Archives available at journals.mriindia.com

International Journal of Advanced Scientific Research and Engineering Trends

ISSN: 2456-0774

Volume 10 Issue 03, 2026

MINDGUARD: Offline AI-Based Mental Health Assessment System with Visual Analytics and Crisis Intervention Support

[1]Manasi Mukesh Patil, [2]Dr. Ankita Karale, [3]Dr. Naresh Thoutam
[1]Student, Computer Department, Sandip Institute of Technology and Research Centre, Nashik, India
[2,3]Dr. Computer Department, Sandip Institute of Technology and Research Centre, Nashik, India
Email: [1]manasi.patil4844@gmail.com, [2]ankita.karale@sitrc.org, [3]naresh.thoutam@sitrc.org

Peer Review Information

Submission: 10 Feb 2026

Revision: 26 Feb 2026

Acceptance: 11 March 2026

Keywords

Mental Health Assessment, Natural Language Processing, Offline AI System, Emotion Detection, Depression Prediction, Crisis Intervention, Visual Analytics Dashboard, Wellness Monitoring, Text Analysis, Privacy-Preserving Systems

Abstract

Mental health issues such as stress, anxiety, and depression are increasing rapidly, yet early identification remains limited due to social stigma, lack of accessibility, and privacy concerns in existing online systems. This work presents MindGuard, an offline artificial intelligence-based system designed to analyze user-generated text and provide mental health assessment along with visual insights and crisis intervention support. The system focuses on practical usability by combining text analysis, emotion detection, wellness evaluation, and interactive dashboards within a single platform. The system operates through a structured workflow where user input is processed using natural language processing techniques to detect emotional patterns and compute a depression risk score. In addition, the platform integrates multiple assessment methods, including text-based analysis, simulated voice evaluation, facial expression input, and heart rate indicators, to provide a more comprehensive understanding of mental health conditions. A built-in crisis detection module identifies high-risk expressions and immediately provides support resources such as helpline recommendations. The implementation emphasizes a user-friendly interface with real-time dashboards, analytics panels, and interactive modules that allow users to monitor their emotional state over time. The system is designed to function entirely offline using local storage, ensuring that sensitive user data remains secure and private. Overall, MindGuard demonstrates how an AI-driven system can be transformed into a practical application with visual feedback, modular assessment tools, and immediate support mechanisms, making it suitable for academic environments, counseling centers, and offline deployment scenarios.

Introduction

Mental health has become a serious concern in modern society, affecting individuals across different age groups including students, professionals, and young adults. Issues such as stress, anxiety, and depression are increasing due to academic pressure, lifestyle changes, and constant digital exposure. Despite growing awareness, early detection of mental health conditions remains difficult because many individuals hesitate to seek professional help or openly discuss their emotions. [17]

Traditional methods of mental health assessment rely on counselling sessions, questionnaires, or clinical evaluations. While these approaches are effective, they require time, availability of trained professionals, and active participation from individuals. In many cases, especially in academic or rural environments, access to mental health experts is limited. Additionally, social stigma prevents many people from sharing their thoughts, which delays timely intervention.

With advancements in artificial intelligence and natural language processing, it has become possible to analyze human language and identify emotional patterns from text. People often express their feelings through written content such as messages, journal entries, or social media posts. These expressions can be used to understand emotional states and detect early signs of depression or distress. However, most existing systems are cloud-based and depend on internet connectivity, which raises concerns related to data privacy and reliability.[4]

To address these challenges, the MindGuard system is developed as an offline mental health assessment platform that focuses on system usability, visual analytics, and real-time interaction. The system allows users to input their thoughts and receive immediate analysis through an integrated dashboard. It combines multiple assessment methods such as text analysis, simulated voice input, facial expression indicators, and heart rate-based evaluation to provide a broader understanding of mental health conditions.[2]

A key aspect of the system is its visual and interactive design. Instead of providing only textual feedback, the system presents results through dashboards, distribution charts, and structured reports. It also includes a crisis detection mechanism that identifies high-risk expressions and provides immediate support resources. The offline architecture ensures that all data is processed and stored locally, maintaining complete confidentiality.[16]

Overall, the need for a practical, privacy-focused, and user-friendly mental health assessment system forms the foundation of this work. The proposed system aims to bridge the gap between technical capability and real-world usability by offering an accessible platform that supports early detection and timely intervention.

