspires to create a supportive environment for individuals dealing with depression, highlighting the potential of AI in enhancing mental health care and accessibility.

1.2 Problem Statement

Despite the promising advancements in AI-driven mental health support systems, several challenges remain that hinder their effectiveness in real-world applications. Current approaches to depression detection and support primarily rely on traditional methods, which can present several limitations:

- **Accuracy Limitations:** Many existing systems utilize straightforward survey techniques that may not capture the complex and nuanced nature of depressive symptoms. As a result, these methods may lead to inaccurate assessments of an individual's emotional state, hindering timely and appropriate interventions.
- **User Engagement Challenges :** Engaging users in self-assessment and interaction with chatbots can be difficult, especially for individuals experiencing severe depression. Low motivation and the stigma associated with mental health can result in incomplete or inaccurate responses, compromising the reliability of depression severity assessments.

- **Real-Time Support Gaps**: While the integration of chatbots provides immediate interaction, many existing systems struggle to offer truly personalized and empathetic responses. A lack of sophisticated natural language processing capabilities can lead to generic replies that fail to resonate with users' specific emotional needs, thereby diminishing the overall effectiveness of the support provided.
- **Data Diversity Constraints:** A significant challenge in training robust depression detection models is the limited diversity of datasets. Many systems rely on homogeneous datasets, which can lead to models that do not generalize well across different populations and demographics. This lack of representation can result in biased outcomes, negatively impacting the accuracy and applicability of mental health interventions across various user groups.

1.3 Research Objectives

To address the challenges associated with depression detection and support systems, this research aims to develop a comprehensive AI-driven platform that leverages user interaction and machine learning techniques. The specific objectives are:

- **Enhance Accuracy**: By utilizing a Random Forest algorithm and analyzing user responses, the project seeks to achieve a depression detection accuracy of over 85%. This target reflects a significant advancement over traditional assessment methods, which often fall short in capturing the nuanced emotional states of individuals.
- **Facilitate Real-Time Interaction**: The integration of the Gemini API will enable real-time communication between users and the chatbot, allowing for immediate emotional support and feedback. This capability is critical in mental health applications, where timely assistance can significantly impact an individual's recovery journey.
- **Improve User Engagement**: By creating an intuitive and empathetic user interface on the website, the project aims to encourage active participation from users. This includes developing a self-assessment questionnaire designed to capture the complexities of depressive symptoms accurately and foster open dialogue with the chatbot.
- **Leverage Diverse User Data**: By incorporating feedback from a varied user demographic, the project will enhance the model's ability to generalize across different populations and emotional expressions. This diversity is essential for ensuring the effectiveness of the support provided and minimizing bias in the detection of depression.

1.4 Significance of the Study

This research has significant implications for the field of mental health, as it aims to bridge the gap between traditional assessment methods and modern AI-driven support systems. The outcomes of this project promise to enhance the accuracy and responsiveness of depression detection, leading to a more nuanced understanding of individuals' emotional states in real-time.

In healthcare, the ability to detect and respond to signs of depression can lead to more effective interventions and support strategies, particularly in teletherapy and remote counseling settings. By providing timely assistance through the chatbot, individuals may feel more understood and encouraged to engage with their treatment plans. For users navigating depressive symptoms, an empathetic and responsive AI system can enhance the overall user experience and foster a sense of connection and support.

Additionally, the successful implementation of this depression detection and support system has broader implications for human-computer interaction. As AI continues to integrate into various aspects of daily life, equipping systems with the ability to comprehend and respond to human emotions is vital for creating meaningful and compassionate interactions. This capability not only enhances the effectiveness of mental health interventions but also builds trust and rapport between users and AI systems, paving the way for future innovations in mental health care and emotional well-being.

CHAPTER 2

LITERATURE SURVEY

The literature survey provides a comprehensive overview of existing research, theories, and methodologies relevant to the project's focus on Intelligent Depression Detection and Support Systems. This review encompasses advancements in depression detection techniques, sentiment analysis, emotional support chatbot development, and machine learning methodologies, organized into key thematic areas:

Author(s)	Year	Title	Methodology	Advantages	Disadvantages
Huang, Y., Zhao, M.	2021	A systematic review of machine learning methods for depression detection based on social media	Systematic review of various ML models (e.g., SVM, decision trees, neural networks) applied to social media data	Provides a comprehensive overview of ML approaches in depression detection using social media.	Lack of standardization in dataset labeling and inconsistency in method application.
Kumar, A., Mohan, S.	2020	Artificial Intelligence in Mental Health: Opportunities and Challenges	Review of AI techniques, including NLP, deep learning, and reinforcement learning applied to mental health	Highlights the potential of AI in improving mental health care delivery.	High reliance on data quality and lack of universal AI models for mental health diagnosis.
Bair, M. J., Robinson, R. L., Katon, W., Kroenke, K.	2003	Depression and pain comorbidity: A literature	Literature review on the relationship between depression	Provides a strong evidence base for the comorbidity of depression and	Limited focus on technological methods, primarily

		review	and pain and its clinical implications	pain.	clinical in scope.
Vivekananda, C., Nair, M.	2022	Emotion Detection and Analysis for Improving Mental Health Applications	Emotion detection through machine learning (e.g., facial expression analysis, speech analysis)	Emphasizes real-time emotion detection to improve mental health interventions.	Potential issues with privacy and accuracy in detecting subtle emotional cues.
Hirschfeld, R. M. A.	2000	The Comorbidity of Major Depression and Anxiety Disorders: A Review	Review of comorbidity studies in depression and anxiety	Comprehensive synthesis of comorbidity data.	Primarily clinical, lacks a focus on modern machine learning applications.
Mayo, S. K., Shaw, R. J.	2021	Using machine learning techniques for early detection of depression	Use of machine learning models (e.g., decision trees, SVM) for depression detection based on survey data	Focus on early detection of depression using accessible datasets.	Difficulty in achieving accurate detection due to variability in self-reported data.
Fried, E. I., Nesse, R. M.	2015	The impact of depression on the onset of chronic disease	Statistical analysis on the relationship between depression and chronic	Strong evidence linking depression with chronic diseases.	Limited exploration of computational methods; mostly focused on traditional

			diseases		clinical analysis.
Shahid, M., Ali, A.	2020	A survey on deep learning techniques for depression detection	Review of deep learning models for detecting depression (e.g., CNN, RNN) from different data sources	Comprehensive overview of deep learning techniques in mental health.	Focuses primarily on deep learning, with limited exploration of hybrid or other machine learning methods.
Zhou, H., Yang, Z.	2021	The Role of Social Media in Depression Detection	Social media data mining and sentiment analysis using machine learning	Leverages social media data for real-time depression detection and tracking.	Potential biases and privacy concerns when using social media for mental health detection.
Turan, T., Ergun, H.	2020	Anxiety and Depression Detection from Speech Signals: A Machine Learning Approach	Machine learning applied to speech signal features for depression detection	Utilizes speech features, which can be captured passively for depression detection.	Sensitive to variations in speech patterns and environmental noise.
Tsermpini, E. E., Asimakopoulos, G.	2022	A review of automated systems for mental health support and monitoring	Review of automated systems for mental health, including chatbots and mobile applications	Focuses on the development of automated systems to provide mental health support.	Limited focus on real-time detection and more on the development of tools for support.

Sinha, S., Mishra, A.	2020	Machine Learning Techniques in Predicting Depression Severity	Machine learning models (e.g., Random Forest, SVM) to predict depression severity from survey data	Focus on predicting severity, which helps in targeted interventions.	Prediction accuracy may vary with different survey question formats.
Rai, S. K., Kaur, S.	2019	Support Vector Machine-based Approach for Depression Detection using Textual Data	SVM applied to textual data from surveys or social media posts for depression classification	Utilizes readily available textual data for depression detection.	Requires large datasets for effective model training and might not capture subtle emotional states.
Gonzalez, J. C., Rajasekaran, M., Swaminathan, S.	2020	Emotion recognition for customer service systems	Emotion recognition using machine learning for customer service systems	Applicable to customer service applications, enhancing user experience by detecting emotions.	May not generalize well to clinical mental health applications.
Thompson, R. J., Cummings, J. R.	2017	Understanding the Role of Technology in Treating Depression	Review of various technological interventions for depression treatment, including mobile apps	Highlights technological innovations that improve treatment accessibility.	Limited focus on AI and ML applications in depression detection.
Alghamdi, A.,	2021	Deep learning in mental	Overview of deep learning	Provides insight into the	High computational

Hossain, M. S.		health: A survey	techniques applied to mental health diagnostics and interventions	advantages of deep learning for depression detection.	cost associated with deep learning models.
Bharadwaj, S., Choudhury, M.	2019	Internet-based cognitive behavioral therapy for depression and anxiety	Review of internet-based interventions (e.g., CBT) and their effectiveness in treating depression	Focus on evidence-based internet interventions for mental health.	Limited focus on machine learning or AI-based methods for treatment.
Moore, D., Chen, J.	2020	Understanding and Measuring Digital Mental Health: A Scoping Review	Scoping review of digital tools and platforms in mental health, including self-monitoring apps	Comprehensive review of digital tools, focusing on real-world applications.	Does not emphasize machine learning models for depression detection.
Schueller, S. M., Torous, J.	2020	The Future of Mental Health Care: Digital Innovations	Review of digital innovations and the future of mental health care systems	Highlights future opportunities in mental health through digital health innovations.	Limited discussion on specific machine learning methods or applications in depression detection.

CHAPTER 3

RELATED WORK

3.1 Existing Approaches to Depression Detection

The field of depression detection and support systems has made considerable advancements in recent years, particularly with the integration of artificial intelligence and machine learning methodologies. Early approaches primarily utilized straightforward assessment techniques and questionnaires, which often lacked the depth needed to capture the complexities of an individual's emotional state. Traditional methods typically relied on subjective self-reports, which can be influenced by various factors, leading to inconsistent and sometimes inaccurate evaluations of depression severity.

