

AI-Powered Mental Health Monitoring and Recommendation System

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Abstract—Mental health is an essential part of a person's overall well-being, but in today's fast-paced and stressful lifestyle, many individuals face emotional problems such as stress, anxiety, sadness, and mood fluctuations. Due to lack of awareness, busy schedules, and limited access to mental health support, these issues often go unnoticed and untreated. The AI-Powered Mental Health Monitoring and Recommendation System is a web-based application developed to help users monitor and improve their emotional well-being using Artificial Intelligence and Machine Learning techniques. The system interacts with users through dynamically generated daily questions using the Gemini API, allowing users to express their thoughts, feelings, and daily experiences. The collected responses are processed using Natural Language Processing (NLP) techniques such as tokenization, stopword removal, lowercase conversion, and TF-IDF feature extraction. A trained Machine Learning model then analyzes the processed text and predicts the emotional state of the user, such as Happy, Sad, Stressed, or Relaxed. Based on the predicted emotion, the system provides personalized video recommendations including motivational, meditation, relaxation, and entertainment content to support emotional improvement and mental wellness. The application also stores user responses, predicted emotions, and timestamps in a database, enabling users to view their emotional history and track mood patterns over time. Additionally, graphical visualizations are generated to help users understand emotional trends and identify changes in their mental condition. Developed using Flask, Python, Machine Learning, and AI technologies, the proposed system offers a simple, interactive, and user-friendly platform that promotes mental health awareness, self-monitoring, and emotional self-care through intelligent analysis and personalized recommendations.

Index Terms—Artificial Intelligence (AI), Machine Learning (ML), Mental Health Monitoring, Natural Language Processing (NLP), Emotion Detection,

Recommendation System, Gemini API, Flask Web Application.

I. INTRODUCTION

Mental health is one of the most important aspects of human well-being and plays a significant role in maintaining a healthy and productive lifestyle. In recent years, the number of people experiencing mental health issues such as stress, anxiety, depression, emotional instability, and mood disorders has increased considerably. Academic pressure, work-related stress, social isolation, financial challenges, and personal responsibilities are some of the major factors that affect an individual's emotional health. Unfortunately, many people ignore their mental well-being due to lack of awareness, social stigma, limited access to professional support, and high treatment costs. As a result, emotional problems often remain unnoticed and may negatively impact both personal and professional life [1].

With the rapid advancement of Artificial Intelligence (AI) and Machine Learning (ML), intelligent systems are increasingly being used in healthcare applications to assist users in monitoring and improving their health conditions. Natural Language Processing (NLP), a branch of AI, enables computers to understand and analyze human language. NLP techniques have been widely applied in sentiment analysis, emotion detection, virtual assistants, and healthcare monitoring systems. These technologies provide an opportunity to develop automated systems capable of identifying emotional states from user-generated text and offering appropriate support based on the detected emotions [2].

Emotion detection through textual analysis has become an active research area in recent years.

Researchers have demonstrated that machine learning algorithms can effectively classify emotions by analyzing patterns in written text. Various NLP techniques such as tokenization, stopword removal, stemming, and feature extraction methods like TF-IDF have significantly improved the accuracy of text classification systems. Modern AI models are capable of understanding human emotions and sentiments with high efficiency, making them suitable for applications related to mental health monitoring and emotional well-being assessment [3].

The proposed AI-Powered Mental Health Monitoring and Recommendation System aims to provide an intelligent and user-friendly platform for monitoring emotional health. The system interacts with users through dynamically generated daily questions using the Gemini API. Unlike traditional systems that rely on fixed questionnaires, the proposed solution generates unique and engaging questions that encourage users to share their thoughts, feelings, and daily experiences more naturally. The collected responses are processed using NLP techniques and analyzed using a Machine Learning model to predict emotions such as Happy, Sad, Stressed, and Relaxed. This approach enables continuous emotional monitoring and helps users become more aware of their mental condition [4].

In addition to emotion prediction, the system provides personalized video recommendations based on the detected emotional state. For example, users experiencing stress may receive meditation or relaxation videos, while users feeling sad may be provided with motivational content. The system also stores emotional history and generates graphical visualizations that allow users to track mood trends over time. By combining Artificial Intelligence, Machine Learning, NLP, recommendation systems, and web technologies, the proposed application offers a practical solution for promoting mental health awareness and emotional self-care. The project demonstrates how modern AI technologies can be utilized to create supportive systems that encourage users to maintain a balanced and healthy lifestyle [5].