Objectives Of the System

The primary objective of the MindGuard system is to design a practical and user-friendly mental health assessment platform that combines artificial intelligence with visual interaction and offline processing. The system focuses on early detection, privacy, and real-time support while maintaining simplicity and usability.

The key objectives are as follows:

- To develop an AI-based text analysis system
The system aims to analyze user-entered textual content and identify emotional patterns such as sadness, stress, or anxiety using natural language processing techniques.
- To integrate emotion detection and depression risk assessment
The objective is to convert textual input into measurable outputs such as emotion categories and depression risk scores for better understanding of mental state.
- To design a complete offline framework
The system is built to function without internet connectivity, ensuring that all data processing and storage occur locally, thereby maintaining user privacy and confidentiality.
- To implement a crisis detection and intervention module
The system should identify high-risk expressions and provide immediate guidance through alerts and support resources such as helplines.
- To provide multiple assessment methods
The platform integrates different input approaches including text analysis, simulated voice input, facial expression indicators, and heart rate-based evaluation to enhance analysis coverage.
- To create an interactive analytics dashboard
The system includes visual components such as dashboards, distribution charts, and summary panels to present results in an easy-to-understand format.
- To generate structured reports for users and professionals
The objective is to produce clear and interpretable reports that summarize emotional trends, risk levels, and analysis outcomes for further review.

System Overview

The MindGuard system is designed as an integrated offline platform that enables users to assess their mental health through multiple interactive modules. The system focuses on combining artificial intelligence-based analysis with a simple and visually guided user interface, allowing users to understand their emotional state in a clear and structured manner. [3]

At a high level, the system operates as a multi-module application where each module performs a specific function, and together they form a complete assessment pipeline. The user interacts with the system through a dashboard interface that provides access to different analysis features such as text input, simulated voice evaluation, facial expression indicators, heart rate monitoring, and report generation.[10]

The workflow begins when the user provides input in any available form, primarily through text analysis. The system processes this input using natural language processing techniques to identify emotional patterns and compute a depression risk score. Along with text analysis, additional modules simulate other indicators of mental health, providing a broader and more comprehensive evaluation.

The system also includes a wellness assessment component that evaluates factors such as mood, stress, and lifestyle conditions. This ensures that the analysis is not limited to a single input but considers multiple aspects of the user's overall well-being.[5]

A key feature of the system is its visual analytics dashboard. Instead of presenting only raw results, the system displays outputs using graphical elements such as charts, summaries, and categorized indicators. This helps users easily interpret their mental health status without needing technical knowledge.

Another important part of the system is the crisis detection mechanism. When the system identifies high-risk expressions or patterns, it immediately activates a response module that provides guidance, including suggestions to contact a counselor or helpline. This ensures timely support in critical situations.[7]

All data generated during the process, including user inputs and analysis results, are stored locally using a SQLite database. This offline architecture ensures that sensitive information remains secure and eliminates dependency on internet connectivity.

Overall, the system provides a complete, user-centric environment for mental health assessment by combining analysis, visualization, and support features into a single cohesive platform.

System Architecture

The architecture of the MindGuard system is designed as a modular and layered framework that supports offline processing, multiple input methods, and visual output generation. The system ensures smooth interaction between user inputs, analytical modules, and output visualization while maintaining complete data privacy through local storage.

Layered Architecture Overview

The system is organized into three main layers:

1. Input Layer

This layer is responsible for capturing user data through different interfaces. It includes:

- Text input module for user-written expressions
- Simulated voice input module
- Facial expression indicator input
- Heart rate input simulation

These inputs provide multiple perspectives of the user's emotional and physical state.