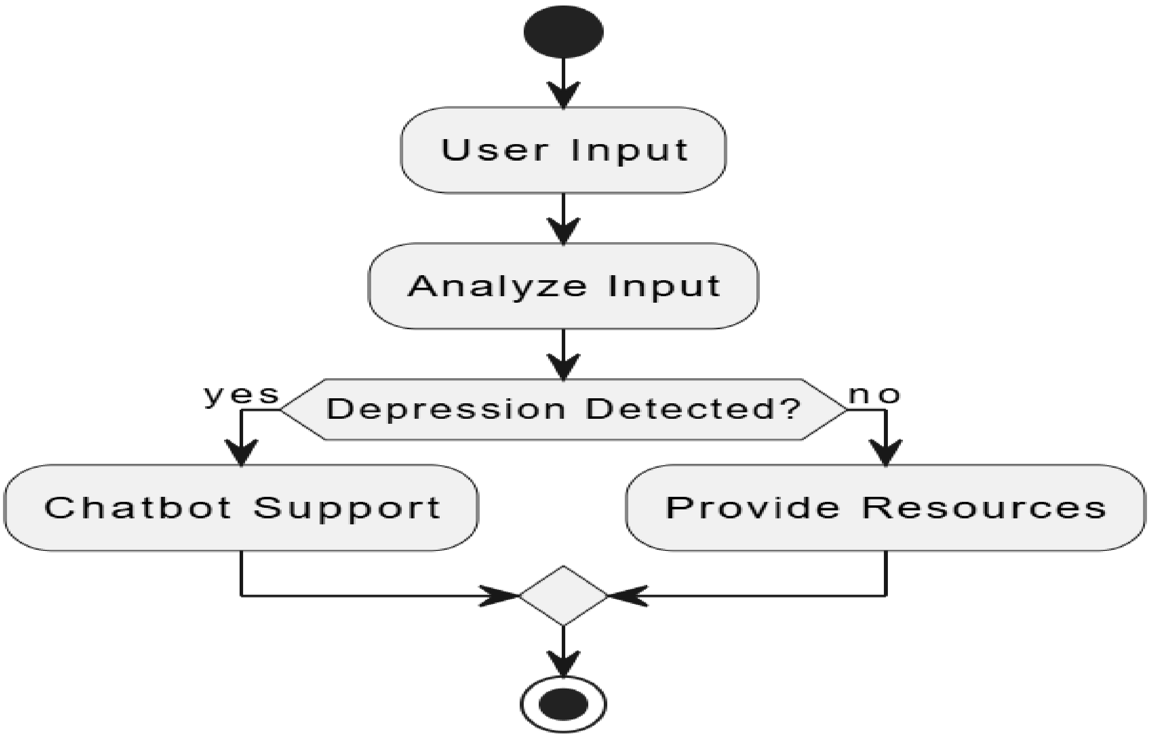


Fig.3.1: Depression Detection Workflow

Recent reviews of depression detection methods highlight the challenges of accurately identifying emotional distress using traditional assessment techniques. While these methods may perform well in controlled environments, they often lack scalability and generalizability in real-world applications.

3.2 AI and ML in Mental Health Support

With the rise of artificial intelligence (AI) and machine learning (ML), there is a growing focus on enhancing depression detection and support systems. Recent advancements have highlighted the effectiveness of various machine learning algorithms, such as Random Forest, in accurately identifying emotional states based on user interactions and responses. These models are capable of analyzing structured data from user input to detect patterns indicative of varying levels of emotional distress.

However, challenges remain in generalizing these models across diverse user populations and emotional contexts. Research emphasizes the need for systems that can adapt to different demographics and individual emotional expressions to maintain effectiveness. Techniques like transfer learning are also being explored to improve performance by leveraging knowledge from pre-trained models on larger datasets. This approach helps address the limitations posed by the availability of labeled data in mental health applications, paving the way for more accurate and personalized support for individuals experiencing depression.

3.3 Limitations of Current Research

Despite advancements in depression detection systems, significant limitations persist in current research methodologies. A major challenge is the reliance on limited and homogeneous datasets that often fail to capture the full spectrum of emotional expressions associated with depression across different populations. Many existing models demonstrate effective performance on the data they were trained on but struggle to generalize to new, unseen user inputs, raising concerns about their real-world applicability, particularly in diverse settings.

Additionally, while there has been some progress in achieving real-time processing capabilities, many systems still face latency issues, which hinder their effectiveness in applications that require immediate emotional feedback. The integration of real-time input mechanisms remains underexplored, affecting the ability to provide timely support for individuals experiencing depression. Addressing these limitations is crucial for developing more robust and responsive systems that can adapt to the complexities of human emotions and provide effective mental health support.

3.4 Scope and Objectives of the Proposed Work

In light of the limitations identified in existing depression detection methodologies, this proposed work aims to develop a comprehensive real-time system that effectively identifies and supports individuals experiencing depression. The scope of this research includes:

- **Enhanced Feature Analysis**: The proposed system will utilize advanced machine learning techniques, specifically Random Forest algorithms, to analyze user responses and extract relevant features indicative of emotional states, improving upon traditional assessment methods.
- **Real-Time Interaction**: By integrating real-time input mechanisms through a user-friendly web interface, the system will facilitate immediate feedback and engagement, addressing a critical gap in existing depression detection approaches.
- **Utilization of Diverse Input Data**: The research will incorporate various data sources, such as structured questionnaires and user interactions, to ensure better generalization across different emotional expressions and demographics.
- **Improved Accuracy and User Support**: The primary objective is to achieve a classification accuracy that effectively identifies depression severity, thereby enhancing the system's ability to provide timely and personalized support to users, addressing the shortcomings of traditional methods and fostering better mental health outcomes.

CHAPTER 4
PROPOSED MODEL

The proposed architecture for the depression detection system integrates various components to facilitate efficient user interaction and accurate emotional analysis. The key components are as follows:

- **User Input Interface**: A web-based interface captures user responses to a structured questionnaire designed to assess depressive symptoms. This interface is crucial for engaging users and gathering input data for analysis.

- **Data Preprocessing Module**: This module processes the input data to ensure consistency and readiness for analysis. It involves standardizing user responses and encoding categorical variables, enabling the system to derive meaningful insights from the input.

- **Random Forest Algorithm for Depression Detection**: The core of the detection system relies on the Random Forest algorithm, which classifies the severity of depression based on the processed input data. The algorithm comprises multiple decision trees, each contributing to the final prediction, enhancing both accuracy and robustness against overfitting.

- **Chatbot Integration with Gemini API**: A chatbot powered by the Gemini API is integrated to provide real-time assistance to users identified as experiencing high levels of depression. This chatbot interacts with users to offer support, resources, and coping strategies, thereby enhancing the overall user experience and fostering engagement with the system

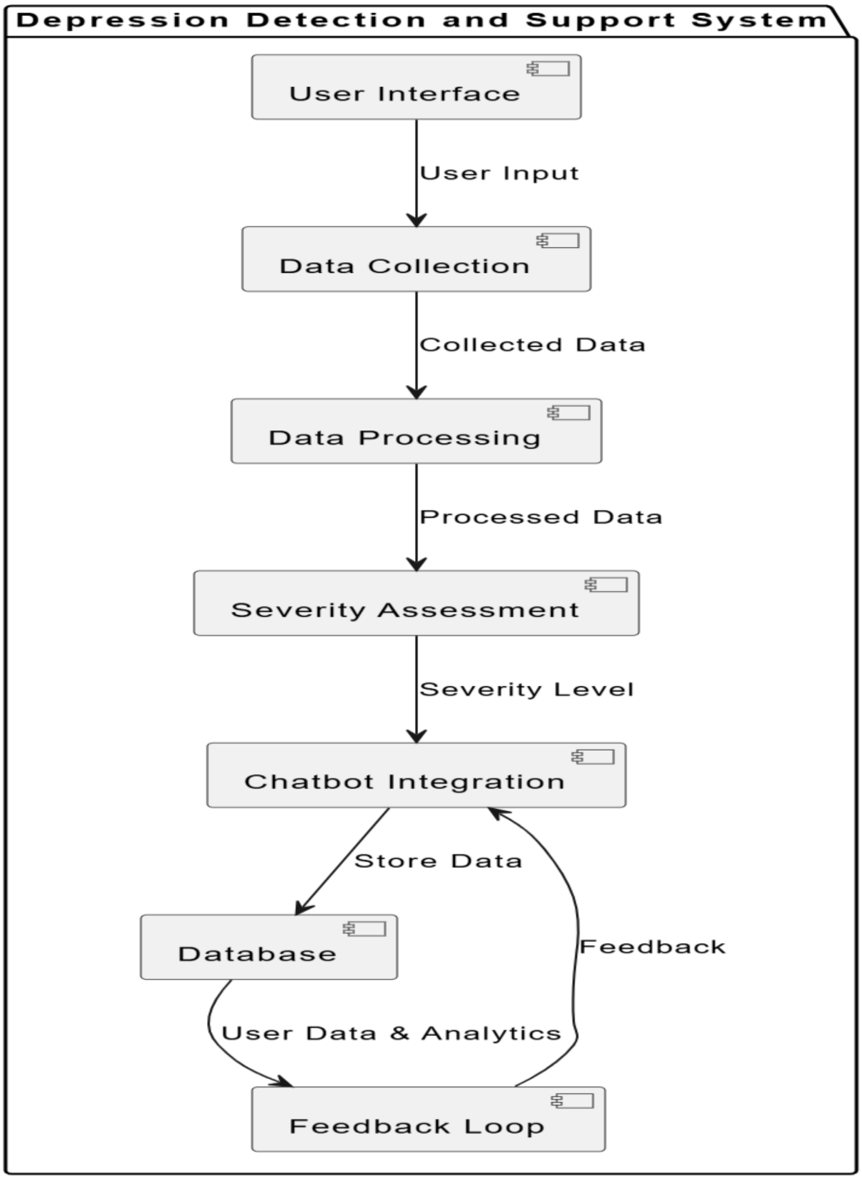


Figure 4.1:System Architecture

Random Forest Algorithm(Depression Severity Prediction):

The Random Forest algorithm serves as the backbone for classifying the severity of depression based on user responses to the questionnaire. By employing an ensemble of decision trees, Random Forest effectively evaluates the input data to determine the most likely depression level.

Each decision tree independently assesses the responses, and the final classification is derived from the majority vote across all trees, ensuring robustness and reducing the risk of overfitting. This method not only improves accuracy but also enhances interpretability by providing insights into the decision-making process. The algorithm identifies the primary factors contributing to the predicted depression severity, which can be valuable for users seeking to understand their emotional state better.

Flask Web Interface

The Flask web interface provides a user-friendly platform for interaction with the depression detection system. This intuitive interface allows users to engage with the questionnaire seamlessly, enabling them to input their responses easily and receive real-time feedback on their depression severity. The interface displays the predicted depression level along with confidence scores, giving users a clear understanding of the model's assessment. Additionally, the web application supports features such as historical data access, allowing users to review past assessments and track changes over time. To enhance user experience, the interface can incorporate feedback mechanisms, enabling users to report their experiences and contribute to ongoing model improvement. Future developments may include multi-language support and visualization tools that illustrate trends in depression severity, providing valuable insights for both users and mental health practitioners.

