IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 15, Issue 1, January 2026

DOI: 10.17148/IJARCCE.2026.151126

AI BASED DEPRESSION INTENSITY ANALYZER

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Abstract: This project presents a web-based AI-powered mental health analysis system designed to identify depression intensity from user-provided text. The system analyzes written content such as personal thoughts, journal entries, or social media text to detect emotional patterns and assess mental health risk levels. By applying natural language processing and machine learning techniques, the system provides an effective approach for early mental health awareness and support.

The proposed system integrates text preprocessing, emotion analysis, and a trained machine learning model within a user-friendly web application to deliver real-time analysis results. In addition to prediction, the platform offers visual dashboards, emotion breakdowns, and personalized recommendations to help users understand their mental health condition. The system also supports result storage and advisor-level summaries, making it suitable for both individual use and guided mental health assessment. This project demonstrates how AI-based text analysis can provide a scalable, reliable, and accessible solution for mental health monitoring.

Keywords: Mental Health Analysis, Depression Detection, Natural Language Processing, Machine Learning, Emotion Analysis, Web Application.

I. INTRODUCTION

With the rapid growth of digital communication and social media platforms, large amounts of textual data are generated every day in the form of messages, posts, and personal writings. Many individuals express their emotions, stress, and mental state through written content, making text a valuable source for understanding mental health conditions. However, identifying mental health issues such as depression at an early stage remains a challenge due to the lack of accessible and user-friendly analysis tools. Traditional mental health assessments often require direct clinical interaction, which may not always be feasible or timely. This project introduces a web-based AI-powered mental health analysis system designed to analyze user-provided text and estimate depression intensity using machine learning techniques. By leveraging natural language processing, the system helps in identifying emotional patterns and risk levels in written content, providing early awareness and support in a simple and non-intrusive manner.

1.1 Project Description

This project implements an AI-based depression intensity analysis system that evaluates textual input provided by users. The system allows users to enter text such as personal thoughts, journal entries, or social media content through a web interface. The input text is processed using natural language processing techniques, including preprocessing and feature extraction, before being analyzed by a trained machine learning model. Based on the analysis, the system predicts the depression intensity level and categorizes the associated risk. The web application also presents visual summaries, emotion profiles, and personalized recommendations to help users understand their mental health condition. The backend manages text processing, model execution, and result storage, while the frontend ensures an intuitive and user-friendly interaction. Overall, the project provides a practical and scalable solution for text-based mental health assessment.

1.2 Motivation

The motivation for this project arises from the growing concern over mental health issues and the increasing use of digital platforms for self-expression. Many individuals may not seek professional help due to social stigma, lack of awareness, or limited access to mental health services. An automated and text-based analysis system can act as an early support tool by identifying potential risk patterns from written content. By using machine learning and natural language processing, the system can analyze large volumes of text efficiently and provide timely insights. The goal of this project is to promote mental health awareness, encourage early intervention, and demonstrate how AI-driven solutions can support mental well-being in an accessible and user-friendly manner.

II. RELATED WORK

Paper [1] studies traditional text classification systems that use basic machine learning algorithms such as Naive Bayes and Logistic Regression. These approaches are simple to implement and perform reasonably well on structured datasets; however, they struggle to capture complex emotional patterns present in real-world text, limiting their effectiveness for mental health analysis.

Paper [2] focuses on sentiment analysis techniques applied to user-generated content such as social media posts and reviews. While sentiment-based models help identify positive and negative emotions, the study highlights that sentiment polarity alone is insufficient for accurately assessing depression intensity or mental health risk.

Paper [3] explores the use of natural language processing techniques such as tokenization, stop-word removal, and term frequency-based feature extraction for emotion detection. The results show improved classification accuracy, but the system lacks integration with a real-time web application for user interaction and result visualization.

Paper [4] investigates machine learning models for detecting mental health indicators from textual data. Although the study demonstrates promising prediction results, it relies on offline analysis and does not provide personalized feedback or recommendations for end users.

Paper [5] reviews recent AI-based mental health assessment systems and emphasizes the importance of combining text preprocessing, emotion analysis, and machine learning prediction within a single platform. The survey concludes that an integrated, web-based solution with user-friendly visualization and recommendations is essential for practical and scalable mental health support.