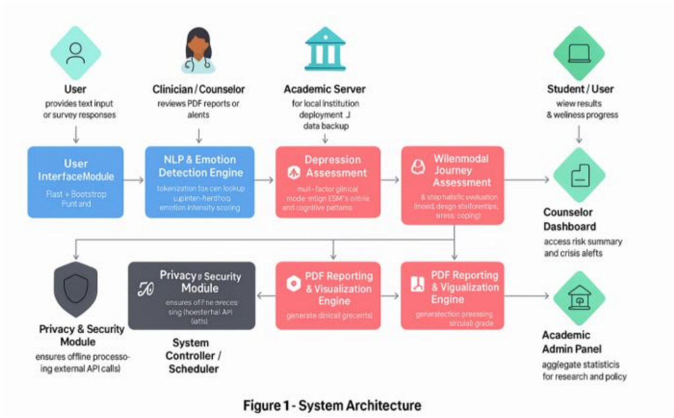

Figure 1 - System Architecture

Figure 1; System Architecture

2. Processing and Analysis Layer

This is the core layer where all computations and decision-making take place. It consists of several interconnected modules:

- Pre-processing Module:

Cleans and prepares input data by removing noise, normalizing text, and converting it into structured format.

- Emotion Detection Module:

Analyzes textual input using lexicon-based techniques to identify emotional categories such as sadness, stress, or neutral state.

- Depression Risk Assessment Module:

Computes a numerical risk score based on emotional intensity and frequency.

- Wellness Evaluation Module:

Incorporates user responses related to sleep, stress, and lifestyle to enhance the assessment.

- Crisis Detection Module:

Monitors for high-risk expressions and triggers alerts when critical conditions are detected.

All modules operate sequentially and share intermediate results to produce a final decision.

3. Output and Visualization Layer

This layer presents the results in an understandable and interactive format:

- Dashboard displaying emotional trends and summaries
- Risk level indicators and categorized outputs
- Visual charts representing data distribution
- Report generation module for structured output

The system ensures that results are not only accurate but also easy to interpret.

Data Flow and Interaction

The data flow follows a linear yet interconnected pipeline:

User Input → Pre-processing → Emotion Detection → Risk Scoring → Wellness Evaluation → Crisis Detection → Visualization & Report Generation
Each module passes processed information to the next stage, ensuring continuity and consistency in analysis.

Storage Architecture
The system uses a local SQLite database for storing:
- User input data
- Processed tokens and intermediate results
- Final analysis outputs
- Generated reports

This ensures:
- Complete data privacy
- No dependency on cloud storage
- Secure and controlled data access

Key Architectural Features
- Offline Functionality: Entire system runs without internet connectivity
- Modular Design: Each module can be updated independently
- Real-Time Processing: Immediate response after input submission
- Scalability: Can be extended with additional input modules in future
- Privacy Preservation: No external data transmission

Architectural Significance
The architecture ensures that the system remains:
- Lightweight and efficient
- Easy to deploy in academic or low-resource environments
- Capable of handling multiple input types
- Reliable for real-time mental health assessment

By combining structured data flow, modular processing, and visual output, the system provides a balanced design that supports both functionality and usability.

Methodology
The working of the MindGuard system follows a structured and sequential workflow that transforms raw user input into meaningful mental health insights. The methodology focuses on clarity, modular execution, and real-time processing while maintaining simplicity and offline operation.

Step-by-Step Workflow
Step 1: User Interaction and Input
The process begins when the user interacts with the system through the dashboard interface. The user can provide input in different forms such as text entry, simulated voice, or other available modules. The primary analysis is performed on textual input describing the user's emotional state.
Step 2: Data Pre-processing
The input text is cleaned and normalized to remove unnecessary elements. This includes:
- Converting text to lowercase
- Removing special characters and punctuation
- Breaking text into tokens
- Filtering out irrelevant words

This step ensures that the input is structured for accurate analysis.
Step 3: Emotion Detection
The processed tokens are compared with a predefined emotion lexicon. Based on matching words and their intensity, the system identifies emotional categories such as sadness, stress, or neutral state. The output is an emotional profile representing the user's current condition.
Step 4: Depression Risk Evaluation
Using the detected emotional patterns, the system calculates a depression risk score. The score reflects the severity of emotional distress and is categorized into levels such as low, medium, or high. This allows the system to quantify the mental state rather than only describing it.
Step 5: Wellness Assessment Integration
The system incorporates additional inputs related to lifestyle factors. These include:
- Sleep quality
- Stress level
- Mood consistency
- Social support
- Coping mechanisms