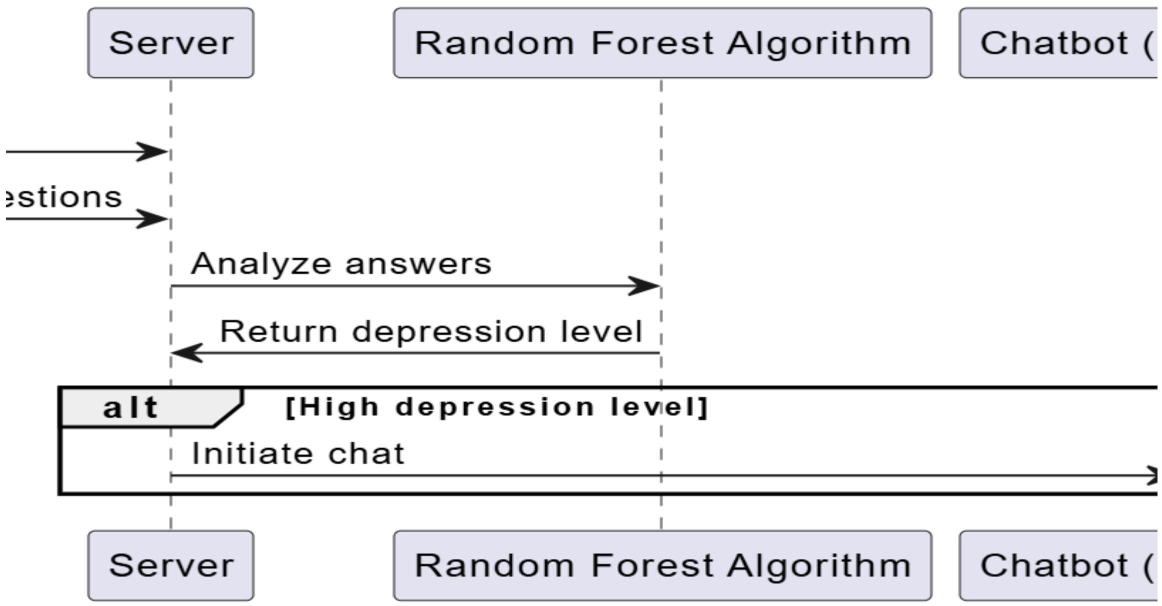


Figure.4.2: Random Forest Algorithm

4.1 Random Forest Algorithm

Step 1:User Interaction and Data Collection

Users engage with the platform through a user-friendly web interface, where they are prompted to complete a structured questionnaire designed to assess their mental health status. The questionnaire consists of multiple-choice questions that cover various aspects of their emotional and psychological well-being. User responses are collected and digitized for further analysis, ensuring data integrity and confidentiality.

Step 2: Data Preprocessing

Once the user responses are collected, the data undergoes preprocessing to ensure accuracy and reliability. This stage involves cleaning the data to remove any inconsistencies or incomplete responses. The processed data is then standardized to facilitate effective analysis. Additionally, relevant features such as frequency of negative thoughts, emotional fluctuations, and coping mechanisms are extracted to provide meaningful insights into the user's mental health state.

Step 3: Severity Assessment (Random Forest Algorithm)

The processed data is analyzed using a Random Forest algorithm, which is employed to classify the severity of depression based on user responses. The algorithm constructs multiple decision trees during training, utilizing various features from the questionnaire to identify patterns associated with different levels of depressive symptoms. This ensemble learning technique enhances accuracy and robustness, allowing the model to evaluate the severity of depression effectively.

Step 4: Chatbot Interaction for Support

For users identified with higher levels of depression severity, the platform seamlessly integrates an AI-powered chatbot developed using the Gemini API. The chatbot engages users in empathetic dialogue, providing immediate emotional support. It offers personalized coping strategies, resources, and guidance tailored to the user’s needs. The interaction with the chatbot is designed to create a supportive environment, encouraging users to express their feelings and seek help.

Step 5: Feedback and Continuous Improvement

The system incorporates a feedback mechanism, allowing users to provide insights about their experiences with the platform and chatbot interaction. This feedback is crucial for continuous improvement, enabling adjustments to the questionnaire, chatbot responses, and overall user experience.

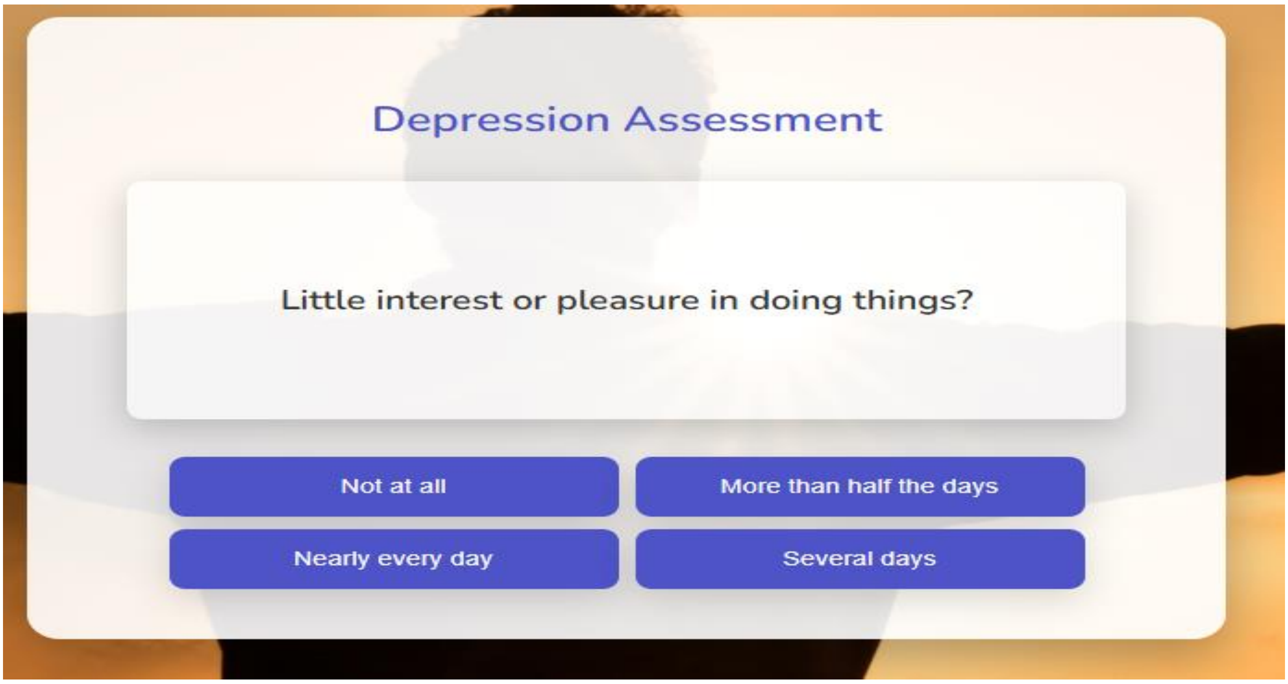


Fig.4.3: User Interface for Self-Assessment

4.2 Improvements

- **Real-Time Assessment**: Provides immediate feedback on users' depression severity through quick processing of questionnaire responses, enabling timely support and intervention.
- **High Accuracy**: Utilizes a Random Forest algorithm to achieve high accuracy in detecting depression levels based on user inputs, ensuring reliable assessments.
- **User-Friendly Interface**: Features an intuitive web interface that simplifies navigation for users, making it easy to access mental health resources and interact with the AI chatbot

CHAPTER 5
PROJECT MODULES

The Depression Detection and Support System is organized into four primary modules, focusing on effectively assessing depression levels and providing real-time support to users:

1. **Data Acquisition and Preprocessing**
2. **Feature Selection and Engineering**
3. **Depression Severity Classification**
4. **User Interface and Questionnaire Classification**
5. **Chatbot Interaction For Real Time Support**

5.1 Data Acquisition and Preprocessing

Data Collection: Gather user responses from a set of 9 structured questions designed to assess depressive symptoms. Ensure data privacy and compliance with relevant standards (e.g., GDPR).

Data Cleaning: Handle any missing or incomplete responses by imputing values or prompting the user to complete all questions.

Normalization: Normalize the data if additional sources are introduced, ensuring consistency across all responses.

Validation: Verify that each response is within the valid range and check for any inconsistencies.

5.2.Feature Selection and Engineering

Selecting Key Features: Analyze which of the 9 questions (or combinations thereof) best predict depression severity, possibly using statistical methods or correlation analysis.

Feature Engineering: Derive new features, such as the total score across questions or weighted scores if certain questions are more indicative of depressive states.

Dimensionality Reduction: If additional data sources are added in the future (e.g., voice, text, or video), consider using PCA (Principal Component Analysis) or other techniques to reduce dimensionality while retaining essential information.

5.3 Depression Severity Classification

Model Selection: Implement a Random Forest Classifier to predict depression severity based on user responses. This classifier should categorize users based on severity levels (e.g., minimal, mild, moderate, severe).

Training and Validation: Train the model on a labeled dataset (with supervised learning) and evaluate it on a validation set to fine-tune its accuracy.

Performance Metrics: Track metrics such as accuracy, precision, recall, and F1-score to ensure reliable classification.

Handling High Severity: Implement a mechanism to trigger the chatbot immediately if a high severity level is detected, offering timely support.

5.4 User Interface and Questionnaire Classification

User-Friendly Interface: Design a secure, intuitive interface where users can answer the 9 questions easily. Use clear and sensitive language to encourage honest responses.

Questionnaire Flow: Present questions in a logical, non-intrusive order, and offer support or guidance as needed.

Real-Time Feedback: Provide real-time feedback based on answers (if appropriate) and direct users to the chatbot for further support if the severity level is high.

Data Security: Implement secure data handling and storage protocols, ensuring confidentiality and compliance with privacy standards.

5.5 Chatbot Interaction for Real-Time Support

Chatbot Development: Utilize the Gemini API to create an AI-powered chatbot that offers immediate, supportive responses based on the user's detected depression level.

Conversational Design:

Natural Language Understanding (NLU): Incorporate NLU to enable the chatbot to understand a wide range of user inputs, including slang and informal language, enhancing its effectiveness.

Predefined Response Library: Develop a comprehensive response library covering various scenarios, from general mental health guidance to crisis support. The library ensures the chatbot can provide relevant, accurate information instantly.

Proactive Engagement: For users with high severity scores, the chatbot can proactively engage, offering resources, guidance, or directing them to additional help.

User Privacy: Ensure all chatbot interactions are secure and private, safeguarding user confidentiality at all times.