III. METHODOLOGY

A. System Environment

The system environment is designed to evaluate the AI-based mental health analysis system under realistic and practical usage conditions. The application operates in a web-based environment where users access the system through standard web browsers. Users interact with the platform by entering textual content such as personal thoughts, journal entries, or social media text to receive mental health analysis and depression intensity insights.

The backend environment consists of a server-side application that manages text processing, emotion analysis, machine learning prediction, and result generation. Once the user submits text input, the backend performs preprocessing and feature extraction using natural language processing techniques. The processed data is then analyzed by a trained machine learning model to predict depression intensity and associated risk levels. All processing is handled securely within the server to ensure data confidentiality.

A data storage component is used to store prediction results, analysis summaries, and model-related information in a structured format. This allows the system to maintain analysis history and support further evaluation or advisory access when required. The system environment simulates a real-world mental health assessment scenario where multiple users can interact with the application simultaneously while ensuring reliability, privacy, and consistent performance. The design supports scalability and future enhancements such as advanced models, additional analysis features, or deployment on cloud-based platforms.

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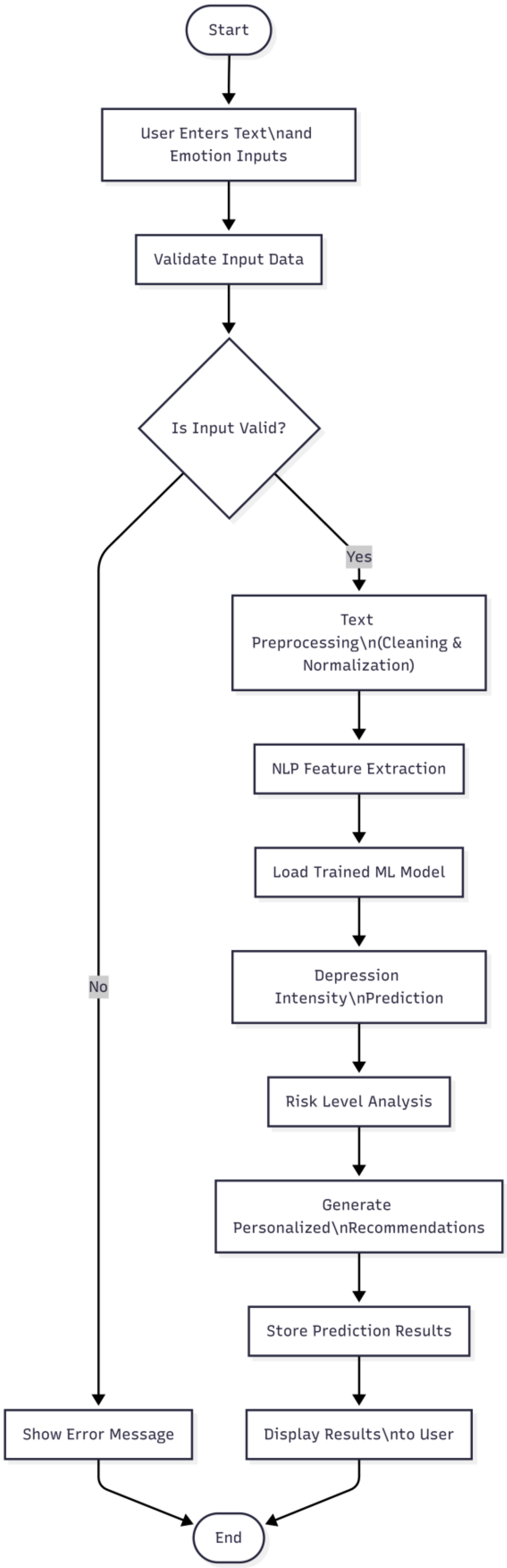

Fig.1.Flowchart of methodology

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B. System Architecture

- Client-Side Interaction:
  In the MindWell system, users interact with the application through a secure web-based interface. The client-side allows users to enter textual content such as personal thoughts, journal entries, or social media text for analysis. Basic validation is performed at the client level to ensure that the input is not empty and follows the required format before it is submitted to the backend. This improves usability and reduces unnecessary processing requests.