These parameters are combined with the emotion analysis to improve the overall reliability of the assessment.
Step 6: Crisis Detection Mechanism
The system continuously checks for critical expressions that indicate severe distress. If such patterns are detected:
- The system marks the condition as critical
- An alert is generated
- Immediate guidance or support suggestions are provided

This ensures that urgent situations are handled without delay.
Step 7: Result Generation and Visualization
After processing all inputs, the system generates:
- Emotion classification

- Depression risk level
- Wellness summary
- Crisis alerts (if applicable)

The results are displayed through dashboards and visual panels for easy understanding.

Step 8: Data Storage and Reporting

All results are stored locally in the SQLite database. The system also generates structured reports that can be reviewed later or shared with professionals if required.

Workflow Characteristics

- The process is fully offline and independent of external systems
- Each module operates in a defined sequence ensuring consistency
- The workflow supports real-time analysis and response
- Multiple input factors improve the reliability of results

Overall Flow Summary

User Input → Pre-processing → Emotion Detection → Risk Evaluation → Wellness Integration → Crisis Detection → Visualization → Storage

This methodology ensures that the system remains simple, efficient, and user-friendly while still providing meaningful mental health insights through a structured workflow.

System Implementation

The implementation of the MindGuard system focuses on providing a user-friendly interface with multiple interactive modules that allow users to perform mental health assessment through different input methods. The system is designed to guide the user step-by-step, starting from input selection to final result visualization. The implementation emphasizes usability, clarity, and real-time feedback through visual components.

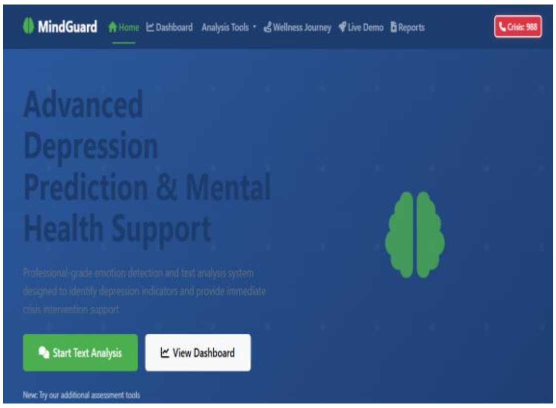

Figure 2: Dashboard Interface

The dashboard acts as the central entry point of the system where users can access all available modules such as text analysis, facial expression input, voice input, heart rate monitoring, and report generation.

It provides a clean and organized layout that helps users easily navigate through different functionalities.

This screen is important because it integrates all features into a single interface, improving usability and user experience.

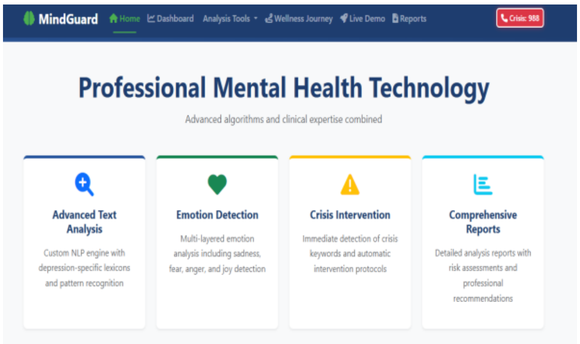

Figure 3: Text Analysis Input Module

This screen allows the user to enter their thoughts or feelings in textual form.

Once the input is submitted, the system processes the text using natural language processing techniques to detect emotions and calculate a depression risk score.

This module is the core component of the system as it directly captures user expressions for analysis.