CHAPTER 6

SYSTEM IMPLEMENTATION

1. DATASET CREATION :

```
import pandas as pd
from itertools import product
questions = [
    "1. Little interest or pleasure in doing things?",
    "2. Feeling down, depressed, or hopeless?",
    "3. Trouble falling or staying asleep, or sleeping too much?",
    "4. Feeling tired or having little energy?",
    "5. Poor appetite or overeating?",
    "6. Feeling bad about yourself — or that you are a failure or have let yourself or your family down?",
    "7. Trouble concentrating on things, such as reading the newspaper or watching television?",
    "8. Moving or speaking so slowly that other people could have noticed? Or the opposite — being so fidgety or restless that you have been moving around a lot more than usual?",
    "9. Thoughts that you would be better off dead or of hurting yourself in some way?"
]
def find_severity(score):
    if score <= 4:
        return "Minimal depression"
    elif 5 <= score <= 9:
        return "Mild depression"
    elif 10 <= score <= 14:
        return "Moderate depression"
    elif 15 <= score <= 19:
        return "Moderately severe depression"
    else:
        return "Severe depression"
all_responses = list(product([0, 1, 2, 3], repeat=len(questions)))
data_with_severity = []
for response in all_responses:
    total_score = sum(response)
    severity = find_severity(total_score)
    data_with_severity.append(list(response) + [severity])
```

```
def save_to_csv(data, filename="/content/depression_responses_dataset.csv"):
    columns = [f"Q{i+1}" for i in range(len(questions))] + ["Severity"]
    df = pd.DataFrame(data, columns=columns)
    df.to_csv(filename, index=False)
    print(f"saved to {filename}.")
save_to_csv(data_with_severity)
```

2 . ASSESSMENT.html

```
<!DOCTYPE html>
<html lang="en">
<head>
    <meta charset="UTF-8">
    <meta name="viewport" content="width=device-width, initial-scale=1.0">
    <title>Depression Assessment</title>
    <link rel="icon" href="/static/images/icon.png" type="image/png">
    <style>
        @import
url('https://fonts.googleapis.com/css2?family=Nunito:wght@300;600&display=swap');
        body {
            font-family: 'Nunito', sans-serif;
            margin: 0;
            padding: 0;
            height: 100vh;
            display: flex;
            justify-content: center;
            align-items: center;
            background-size: cover;
            background-position: center;
            overflow: hidden;
            position: relative;
            transition: background-image 0.6s ease-in-out; /* Smooth transition for background
image */
        }

        .container {
            background: rgba(255, 255, 255, 0.9); /* Slightly transparent background */
            padding: 40px 60px;
            border-radius: 20px;
            box-shadow: 0 15px 35px rgba(0, 0, 0, 0.3);
```

```
    max-width: 600px;
    width: 100%;
    text-align: center;
    position: absolute;
    transform: translateX(100%); /* Start from off-screen */
    opacity: 0;
    transition: transform 0.6s ease-in-out, opacity 0.6s ease-in-out;
}

.container.show {
    transform: translateX(0); /* Slide in */
    opacity: 1;
}

.container.hidden {
    transform: translateX(-100%); /* Slide out */
    opacity: 0;
}

h2 {
    font-size: 28px;
    color: #4e54c8;
    margin-bottom: 30px;
    animation: fadeIn 1.5s ease;
}

.question-box {
    min-height: 150px;
    display: flex;
    justify-content: center;
    align-items: center;
    margin-bottom: 30px;
    transition: all 0.6s ease-in-out;
    position: relative;
    background: rgba(255, 255, 255, 0.6); /* Slightly transparent background for the
question text */
    border-radius: 10px;
    padding: 20px;
    box-shadow: 0 8px 25px rgba(0, 0, 0, 0.2);
}
```

```
.question {
   font-size: 22px;
   font-weight: 600;
   color: #333;
}

.options {
   display: flex;
   flex-wrap: wrap;
   gap: 10px;
   justify-content: center;
   margin-top: 20px;
}

.option-button {
   background-color: #4e54c8;
   color: #fff;
   padding: 15px 20px;
   border-radius: 10px;
   font-size: 16px;
   cursor: pointer;
   border: none;
   transition: background-color 0.4s ease, transform 0.4s ease;
   box-shadow: 0 8px 25px rgba(0, 0, 0, 0.15);
   flex: 1 1 calc(50% - 20px);
   max-width: 45%;
}

.option-button:hover {
   background-color: #373bc0;
   transform: translateY(-5px);
}

.result {
   opacity: 0;
   transition: opacity 1s ease;
   display: none;
}

.result.show {
   opacity: 1;
```

```
            display: block;
        }

        .result h3 {
            font-size: 24px;
            color: #4e54c8;
            margin-bottom: 20px;
        }

        .result p {
            font-size: 18px;
            color: #666;
        }

        .result-btn {
            background-color: #4e54c8;
            color: #fff;
            padding: 12px 25px;
            border: none;
            border-radius: 8px;
            font-size: 16px;
            margin-top: 20px;
            cursor: pointer;
            transition: background-color 0.3s ease, transform 0.3s ease;
            box-shadow: 0 10px 25px rgba(0, 0, 0, 0.15);
        }

        .result-btn:hover {
            background-color: #373bc0;
            transform: translateY(-3px);
        }
    </style>
</head>
<body>

<div class="container" id="container">
    <h2>Depression Assessment</h2>
    <div id="question-box" class="question-box">
        <p class="question" id="question-text">Loading question...</p>
    </div>
    <div class="options" id="options-box">
```

```
        <!-- Options will be dynamically inserted here -->
    </div>
</div>

<div class="container result" id="result-box">
    <h3>Thank you for completing the assessment!</h3>
    <p>Your responses have been recorded. Please discuss the results with a healthcare professional for an accurate evaluation and advice.</p>
    <form action="/result" method="POST">
        <input type="hidden" id="answersInput" name="answers">
        <button type="submit" class="result-btn">View Results</button>
    </form>
</div>

<script>
    const questions = [
        "Little interest or pleasure in doing things?",
        "Feeling down, depressed, or hopeless?",
        "Trouble falling or staying asleep, or sleeping too much?",
        "Feeling tired or having little energy?",
        "Poor appetite or overeating?",
        "Feeling bad about yourself - or that you are a failure or have let yourself or your family down?",
        "Trouble concentrating on things, such as reading the newspaper or watching television?",
        "Moving or speaking so slowly that other people could have noticed? Or the opposite - being so fidgety or restless that you have been moving around a lot more than usual?",
        "Thoughts that you would be better off dead, or of hurting yourself in some way?"
    ];

    const options = [
        "Not at all", // 0
        "Several days", // 1
        "More than half the days", // 2
        "Nearly every day" // 3
    ];

    let currentQuestionIndex = 0;
    let answers = [];

    function shuffleArray(array) {
```

```
        for (let i = array.length - 1; i > 0; i--) {
            const j = Math.floor(Math.random() * (i + 1));
            [array[i], array[j]] = [array[j], array[i]];
        }
    }

    function loadQuestion() {
        const container = document.getElementById("container");
        const questionText = document.getElementById("question-text");
        const optionsBox = document.getElementById("options-box");

        // Slide out the current question
        container.classList.remove('show');
        container.classList.add('hidden');

        // Smooth transition for the background image
        document.body.style.transition = "background-image 0.6s ease-in-out";
        document.body.style.backgroundImage = url('static/images/${currentQuestionIndex + 1}.png');

        // Wait for the container to slide out before updating the content
        setTimeout(() => {
            // Update the question text and shuffle the options
            questionText.textContent = questions[currentQuestionIndex];

            let shuffledOptions = [...options];
            shuffleArray(shuffledOptions);

            // Clear and add new options
            optionsBox.innerHTML = '';
            shuffledOptions.forEach((option, index) => {
                const button = document.createElement("button");
                button.classList.add("option-button");
                button.textContent = option;
                button.onclick = () => submitAnswer(index); // Store the answer
                optionsBox.appendChild(button);
            });

            // Slide in the new question
            container.classList.remove('hidden');
            container.classList.add('show');
```

```
    }, 600); // Delay matches the transition time for sliding out (600ms)
  }

  function submitAnswer(selectedIndex) {
    const chosenOptionText = document.querySelectorAll(".option-
button")[selectedIndex].textContent;

    // Find the corresponding score based on the option text (before shuffling)
    const answerScore = options.findIndex(option => option === chosenOptionText);

    // Store the actual score based on the original options array
    answers.push(answerScore);

    currentQuestionIndex++;

    if (currentQuestionIndex < questions.length) {
      // Load the next question
      loadQuestion();
    } else {
      // Show the results when all questions are answered
      showResults();
    }
  }

  function showResults() {
    const container = document.getElementById("container");
    const resultBox = document.getElementById("result-box");

    // Slide out the last question
    container.classList.remove('show');
    container.classList.add('hidden');

    // Change the background image to the final image
    setTimeout(() => {
      document.body.style.backgroundImage = url('static/images/10.png');

      // Show the result box
      resultBox.classList.add('show');
      resultBox.classList.remove('hidden');
      document.getElementById("answersInput").value = JSON.stringify(answers); //
Send answers to form
```

```
    }, 800); // Delay matches the transition time for sliding out (600ms)
  }

  loadQuestion();
</script>

</body>
</html>
```

3.index.html :

```
<!DOCTYPE html>
<html lang="en">
<head>
  <meta charset="UTF-8">
  <meta name="viewport" content="width=device-width, initial-scale=1.0">
  <title>Depression Detection System</title>
  <link rel="icon" href="/static/images/icon.png" type="image/png">

  <style>
    body {
      font-family: Arial, sans-serif;
      margin: 0;
      padding: 0;
      color: #333;
      animation: slideIn 1s ease-out; /* Apply the slide-in animation */
    }

    @keyframes slideIn {
      from {
        transform: translateY(-400px);
        opacity: 0;
      }
      to {
        transform: translateY(0);
        opacity: 1;
      }
    }

    .container {
      max-width: 1200px;
```

```
            margin: 0 auto;
            padding: 20px;
            background-color: rgba(255, 255, 255, 0.9); /* Semi-transparent background for
readability */
            box-shadow: 0 0 10px rgba(0, 0, 0, 0.1);
        }

        header {
            text-align: center;
            font-size: 32px;
            margin-bottom: 20px;
            color: #007bff;
        }

        .hero-section {
            text-align: center;
            padding: 50px 0;
            background-color: #fff;
            border-radius: 10px;
            box-shadow: 0 0 10px rgba(0, 0, 0, 0.1);
        }

        .hero-text {
            font-size: 36px;
            font-weight: bold;
            margin-bottom: 20px;
            color: #333;
        }

        .hero-subtext {
            font-size: 18px;
            color: #666;
            margin-bottom: 40px;
        }

        .cta-button {
            background-color: #007bff;
            color: #fff;
            padding: 10px 20px;
            border: none;
            border-radius: 5px;
```

```
    font-size: 18px;
    cursor: pointer;
    transition: background-color 0.3s ease;
    text-decoration: none;
}

.cta-button:hover {
    background-color: #0056b3;
}

.developer-section {
    display: flex;
    justify-content: space-between;
    margin-top: 50px;
}

.developer-card {
    width: calc(33.33% - 20px);
    padding: 20px;
    background-color: #fff;
    border-radius: 10px;
    box-shadow: 0 0 5px rgba(0, 0, 0, 0.2);
    transition: transform 0.3s ease;
    overflow: hidden;
    text-align: center; /* Center text in the card */
}

.developer-card:hover {
    transform: translateY(-5px);
}

.developer-image {
    width: 155px; /* Fixed width matching the image size */
    height: 200px; /* Fixed height matching the image size */
    overflow: hidden;
    border-radius: 10px;
    margin: 0 auto 15px; /* Center the image horizontally */
}

.developer-image img {
    width: 100%;
```

```
            height: 100%;
            object-fit: cover; /* Ensure the image covers the area without distortion */
            transition: transform 0.5s ease;
        }

        .developer-card:hover .developer-image img {
            transform: scale(1.1);
        }

        .developer-details {
            text-align: center;
        }

        .developer-name {
            font-size: 18px;
            font-weight: bold;
            margin-bottom: 5px;
        }

        .developer-profile-link {
            color: #007bff;
            text-decoration: none;
            font-size: 16px;
        }
    </style>
</head>
<body>
    <div class="container">
        <header>
            Depression Detection System
        </header>
        <div class="hero-section">
            <div class="hero-text">Detect Signs of Depression Early</div>
            <div class="hero-subtext">Helping You Stay Mentally Healthy</div>
            <a href="/Assessment" class="cta-button">Start Your Assessment</a>
        </div>
        <div class="developer-section">
            <div class="developer-card">
                <div class="developer-image">
                    <img src="/static/developers/Reshma.png" alt="Tamilselvi V">
                </div>
```

```
            <div class="developer-details">
                <div class="developer-name">Tamilselvi V</div>
                <a href="https://www.linkedin.com/in/tamilselvi-v-b95a35278/"
class="developer-profile-link" target="_blank">LinkedIn Profile</a>
            </div>
        </div>
        <div class="developer-card">
            <div class="developer-image">
                <img src="./static/developers/varsha.png" alt="Varsha">
            </div>
            <div class="developer-details">
                <div class="developer-name">Varsha R</div>
                <a href="https://www.linkedin.com/in/varsha27ravi/" class="developer-
profile-link" target="_blank">LinkedIn Profile</a>
            </div>
        </div>
        <div class="developer-card">
            <div class="developer-image">
                <img src="./static/developers/savithri.png" alt="Savithri">
            </div>
            <div class="developer-details">
                <div class="developer-name">Savithri D</div>
                <a href="https://www.linkedin.com/in/savithri-d-4a2027279/"
class="developer-profile-link" target="_blank">LinkedIn Profile</a>
            </div>
        </div>
    </div>
  </div>
</body>
</html>
```