- Analysis Execution:
  The backend processing module receives the validated text input and performs text preprocessing operations such as cleaning and normalization. After preprocessing, natural language processing techniques are applied to extract meaningful features from the text. These features are then passed to a trained machine learning model, which analyzes the content and predicts the depression intensity and associated risk level.

C. Adaptive Analysis Mechanism

The analysis mechanism of the system is designed to be adaptive and extensible. As new datasets, improved NLP techniques, or advanced machine learning models become available, they can be integrated into the system without affecting the existing workflow. This adaptive design ensures that the system remains accurate, scalable, and effective in analyzing diverse text inputs while supporting future enhancements and performance improvements.

D. Implementation Flow

1. The user accesses the MindWell system through a web application.
2. The user enters text content for mental health analysis.
3. The system validates the input text on the client and server side.
4. The backend performs text preprocessing and normalization.
5. NLP-based feature extraction is applied to the processed text.
6. The trained machine learning model predicts depression intensity.
7. The system determines the associated risk level.
8. Personalized recommendations are generated based on the prediction.
9. The analysis results and recommendations are displayed to the user.

E. Hardware and Software Requirements

- Hardware:
  A standard computer system or laptop with a minimum of 4 GB RAM is sufficient to run the application. No specialized hardware is required, as all processing is handled efficiently on the server. Users only need a basic device with internet access to interact with the system.

- Software:
  The system uses modern and open-source technologies including Python for backend development, machine learning libraries such as Scikit-learn and NLP tools, Flask for web application development, SQLite for result storage, and HTML, CSS, and JavaScript for designing the user interface.

IV. SIMULATION AND EVALUATION FRAMEWORK

This section describes the system design, execution flow, and evaluation strategy adopted for the AI-based mental health analysis system. The framework focuses on validating the effectiveness of text processing, emotion detection, and machine learning prediction in identifying depression intensity. The system is implemented using modern web technologies with a secure backend architecture that supports natural language processing, machine learning inference, and result visualization under realistic usage scenarios.

A. System Architecture and Workflow

The overall architecture is designed to provide accurate and reliable mental health analysis while maintaining usability and scalability. The key components of the system are described below:

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- User Interaction Layer: Users interact with the system through a web-based interface where they can enter text for analysis and view mental health insights. The interface is designed to be simple and intuitive, allowing users with different technical backgrounds to use the system comfortably.

- Application Processing Layer: The backend processes user input by performing text validation, preprocessing, and feature extraction using natural language processing techniques. This layer manages data flow and coordinates interaction between different processing modules.

- Analysis and Prediction Module: This module applies a trained machine learning model to analyze the processed text and predict depression intensity along with associated risk levels. The module ensures that predictions are generated accurately before results are forwarded to visualization and recommendation components.

B. Simulation Setup

The simulation environment is designed to represent real-world usage of the mental health analysis system by users with diverse textual inputs.

- Text Analysis Simulation: Multiple test cases are created using different types of text samples, including neutral, emotional, and stress-related content, to evaluate the system's ability to handle varied input patterns.

- Scenario Testing: Various scenarios such as short text input, long text input, emotionally intense content, and neutral content are tested to ensure system robustness, consistency, and reliability.

C. Analysis and Evaluation Process

During simulation, user-provided text is processed through the complete analysis pipeline. The input undergoes preprocessing and feature extraction before being analyzed by the trained machine learning model. The predicted depression intensity and risk level are generated, stored, and displayed to the user along with suitable recommendations. This process is repeated across multiple test cases to evaluate prediction consistency, correctness, and system response time.

D. Results and Observations

- Prediction Accuracy: The system successfully identified different levels of depression intensity from varied text inputs, demonstrating effective text pattern recognition and classification.

- System Reliability: The interaction between the frontend interface, backend processing modules, machine learning model, and data storage remained stable, with minimal processing delay during simulations.

- Usability and Practicality: The evaluation confirmed that the system is easy to use and suitable for non-technical users while providing meaningful mental health insights. The overall workflow proved practical for real-world deployment as a supportive mental health analysis tool.