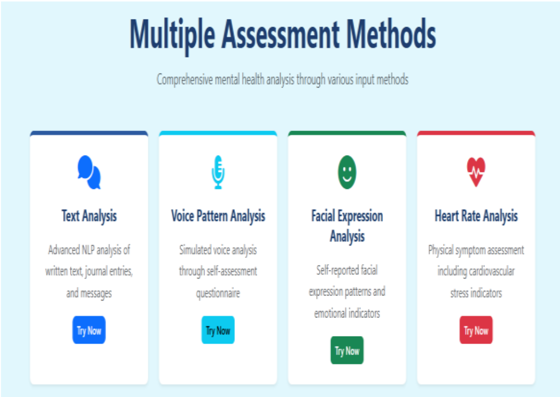

Figure 4: Facial Expression Analysis Module

In this module, users can simulate facial expressions as an additional input method.

The system interprets these expressions to estimate emotional states, which complements the text-based analysis.

This module enhances the system by providing a multimodal approach to mental health assessment.

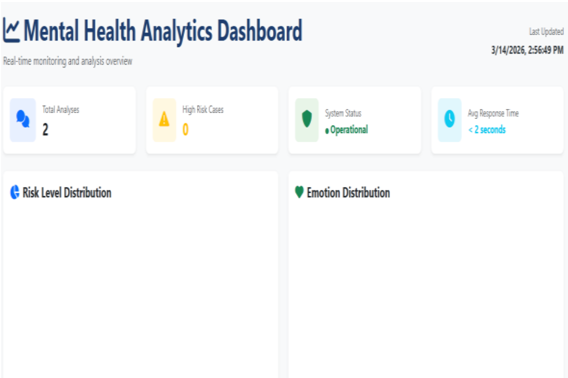

Figure 5: Voice Analysis Module

The voice analysis interface allows users to simulate speech-based input.
The system evaluates patterns in the input to infer emotional indicators related to tone and expression.
This feature improves interaction flexibility and supports users who prefer speaking instead of typing.

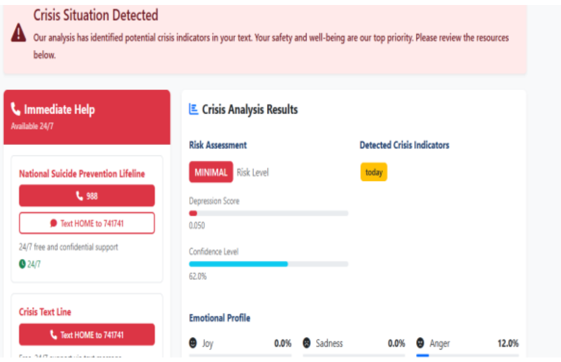

Figure 6: Heart Rate Monitoring Module

This module represents physiological input where heart rate values are used as an indicator of stress or anxiety levels.
The system uses this data to strengthen the assessment by combining emotional and physical indicators.
It adds another dimension to the analysis, making the evaluation more comprehensive.

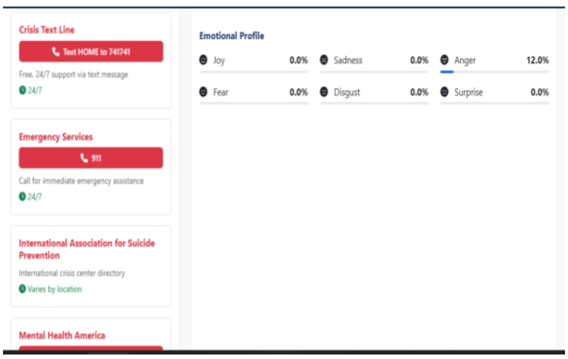

Figure 7: Analytics Dashboard / Results Visualization

This screen displays the results of the analysis using charts, summaries, and categorized indicators.
Users can view their emotional distribution, risk levels, and overall assessment in a graphical format.
This visualization helps users quickly understand their mental health status without technical complexity.

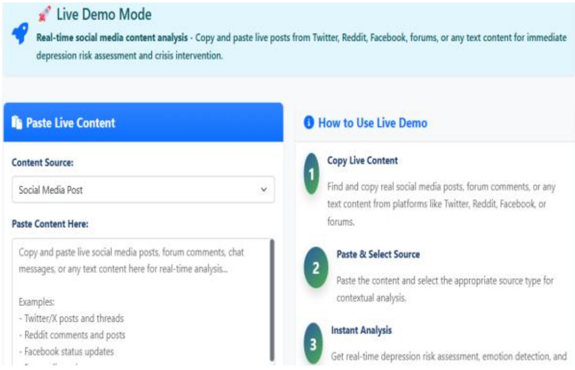

Figure 8: Report Generation Interface

The system provides a report generation feature where users can generate structured summaries of their assessment.
These reports include emotional analysis, risk evaluation, and recommendations.
This is important for academic or clinical use, as it allows results to be documented and reviewed later.