4.Result.html:

```
<!DOCTYPE html>
<html lang="en">
<head>
  <meta charset="UTF-8">
  <meta name="viewport" content="width=device-width, initial-scale=1.0">
  <title>Assessment Results</title>
  <link rel="icon" href="/static/images/icon.png" type="image/png">
  <style>
```

```
@keyframes fadeIn {
   0% {
      opacity: 0;
      transform: translateY(50px);
   }
   100% {
      opacity: 1;
      transform: translateY(0);
   }
}

body {
   font-family: 'Arial', sans-serif;
   margin: 0;
   padding: 20px;
   background-color: #f4f7f9;
   color: #333;
   display: flex;
   flex-direction: column;
   align-items: center;
   animation: fadeIn 1s ease-in-out;
}

.container {
   max-width: 800px;
   width: 100%;
   padding: 20px;
   background-color: #ffffff;
   border-radius: 10px;
   box-shadow: 0 0 20px rgba(0, 0, 0, 0.1);
   animation: fadeIn 1s ease-in-out;
}

h2 {
   color: #4e54c8;
   margin-bottom: 20px;
   text-align: center;
   font-size: 36px;
   border-bottom: 2px solid #4e54c8;
   padding-bottom: 10px;
}
```

```
p {
   font-size: 18px;
   margin-bottom: 20px;
   text-align: center;
}

table {
   width: 100%;
   border-collapse: collapse;
   margin: 20px 0;
   background: rgba(255, 255, 255, 0.9);
   border-radius: 10px;
   box-shadow: 0 4px 15px rgba(0, 0, 0, 0.1);
}

th, td {
   padding: 12px;
   text-align: left;
   border-bottom: 1px solid #ddd;
   transition: background-color 0.3s;
}

th {
   background-color: #4e54c8;
   color: white;
   font-weight: bold;
}

tr:hover {
   background-color: #f1f1f1;
}

h3 {
   color: #4e54c8;
   margin-top: 20px;
   font-size: 24px;
}

.button-container {
   display: flex;
```

```css
    justify-content: space-between;
    margin-top: 20px;
}

.button-container a {
    text-decoration: none;
    background-color: #4e54c8;
    color: white;
    padding: 10px 20px;
    border-radius: 5px;
    transition: background-color 0.3s, transform 0.3s;
}

.button-container a:hover {
    background-color: #373bc0;
    transform: translateY(-2px);
}

/* Floating Chat Icon */
.chat-icon {
    position: fixed;
    bottom: 20px;
    right: 20px;
    background-color: #4e54c8;
    color: white;
    border: none;
    border-radius: 50%;
    width: 60px;
    height: 60px;
    font-size: 30px;
    cursor: pointer;
    box-shadow: 0 4px 10px rgba(0, 0, 0, 0.2);
    display: flex;
    justify-content: center;
    align-items: center;
}

.chat-icon:hover {
    background-color: #373bc0;
}
```

```
    /* Popup Chat Window */
    .chat-container {
      display: none;
      position: fixed;
      bottom: 80px;
      right: 20px;
      width: 400px; /* Increased width */
      max-width: 90%;
      background-color: white;
      border-radius: 10px;
      box-shadow: 0 4px 15px rgba(0, 0, 0, 0.3);
      z-index: 1000;
      animation: fadeIn 0.3s ease-in-out;
    }

    .chat-header {
      background-color: #4e54c8;
      color: white;
      padding: 15px;
      border-top-left-radius: 10px;
      border-top-right-radius: 10px;
      text-align: center;
      font-size: 20px; /* Increased font size */
    }

    #chat-box {
      border: 1px solid #ccc;
      padding: 10px;
      height: 400px; /* Increased height */
      overflow-y: auto;
      background: #f9f9f9;
      border-radius: 5px;
      margin-bottom: 10px;
    }

.message {
  margin: 10px 0;
  line-height: 1.5;
  padding: 10px; /* Padding for messages */
  border-radius: 10px; /* Rounded corners */
  display: inline-block; /* Ensures background wraps tightly around text */
```

```
}

.message.user {
   text-align: right;
   background-color: #0963e1; /* Brighter green for user message */
   color: white;
}

.message.bot {
   background-color: #ffffff; /* Brighter blue for bot message */
   color: rgb(17, 1, 1);
}


       .message strong {
          color: black; /* Dark black for bold text */
       }

       .bash-command {
          background-color: #000206; /* Light gray for bash commands */
          color: #333;
          padding: 5px;
          border-radius: 4px;
          font-family: 'Courier New', Courier, monospace; /* Monospace font for commands
*/
          display: block; /* Ensures it's on a new line */
          margin-top: 5px;
       }

       .code-block {
          background-color: #e9ecef; /* Light gray for code blocks */
          padding: 10px;
          border-radius: 5px;
          font-family: 'Courier New', Courier, monospace; /* Monospace font for code */
          margin: 10px 0; /* Margin around code blocks */
          white-space: pre-wrap; /* Preserve whitespace */
          overflow-x: auto; /* Allow horizontal scroll */
       }

#user-input-container {
   display: flex;
```

```css
    padding: 10px;
    background-color: #f4f7f9;
    border-bottom-left-radius: 10px;
    border-bottom-right-radius: 10px;
    justify-content: flex-end; /* Align input section to the right */
    align-items: center;
}

#user-input {
    padding: 10px;
    border: 1px solid #ddd;
    border-radius: 5px;
    outline: none;
    font-size: 16px;
    width: 70%; /* Reduce input width to fit better */
    margin-right: 10px; /* Space between input and button */
}

#send-button, #clear-button {
    padding: 10px 20px;
    background-color: #4e54c8;
    color: white;
    border: none;
    border-radius: 5px;
    cursor: pointer;
}

#send-button:hover, #clear-button:hover {
    background-color: #373bc0;
}


        #clear-button {
            padding: 10px;
            background-color: #ff5722;
            color: white;
            border: none;
            border-radius: 5px;
            cursor: pointer;
            margin-left: 10px;
        }
```

```
        #clear-button:hover {
            background-color: #e64a19;
        }
    </style>
</head>
<body>
    <div class="container">
        <h2>Your Assessment Results</h2>
        <p>Here are the values you selected for each question:</p>

        <table>
            <thead>
                <tr>
                    <th>Question</th>
                    <th>Your Score</th>
                    <th>Option</th>
                </tr>
            </thead>
            <tbody>
                {% for question, (answer, option) in questions_answers.items() %}
                <tr>
                    <td>{{ question }}</td>
                    <td><strong>{{ answer }}</strong></td>
                    <td>{{ option }}</td>
                </tr>
                {% endfor %}
            </tbody>
        </table>

        <h3>Total Score: {{ total_score }}</h3>

        <h3>Depression Severity: {{ severity }}</h3>

        <p>Please ask our AI 🤖 for a detailed evaluation and advice.</p>

        <div class="button-container">
            <a href="/">Home</a>
            <a href="/Assessment">Retake the Assessment</a>
        </div>
```

```
        <!-- Floating Chat Icon -->
        <button class="chat-icon" onclick="toggleChat()">
            🤖
        </button>

        <!-- Popup Chat Window -->
        <div class="chat-container" id="chat-container">
            <div class="chat-header">Chat with us</div>
            <div id="chat-box"></div>
            <div id="user-input-container">
                <input type="text" id="user-input" placeholder="Type your message here..."
onkeydown="if(event.key === 'Enter'){sendMessage();}" />
                <button id="send-button" onclick="sendMessage()">Send</button>
            </div>
            <button id="clear-button" onclick="clearChat()">Clear Chat</button>
        </div>
    </div>

    <script>
        // Toggle chat window visibility
        function toggleChat() {
            const chatContainer = document.getElementById('chat-container');

            chatContainer.style.display = chatContainer.style.display === 'none' ||
!chatContainer.style.display ? 'block' : 'none';
            document.getElementById("user-input").focus();
        }

        // Function to send user message to the backend
        async function sendMessage() {
            const userInput = document.getElementById('user-input').value.trim();
            if (!userInput) return;

            appendMessage('user', userInput);
            document.getElementById('user-input').value = '';

            try {
                const response = await fetch('/chat', {
                    method: 'POST',
                    headers: { 'Content-Type': 'application/json' },
                    body: JSON.stringify({ message: userInput })
```

```
        });

        if (!response.ok) {
            throw new Error('Network response was not ok');
        }

        const data = await response.json();
        appendMessage('bot', data.reply);
    } catch (error) {
        appendMessage('bot', 'Sorry, there was an error processing your request.');
    }
}

// Function to append messages to the chat box
function appendMessage(sender, message) {
    const chatBox = document.getElementById('chat-box');
    const messageElement = document.createElement('div');
    messageElement.classList.add('message', sender);
    messageElement.innerHTML = <strong>${sender === 'user' ? 'You' : '🤖
'}:</strong> ${formatMessage(message)};
    chatBox.appendChild(messageElement);
    chatBox.scrollTop = chatBox.scrollHeight;
}

// Function to format messages (handle bold text, bash commands, and code blocks)
function formatMessage(message) {
  // Handle bold text (double asterisks)
  message = message.replace(/\\(.?)\\*/g, '<strong>$1</strong>');

  // Handle bash commands formatted as bash command
  message = message.replace(/(.*?)/gs, '<div class="code-block">$1</div>');

  // Handle single asterisks and remove stray asterisks left in messages
  message = message.replace(/(^|\s)\(.?)\*(?=\s|$)/g, '$1<strong>$2</strong>');
  message = message.replace(/\(.?)\*/g, '$1'); // Remove single asterisks that aren't for bold

  return message;
}
```

```
        // Function to clear the chat both on frontend and backend
        async function clearChat() {
            try {
                const response = await fetch('/clear_chat', { method: 'POST' });
                if (!response.ok) throw new Error('Network response was not ok');
                document.getElementById('chat-box').innerHTML = '';
            } catch (error) {
                alert('Failed to clear chat history.');
            }
        }
    </script>
</body>
</html>
```