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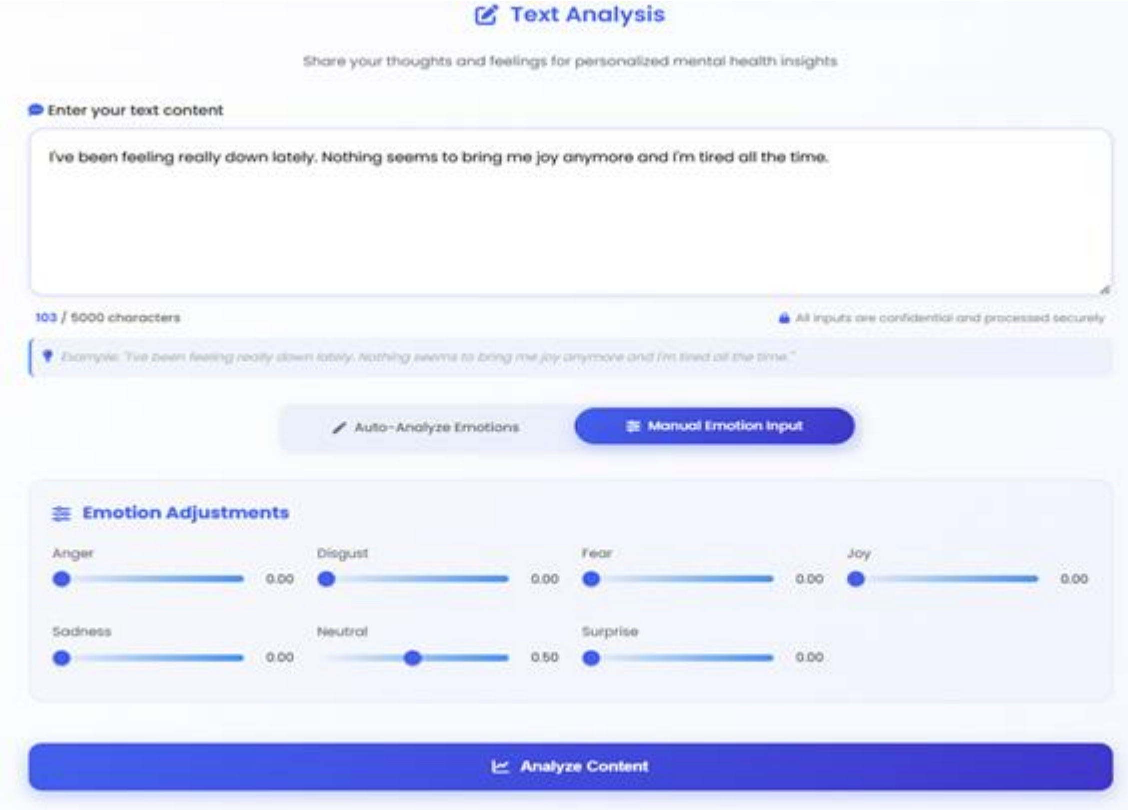

Fig. 2. Text Analysis Page

Model Performance and Adaptability Analysis

- Prediction Stability and Consistency: The machine learning model demonstrated stable and consistent performance during testing and simulation. Across repeated text analyses with similar emotional patterns, the system produced reliable depression intensity predictions, indicating dependable behavior of the analysis pipeline.

- Effectiveness of Text-Based Analysis: The prediction accuracy improved through the combined use of text preprocessing, emotion analysis, and machine learning classification. This integrated approach enabled the system to capture meaningful emotional cues from text more effectively than basic sentiment analysis methods.

- Handling of Diverse Text Inputs: The system effectively handled different types of textual content, including short and long text inputs, neutral expressions, and emotionally intense content. It adapted well to varied writing styles and emotional tones while maintaining consistent prediction quality.

- Result Transparency and Interpretation: The analysis results were clearly presented to users through intensity scores, risk levels, emotion profiles, and visual dashboards. This transparent presentation improved user understanding and trust by making the model's predictions interpretable and easy to validate.