Implementation Highlights

- The system is designed with a modular interface where each feature is accessible independently
- All modules are interconnected through a centralized workflow
- Real-time processing ensures immediate feedback after user input
- Visual representation improves interpretability of results
- Offline storage ensures data privacy and secure handling

Overall Implementation Flow

User selects module → Provides input → System processes data → Results are visualized → Report is generated
The implementation successfully transforms the conceptual model into a practical application by combining multiple input methods, interactive dashboards, and structured output generation within a single platform.

Discussion

The developed MindGuard system demonstrates how a mental health assessment platform can be designed with a strong focus on usability, privacy, and real-time interaction. Unlike traditional systems that rely heavily on clinical processes or online services, this implementation provides a self-contained environment where users can interact freely and receive immediate feedback.

One of the key strengths of the system lies in its offline architecture. By eliminating the need for internet connectivity, the system ensures uninterrupted operation and complete data confidentiality. This makes it particularly useful in environments such as educational institutions, remote areas, or situations where privacy is a major concern. Users can express their thoughts without fear of data exposure, which encourages more honest input and improves the quality of analysis.

Another important aspect is the multi-modal input design. The system does not depend on a single source of data but integrates text, simulated voice, facial indicators, and physiological signals such as heart rate. This combination allows a broader understanding of the user's condition. Even if one input method is limited, other modules help maintain the overall reliability of the assessment.

The visual analytics dashboard plays a crucial role in improving user experience. Instead of presenting complex data in textual form, the system uses charts, summaries, and categorized outputs. This makes it easier for users to interpret their mental health status quickly. The structured visualization also supports academic and clinical use, where clear representation of results is necessary.

The crisis detection capability enhances the practical value of the system. By identifying high-risk expressions and triggering immediate guidance, the system moves beyond simple analysis and provides actionable support. This feature is especially important for early intervention and can help reduce the delay in seeking professional help.

From an implementation perspective, the system maintains a modular design, allowing each component to function independently while still contributing to the overall workflow. This makes the system flexible and easy to extend in the future. Additional modules or improvements can be integrated without affecting the core structure.

However, the system also has certain limitations. Since it relies on predefined lexicon-based methods and simulated inputs for some modules, the depth of analysis may be limited compared to advanced machine learning or real sensor-based systems. Additionally, the system is currently designed as a prototype, and further validation in real-world scenarios would be required to evaluate its effectiveness at a larger scale.

Overall, the system provides a balanced approach by combining technical functionality with practical usability. It successfully demonstrates how mental health assessment tools can be designed to be accessible, private, and interactive while still maintaining meaningful analytical capability.

Conclusion

The MindGuard system presents a practical approach to mental health assessment by combining artificial intelligence techniques with an interactive and offline application design. The system successfully transforms user input into meaningful insights through emotion detection, depression risk evaluation, wellness assessment, and crisis detection within a single platform.

A key contribution of this work is the integration of multiple modules into a unified and easy-to-use interface. The system not only performs analysis but also presents results through visual dashboards and structured reports, making it accessible for both general users and academic environments. The inclusion of multiple input methods further enhances the flexibility and usability of the platform.

The offline architecture plays an important role in ensuring data privacy and system reliability. By storing all data locally and avoiding cloud dependency, the system addresses one of the major concerns associated with mental health applications. This design also enables deployment in environments with limited connectivity, expanding the reach of such tools.

The implementation demonstrates that a lightweight, modular system can effectively provide real-time feedback and support without requiring complex infrastructure. The crisis detection feature adds practical value by enabling timely intervention in high-risk situations.

In summary, the system offers a user-centric solution that balances technical capability with real-world applicability. It highlights how mental health assessment tools can be made more accessible, secure, and visually interpretable through thoughtful system design and implementation.

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