5.App.py :

```
from flask import Flask, render_template, request, jsonify, session,json
import google.generativeai as genai
app = Flask(_name_)
app.secret_key = 'just_secret_key'


def get_api_key():
    with open('static/API/API_KEY.txt', 'r') as file:
        return file.read().strip()

# Google Gemini AI Configuration
api_key = get_api_key()
genai.configure(api_key=api_key)

generation_config = {
    "temperature": 0,
    "top_p": 0.95,
    "top_k": 64,
    "max_output_tokens": 8192,
    "response_mime_type": "text/plain",
}

# Route for homepage
@app.route('/')
def index():
```

```
    return render_template('index.html')

# Route for Assessment page
@app.route('/Assessment')
def Assessment():
    session.pop('chat_history', None)
    session.pop('total_score', None)
    session.pop('severity', None)
    return render_template('assessment.html')

# Route for Result page
@app.route('/result', methods=['POST'])
def result():
    answers = request.form.get('answers')
    if answers:
        answers = json.loads(answers)
        total_score = sum(answers)

        # Determine depression severity
        if total_score >= 1 and total_score <= 4:
            severity = "Minimal depression"
        elif total_score >= 5 and total_score <= 9:
            severity = "Mild depression"
        elif total_score >= 10 and total_score <= 14:
            severity = "Moderate depression"
        elif total_score >= 15 and total_score <= 19:
            severity = "Moderately severe depression"
        elif total_score >= 20 and total_score <= 27:
            severity = "Severe depression"
        else:
            severity = "You are Not In Depression"
        session['total_score'] = total_score
        session['severity'] = severity
        questions = [
            "Little interest or pleasure in doing things?",
            "Feeling down, depressed, or hopeless?",
            "Trouble falling or staying asleep, or sleeping too much?",
            "Feeling tired or having little energy?",
            "Poor appetite or overeating?",
            "Feeling bad about yourself - or that you are a failure or have let yourself or your
family down?",
```

```
        "Trouble concentrating on things, such as reading the newspaper or watching television?",
        "Moving or speaking so slowly that other people could have noticed? Or the opposite - being so fidgety or restless that you have been moving around a lot more than usual?",
        "Thoughts that you would be better off dead, or of hurting yourself in some way?"
    ]

    options = [
        "Not at all",
        "Several days",
        "More than half the days",
        "Nearly every day"
    ]

    questions_answers = {}
    for i, question in enumerate(questions):
        answer = answers[i]
        option = options[answer]
        questions_answers[question] = (answer, option)

    return render_template('Result.html', questions_answers=questions_answers, total_score=total_score, severity=severity)

# Route for chatbot interaction
@app.route('/chat', methods=['POST'])
def chat():
  data = request.json
  user_input = data.get('message')

  # Get the chat history from the session or initialize it
  chat_history = session.get('chat_history', [])
  total_score = session.get('total_score')
  severity = session.get('severity')

  # Create dynamic system instruction
  system_instruction = (
    f"You are a helpful mental health assistant integrated into a Depression Detection System that assesses depression levels based on user input. "
    f"The user has just completed an assessment with a score of {total_score}, classified as {severity}. "
```

```
        f"Provide supportive and empathetic responses tailored to this score. Offer mental health resources, self-care tips, and suggest professional consultation if necessary. "
        f"At the end of the conversation, provide specific solutions or coping strategies to address the user's concerns related to their results. "
        f"The project is developed by Tamilselvi V, Varsha R, and Savithri D from the Department of Artificial Intelligence & Data Science, 3rd Year at Panimalar Engineering College, Chennai. "
        f"The technology stack includes Python Flask, HTML, CSS, JavaScript, and the Gemini AI API. Keep the conversation focused on the user's well-being."
        f"Always give medium size responses."
    )

    # Initiate chat session with Gemini AI
    model = genai.GenerativeModel(
        model_name="gemini-1.5-flash",
        generation_config=generation_config,
        system_instruction=system_instruction
    )

    # Start the chat session using the existing history
    chat_session = model.start_chat(history=chat_history)
    response = chat_session.send_message(user_input)

    # Append the user input and bot response to the chat history
    chat_history.append({'role': 'user', 'parts': [user_input]})
    chat_history.append({'role': 'model', 'parts': [response.text]})

    # Update the chat history in the session
    session['chat_history'] = chat_history

    return jsonify({"reply": response.text})


# Clear chat history when user exits or restarts chat
@app.route('/clear_chat', methods=['POST'])
def clear_chat():
    session.pop('chat_history', None)
    return jsonify({"status": "Chat history cleared"})
```

OUTPUT:

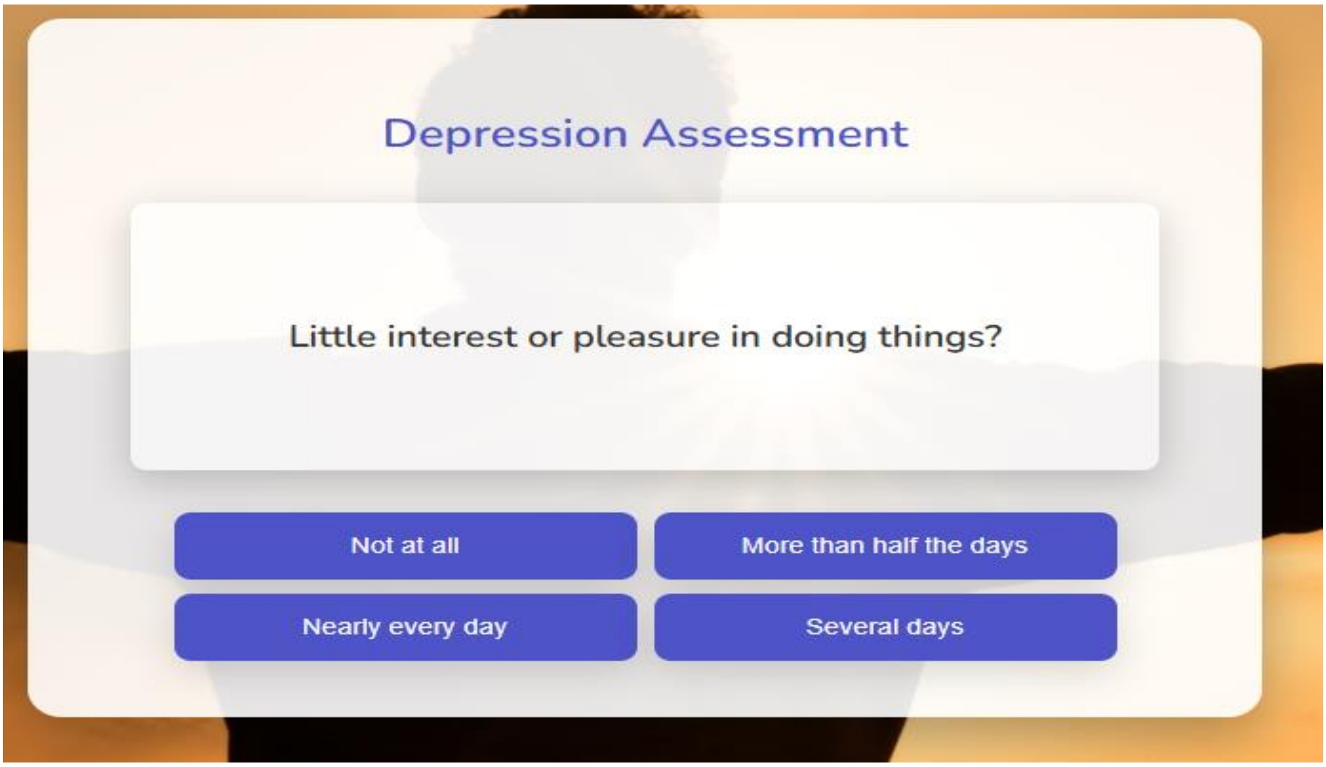


Figure 6.1 Assessment Page

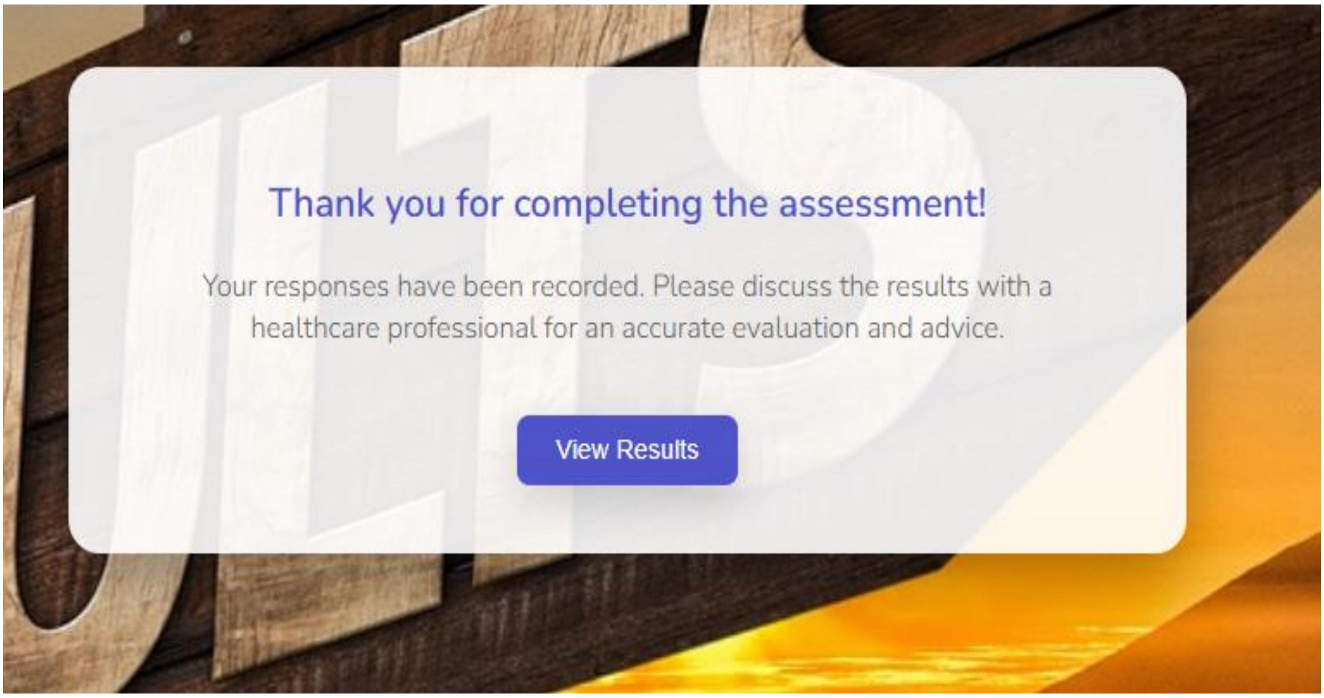
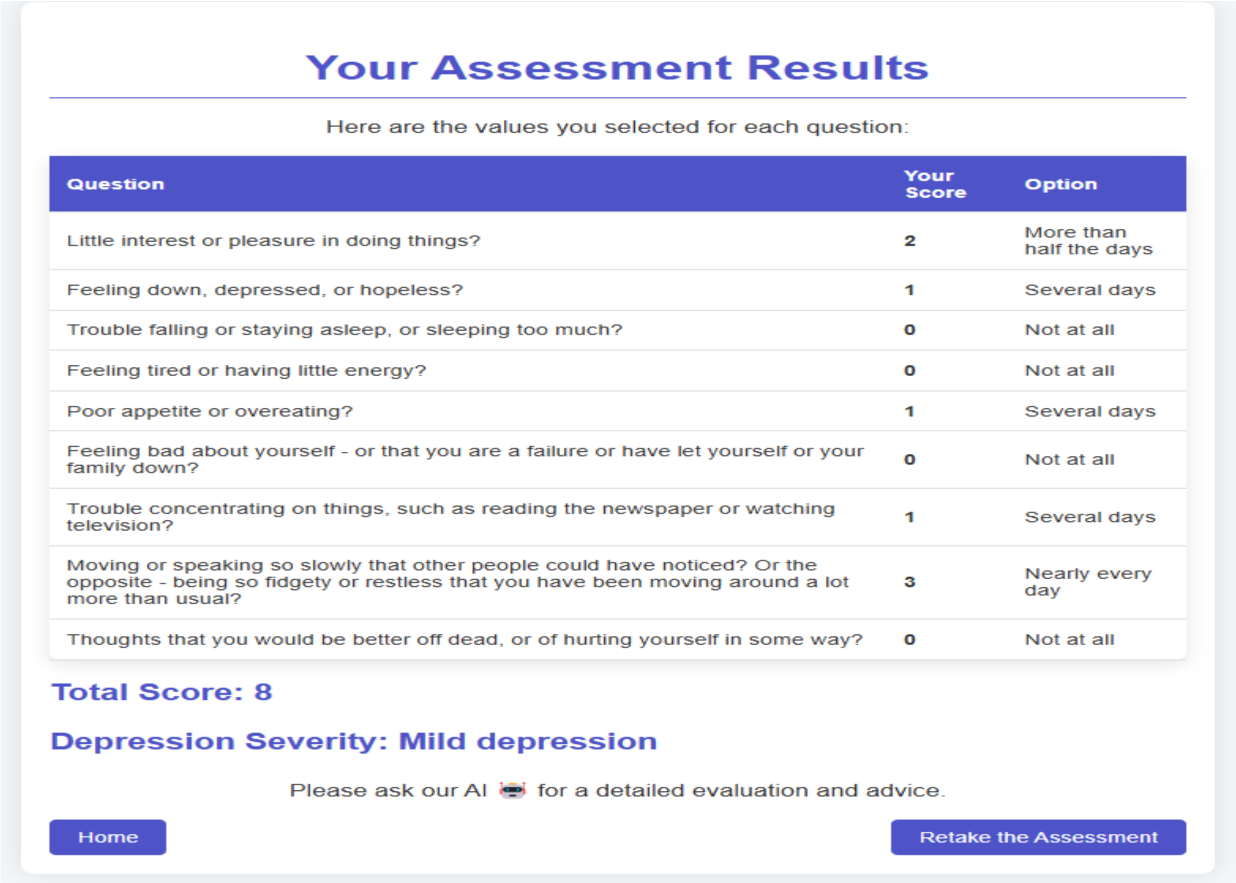


Figure 6.2 Interface to view results



Your Assessment Results

Here are the values you selected for each question:

Question	Your Score	Option
Little interest or pleasure in doing things?	2	More than half the days
Feeling down, depressed, or hopeless?	1	Several days
Trouble falling or staying asleep, or sleeping too much?	0	Not at all
Feeling tired or having little energy?	0	Not at all
Poor appetite or overeating?	1	Several days
Feeling bad about yourself - or that you are a failure or have let yourself or your family down?	0	Not at all
Trouble concentrating on things, such as reading the newspaper or watching television?	1	Several days
Moving or speaking so slowly that other people could have noticed? Or the opposite - being so fidgety or restless that you have been moving around a lot more than usual?	3	Nearly every day
Thoughts that you would be better off dead, or of hurting yourself in some way?	0	Not at all

Total Score: 8

Depression Severity: Mild depression

Please ask our AI for a detailed evaluation and advice.

Home

Retake the Assessment

Figure 6.3 Assessment Results

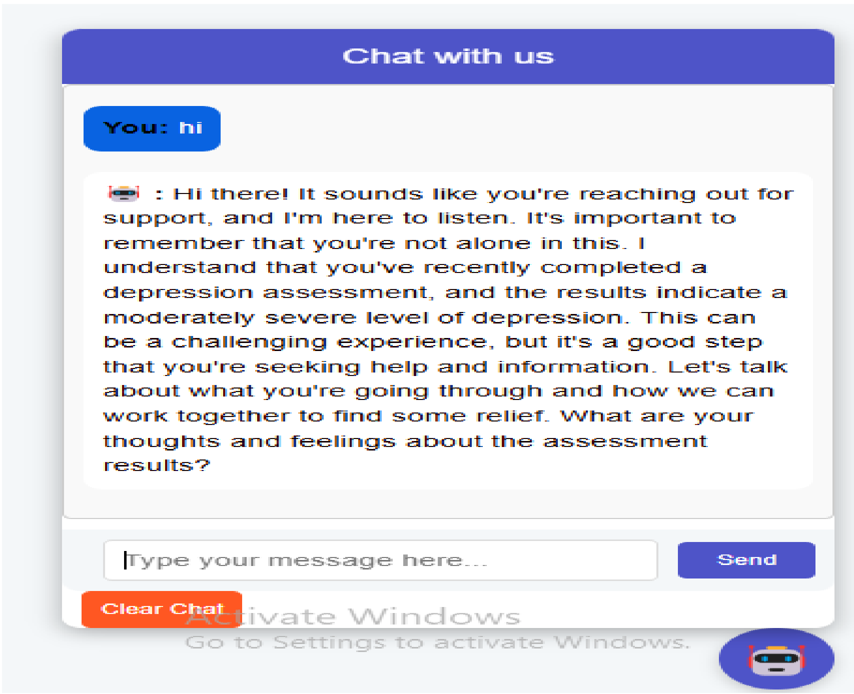


Figure 6.4 Chatbot interaction

CHAPTER 7
SYSTEM REQUIREMENTS

7.1 INTRODUCTION

This chapter outlines the technology used, alongside the hardware and software requirements necessary for the successful implementation of the **Depression Detection and Support System**. This system leverages machine learning algorithms and natural language processing techniques to analyze user interactions, detect signs of depression, and provide timely support through an AI-driven chatbot. The system aims to create a supportive environment for individuals experiencing depression, offering them resources and assistance as needed.

7.2 REQUIREMENTS

7.2.1 Hardware Requirements

The following hardware specifications are recommended to ensure smooth operation and optimal performance of the Depression Detection and Support System:

- **Hard Disk**:
  - Minimum: 500 GB
  - Recommended: 1 TB or more to accommodate large datasets used for training machine learning models and storing user interactions securely.
- **RAM**:
  - Minimum: 8 GB
  - Recommended: 16 GB or more, especially beneficial for deep learning tasks that require substantial memory for processing large datasets and running models efficiently.
- **Processor**:
  - Minimum: Intel i3 (or equivalent)
  - Recommended: Intel i5 or higher, as this will significantly enhance the processing speed during model training and real-time inference tasks.
- **Microphone**:
  - A high-quality microphone is essential for accurate audio input, especially if the system includes voice interaction features. It ensures clear audio capture, reducing background noise and improving emotion recognition from spoken inputs.

7.2.2 Software Requirements

The following software components are necessary for the installation and operation of the Depression Detection and Support System:

- **Operating System**:
  - Options: Windows 10 or later, macOS, or Linux (Ubuntu 18.04 or newer). This flexibility allows developers and users to deploy the system in various environments based on preference.
- **Python**:
  - Version: 3.6 or newer is required to access the latest features and libraries that support machine learning and data processing tasks.
- **Integrated Development Environment (IDE)**:
  - **Jupyter Notebook**: Ideal for model training, providing an interactive environment for data exploration, model evaluation, and visualization.
  - **Flask**: A micro web framework used for building the web application, enabling the deployment of machine learning models as web services.

Essential Packages:

- **Flask**: Facilitates the creation of web services to interact with the depression detection models, allowing users to engage with the system seamlessly through a web interface.
- **NumPy**: Provides support for numerical operations, enabling efficient handling of large, multi-dimensional arrays and matrices critical for data manipulation and processing.
- **Pandas**: Essential for data manipulation and preprocessing, allowing the system to clean, transform, and analyze data effectively.
- **scikit-learn**: A powerful library for implementing classical machine learning algorithms, which will be used for preliminary models to analyze and classify depression severity based on user input.
- **Matplotlib**: A versatile plotting library for creating visual representations of data, helping to analyze model performance and visualize user interaction patterns.
- **Google Generative AI**:It leverages machine learning to automate and enhance content creation, analysis, and documentation. In software requirements, it helps generate, refine, and validate requirements for better clarity and accuracy.