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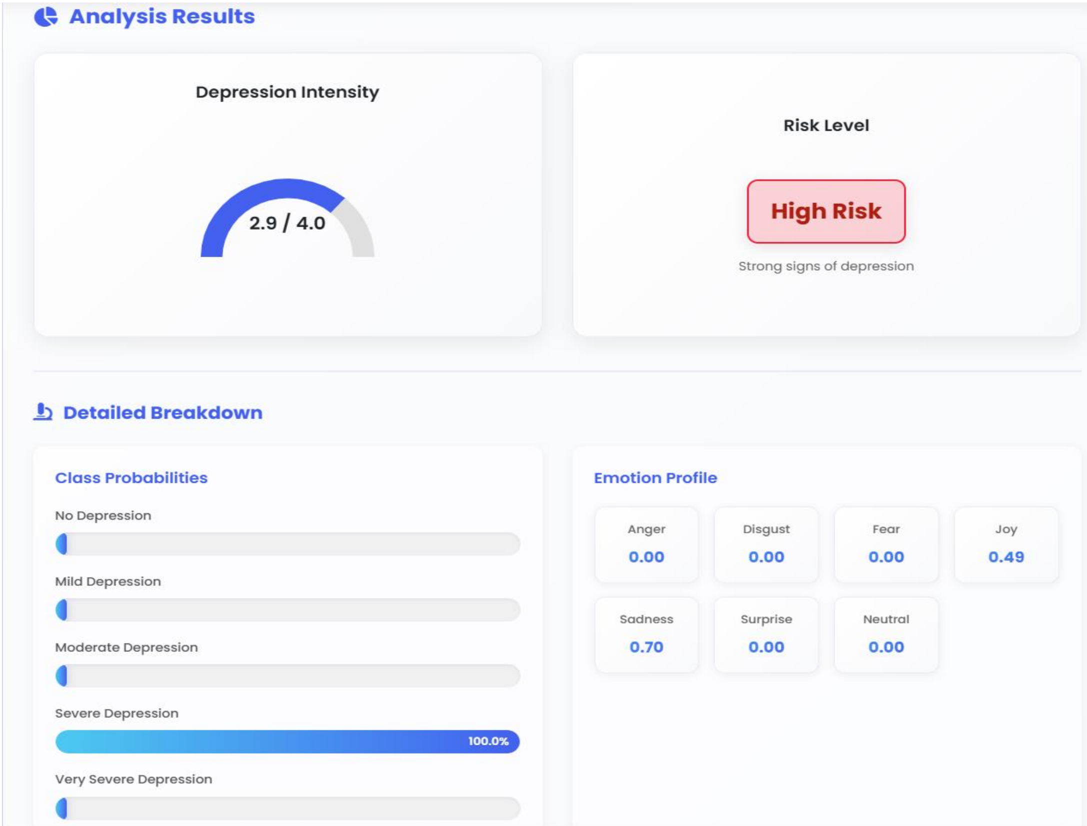

Fig. 3. Prediction Result Page

Impact on System Efficiency:

- Low Computational Overhead: The AI-based mental health analysis system operates efficiently with minimal computational overhead. Text preprocessing, feature extraction, and prediction are optimized to ensure that analysis results are generated quickly without placing excessive load on the system.

- Efficient Text Processing Pipeline: Only relevant textual features and emotional indicators are processed during analysis. This focused processing approach reduces unnecessary computations and ensures fast response times for different types of user input.

- Secure and Controlled Data Handling: User-submitted text and analysis results are processed securely within the system and stored only when required for result tracking or evaluation. This controlled data handling improves system reliability while maintaining user privacy and data confidentiality.

- Scalable Web-Based Architecture: The modular design of the backend allows the system to scale effectively as the number of users increases. The architecture supports higher usage levels without significantly affecting prediction accuracy, response time, or overall system stability.