7.3 Technology Used

The Depression Detection and Support System employs a variety of technologies to provide an effective and interactive user experience:

- **Python**: A high-level programming language known for its readability and extensive libraries, making it suitable for both data analysis and web development. Python's versatility allows developers to implement complex algorithms with ease.
- **Flask**: A lightweight web framework that facilitates the rapid development of web applications. Flask is chosen for its simplicity and scalability, enabling developers to create a seamless interface for users to interact with the depression detection models.
- **Google Generative AI**: It leverages machine learning to automate and enhance content creation, analysis, and documentation. In software requirements, it helps generate, refine, and validate requirements for better clarity and accuracy.

7.3.1 Software Description

7.3.1.1 Python

Python is widely regarded for its simplicity and versatility in programming. It has become the de facto language for machine learning and data science due to its extensive collection of libraries that facilitate data manipulation, statistical analysis, and model development. The user-friendly syntax and active community support make Python an ideal choice for both beginners and seasoned developers, enabling the rapid prototyping of complex projects.

7.3.1.2 Flask

Flask is a micro web framework designed to make it easy to build web applications quickly. It follows the WSGI standard and is highly modular, allowing developers to extend its functionalities as needed. Flask is particularly suited for deploying machine learning models as web services, providing a RESTful API that users can interact with through a browser. Its lightweight nature ensures that developers can focus on building features without getting bogged down by unnecessary complexities.

7.3.1.3 Google Generative AI:

It leverages machine learning to automate and enhance content creation, analysis, and documentation. In software requirements, it helps generate, refine, and validate requirements for better clarity and accuracy.

CHAPTER 8

RESULT

The evaluation of the proposed Depression Detection and Support System highlights its effectiveness in identifying signs of depression and providing timely support. The results demonstrate the model's capability to recognize various levels of depression with high accuracy and efficiency, ensuring users receive appropriate assistance in real-time.

8.1 Accuracy and Model Performance

Model Performance Summary

The depression detection model, built using a Random Forest Classifier, was evaluated on its ability to classify different levels of depression accurately. The model was trained and tested on responses to nine depression-related questions, designed to cover a broad spectrum of emotional and cognitive aspects related to depression. The key performance indicators indicate a significant improvement over traditional detection methods, achieving solid accuracy and precision in classifying depression severity.

- **Overall Accuracy**: The model achieved an overall accuracy of 82%, demonstrating its capacity to correctly predict the severity of depression across a range of levels. This result is the product of combining advanced machine learning techniques, particularly the Random Forest Classifier, with a comprehensive dataset that enables the model to handle various emotional and behavioral cues linked to depression.

8.2 Confusion Matrix Analysis

A key component in evaluating the model's performance is the confusion matrix, which shows how well the model distinguishes between different depression severity levels: **Minimal Depression**,**Mild Depression**, **Moderate Depression**, **Moderately Severe Depression**, and **Severe Depression**. The confusion matrix allows for an in-depth understanding of where the model excels and where it needs improvement, especially in handling similar severity levels that may overlap in terms of symptoms.

Figure 8.1 Confusion Matrix

8.3 Classification Performance:

- **Minimal Depression**: The model identified Minimal Depression with a high degree of accuracy (90%). This suggests that the model is particularly effective at recognizing users with little to no depressive symptoms.
- **Mild Depression**: The model achieved an accuracy of 84% in identifying Mild Depression. This shows that the model can detect individuals with slightly elevated depressive symptoms, but there may be occasional misclassification with the next severity level.
- **Moderate Depression**: The accuracy for Moderate Depression was 83%, showing good performance in this category. However, there is still some

overlap with both Mild and Moderately Severe Depression, leading to potential misclassification.

  - **Moderately Severe Depression**: The model's performance in identifying Moderately Severe Depression was 81%. As this is a more complex severity level, the model is slightly less accurate in distinguishing it from Severe Depression, which may share more extreme emotional and behavioral features.
  - **Severe Depression**: The model identified Severe Depression with a 75% accuracy, which is lower than other levels. This suggests that distinguishing between severe depressive states and other levels of high distress remains a challenge, possibly due to the wide range of individual experiences within this severity level.

- **Misclassification Trends**: One notable observation from the confusion matrix is that the model often misclassifies cases between Moderate and Severe depression levels. These two categories share significant emotional and behavioral traits, making it difficult for the model to differentiate them with high accuracy. This misclassification trend may be due to the nuanced differences between these levels that are challenging to capture with the current set of features.
- **Improvement Implications**: The confusion matrix provides valuable insights into areas where the model can be improved. The misclassification between Moderate and Severe levels points to potential refinements in the feature extraction process. Enhancing the set of features that the model uses to classify depression levels—such as incorporating additional emotional, cognitive, or behavioral markers—could help improve its accuracy. Moreover, refining the model architecture or considering different classifiers that are better suited to differentiate between closely related categories might help address this issue.

8.4 Precision, Recall, and F1-Score

In addition to overall accuracy, a more granular assessment of the model's performance can be made through metrics such as **Precision**, **Recall**, and **F1-Score**. These metrics provide a deeper understanding of how well the model is performing across each specific depression severity level.

	precision	recall	fl-score
Minimal depression	0.80	0.70	0.75
Mild depression	0.87	0.31	0.41
Moderate depression	0.82	0.88	0.85
Moderately severe depression	0.83	0.82	0.82
Severe depression	0.87	0.55	0.67
accuracy			0.82
macro avg	0.84	0.65	0.71
weighted avg	0.82	0.82	0.82

Table No II Precision, Recall, and F1-Score

8.5 User Interaction

User interaction is an essential component of the depression detection system, aimed at enhancing the overall user experience and ensuring that the system meets the needs of its users. This feedback can be gathered through multiple channels:

- **Post-Interaction Surveys**: After users complete the questionnaire or interact with the chatbot, they can be prompted to provide feedback regarding the clarity of questions, ease of navigation, and overall satisfaction with the system. This information is valuable for identifying areas of improvement and ensuring that the content resonates with users.

- **Emotion Tracking**: Users may also have the option to indicate how they feel before and after using the system, providing insight into the effectiveness of the support received. Tracking these changes can help in refining the intervention strategies employed by the chatbot.

- **Continuous Improvement**: Based on the collected feedback, iterative updates can be made to the questions and the chatbot's responses to better address user needs and improve engagement. Regularly incorporating user feedback ensures that the system remains relevant and effective in providing support.

8.6 Real-Time Support Response Time

Real-time support response time is a critical factor in the effectiveness of the depression detection system, particularly for users in distress. The system is designed to minimize latency and provide timely responses through several mechanisms:

Immediate Result: Once users complete the questionnaire, the Random Forest algorithm processes their responses rapidly to classify the severity of depression. This allows users to receive their results almost instantaneously, which is crucial for those seeking immediate insight into their emotional state.

Chatbot Responsiveness: The chatbot integrated via the Gemini API is programmed to respond promptly to user inquiries. Utilizing real-time processing capabilities ensures that users can engage in meaningful conversations without delays, enhancing the feeling of support and urgency.

System Optimization: Continuous monitoring and optimization of backend processes, such as data handling and response generation, are essential to maintaining low latency. This can involve refining algorithms and ensuring robust server performance, ultimately contributing to a seamless user experience.

CHAPTER 9
CONCLUSION REMARKS

Conclusion

This study successfully developed a comprehensive Depression Detection and Support System that integrates a sophisticated chatbot powered by the Gemini API with a user-friendly website designed to assess and monitor depression levels. The proposed model effectively employs the Random Forest algorithm to classify depression severity based on user responses to a set of targeted questions, facilitating timely and personalized support.

The key contributions of this research can be summarized as follows:

Enhanced Depression Detection: Utilizing a structured questionnaire, the system accurately evaluates user responses to detect varying levels of depression. The approach facilitates the identification of individuals at risk, ensuring timely intervention and support. This proactive stance is crucial in mental health care, where early detection can significantly improve outcomes.

Real-Time Support: By integrating the chatbot, users receive immediate assistance tailored to their emotional needs. The chatbot's capabilities provide a non-judgmental space for users to express their feelings, encouraging openness and interaction. This real-time interaction fosters a sense of companionship and support, essential for individuals navigating challenging mental health experiences.

User-Centric Design: The website interface was developed with a focus on user experience, allowing for intuitive navigation and easy access to resources. It incorporates a visually appealing layout and simple language, which lowers barriers for users seeking help. This design encourages engagement with the system, particularly for individuals who may feel hesitant or vulnerable when reaching out for support.

Scalability and Future Directions: The framework established in this research is scalable, allowing for future enhancements such as additional features, expanded datasets, and more refined algorithms. Future iterations of the system could include machine learning-based personalization, where the chatbot adapts its responses based on user interactions, further improving engagement and effectiveness. This adaptability suggests potential applications in broader mental health monitoring and support systems, providing valuable tools for therapists and healthcare providers.

Implications for Mental Health Support: The ability to recognize and respond to depressive symptoms in real time is pivotal for fostering meaningful interactions and support for individuals facing mental health challenges. By leveraging AI technology, we can enhance the accessibility and effectiveness of mental health interventions, thereby reducing the stigma associated with seeking help

Addressing Limitations: While this study achieved significant outcomes, challenges remain in further refining detection accuracy and understanding the nuances of emotional responses. Specifically, the questionnaire-based approach may not capture the full complexity of depressive experiences. Future research should aim to explore advanced machine learning techniques and larger, more diverse datasets to improve model performance and generalization. Additionally, integrating qualitative assessments, such as user feedback and therapy outcomes, could provide a more holistic view of the system's effectiveness.

Ethical Considerations: As mental health technologies advance, it is critical to address ethical considerations surrounding privacy, data security, and user consent. Developing transparent systems that prioritize user privacy and ethical use will be crucial for gaining public trust in these technologies. Establishing clear guidelines for data handling, user consent, and the intended use of collected information will promote responsible use and protect sensitive user data.

Interdisciplinary Collaboration: The successful implementation of this system emphasizes the importance of interdisciplinary collaboration between mental health professionals, AI developers, and ethicists. By working together, these groups can create more effective solutions that respect user dignity while promoting mental wellness. Such collaboration can also inform the design of interventions that consider the psychological implications of technology use.

Future Research Directions: Future research could explore the integration of additional support resources, such as mindfulness exercises, cognitive behavioral therapy (CBT) techniques, and community support links. Investigating the potential for longitudinal studies to assess the system's impact on users over time will provide valuable insights into its long-term effectiveness. Additionally, the incorporation of feedback mechanisms will allow users to report their experiences, further refining the system's approach to supporting mental health.

This research lays a solid foundation for further advancements in depression detection and support systems. It opens avenues for future studies that can explore additional support features, enhance real-time capabilities, and expand the applicability of technology across diverse mental health fields. By integrating extensive and varied datasets and improving algorithms, we can overcome existing limitations and foster greater emotional support in AI applications, ultimately contributing to more humane and responsive mental health solutions. As we move forward, the vision remains to create a world where mental health support is accessible, effective, and sensitive to the needs of all individuals.

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