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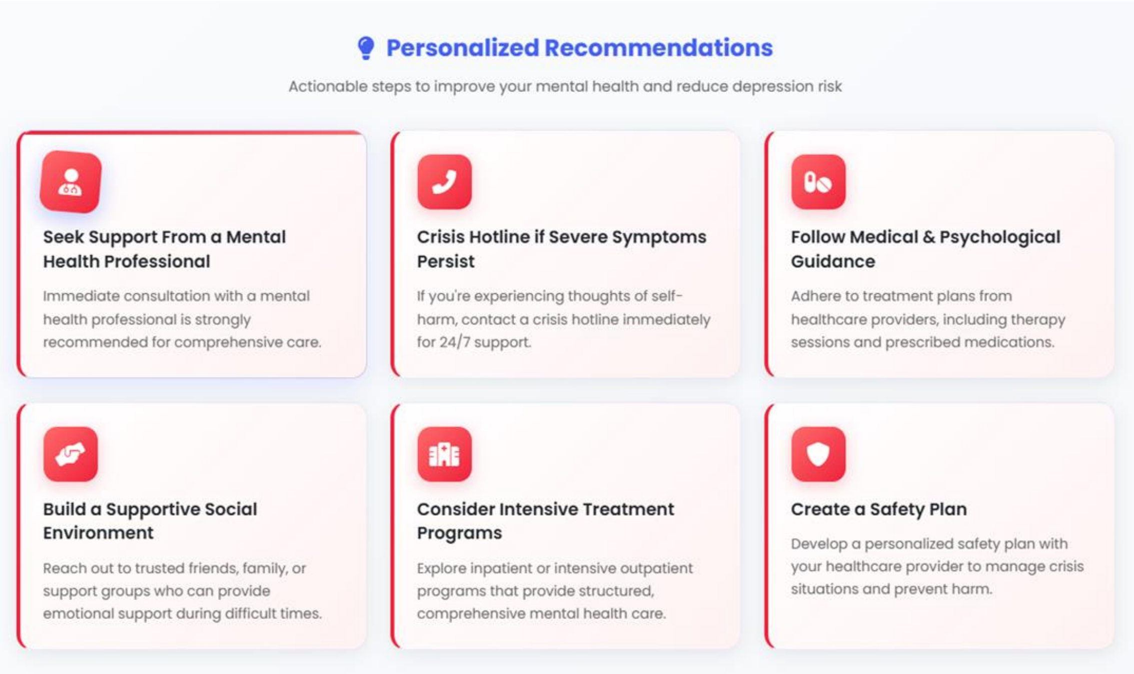

Fig. 4. Personalized Recommendations Page

V. RESULTS AND DISCUSSION

The experimental evaluation of the AI-based mental health analysis system demonstrates the effectiveness of using natural language processing and machine learning techniques to assess depression intensity from textual data. The system performed reliably during testing by accurately analyzing user-provided text and generating meaningful predictions across different emotional scenarios. This confirms that text-based analysis can serve as a useful approach for early mental health assessment.

By integrating the machine learning model within a web-based application, the system delivers real-time analysis results with minimal processing delay. The predicted depression intensity, risk level, and emotion breakdown are clearly presented to users, improving transparency and understanding of the analysis outcome. The ability to store and retrieve analysis results further supports consistent evaluation and user reference.

The evaluation also shows that the system operates efficiently with low computational overhead, as only relevant textual features are processed during analysis. Secure handling of user input and prediction results ensures privacy and data protection throughout the workflow. Overall, the results indicate that the proposed system is accurate, scalable, and user-friendly, making it suitable for real-world deployment as a supportive mental health analysis tool.

VI. CONCLUSION

This paper presented a web-based AI-driven mental health analysis system aimed at identifying depression intensity through text-based machine learning techniques. By combining natural language processing, emotion analysis, and machine learning classification within a unified web platform, the system provides an effective approach for understanding emotional patterns and assessing mental health risk from user-generated text.

The experimental evaluation demonstrated consistent prediction performance, reliable system behavior, and efficient processing across different types of textual input. The system successfully analyzed varied emotional content while maintaining low computational overhead and fast response times. The inclusion of clear result visualization, risk-level interpretation, and personalized recommendations improves transparency and enhances user understanding of the analysis outcomes.

Overall, the proposed system proves to be accurate, scalable, and user-friendly, making it suitable for real-world deployment as a supportive mental health assessment tool. The project highlights the potential of artificial intelligence

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and natural language processing in promoting mental health awareness and enabling early identification of depression-related patterns in a practical and accessible manner.

VI. FUTURE WORK

The future work of this project focuses on enhancing the AI-based mental health analysis system by incorporating more advanced natural language processing and machine learning techniques. Future improvements may include the use of deep learning models such as recurrent or transformer-based architectures to better capture contextual and temporal patterns in textual data, leading to improved prediction accuracy.

The system can also be extended by integrating data from multiple sources such as chat logs, journaling platforms, or wearable-based mental health indicators to provide more comprehensive analysis. Deploying the application on cloud infrastructure can improve scalability and allow the system to support a larger number of concurrent users. Additionally, developing a dedicated mobile application would enhance accessibility and enable users to track mental health trends over time. These enhancements aim to make the system more intelligent, scalable, and practical for real-world mental health support.

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