II. LITERATURE REVIEW

Mental health monitoring and emotion detection have become important research areas due to the increasing prevalence of stress, anxiety, depression, and other

emotional disorders. Researchers have explored various Artificial Intelligence (AI), Machine Learning (ML), and Natural Language Processing (NLP) techniques to analyze human emotions and provide intelligent support systems. Several studies have demonstrated that computational methods can effectively identify emotional states from textual, speech, and behavioral data, making them useful for healthcare and mental health applications.

Calvo and D'Mello presented a comprehensive review of affect detection systems and discussed how emotions can be recognized using different computational approaches. Their study highlighted the importance of emotion-aware systems in healthcare, education, and human-computer interaction. The authors emphasized that emotion detection technologies can improve user experiences and provide better support for individuals facing emotional difficulties. Their research established a strong foundation for the development of AI-based mental health monitoring systems [6].

Devlin et al. introduced the BERT (Bidirectional Encoder Representations from Transformers) model, which significantly improved natural language understanding and text classification performance. BERT utilizes deep learning and transformer architecture to understand contextual relationships between words more effectively than traditional NLP models. The success of BERT demonstrated the potential of advanced NLP techniques in emotion detection, sentiment analysis, and mental health applications. This work inspired many modern text-based emotion recognition systems [7].

Mohammad and Turney developed an emotion lexicon that associates words and phrases with specific emotional categories. Their research showed that textual content contains strong emotional indicators and that specific words can effectively represent emotions such as happiness, sadness, anger, fear, and trust. The emotion lexicon created by their study has been widely used in sentiment analysis and emotion detection applications. Their findings support the use of text-based analysis for understanding users' emotional conditions [8].

Hasan et al. investigated sentiment analysis using various Machine Learning approaches and demonstrated how algorithms can classify emotions from textual data. Their study focused on preprocessing techniques and feature extraction

methods such as TF-IDF and Bag-of-Words. The results showed that proper preprocessing significantly improves classification accuracy and overall system performance. Their work provides valuable guidance for implementing machine learning-based emotion prediction models in mental health monitoring systems [9].

Nguyen et al. conducted a detailed review of emotion recognition techniques using Machine Learning algorithms such as Support Vector Machines (SVM), Naive Bayes, Decision Trees, and Neural Networks. The study concluded that machine learning methods can accurately classify emotions when combined with effective NLP preprocessing techniques. The researchers highlighted the importance of selecting suitable algorithms and datasets to achieve reliable emotion prediction results. Their findings support the use of Machine Learning for automated mental health assessment and emotional analysis [10].

III. KEY FINDINGS

The literature survey and system implementation provide several important findings regarding the use of Artificial Intelligence, Machine Learning, and Natural Language Processing in mental health monitoring applications. The following key findings were observed during the study and development of the proposed system.

A. Artificial Intelligence Improves Mental Health Monitoring

Artificial Intelligence has shown significant potential in analyzing human emotions and supporting mental health-related applications. AI-based systems can process large amounts of user data and identify emotional patterns efficiently. Research studies indicate that AI can provide timely emotional support and improve user awareness regarding mental well-being. This makes AI a valuable technology for developing intelligent healthcare solutions [11].

B. Natural Language Processing Enables Effective Emotion Detection

Natural Language Processing plays a crucial role in understanding and analyzing textual data provided by users. Techniques such as tokenization, stopword removal, text normalization, and feature extraction help convert raw text into meaningful information.

Studies have shown that NLP techniques can successfully identify emotional indicators from user responses, making text-based emotion detection practical and reliable [12].

C. Machine Learning Models Provide Accurate Emotion Classification

Machine Learning algorithms have demonstrated strong performance in emotion prediction tasks. Various classification techniques can effectively categorize emotions such as Happy, Sad, Stressed, and Relaxed based on textual input. Proper preprocessing and feature extraction significantly improve prediction accuracy. The research findings suggest that Machine Learning can be successfully applied to automate emotional analysis and support mental health monitoring systems [13].

D. Dynamic Question Generation Enhances User Engagement

Traditional systems often use fixed questionnaires, which may become repetitive and reduce user interest. Dynamic question generation using AI-based services such as the Gemini API creates more interactive and engaging conversations. This approach encourages users to provide meaningful responses and improves the quality of collected emotional data. Better user engagement leads to more accurate emotion prediction results [14].

E. Personalized Recommendations Improve User Experience

Providing recommendations based on the user's emotional state increases the usefulness of the system. Research indicates that personalized content such as motivational videos, meditation sessions, relaxation exercises, and entertainment resources can positively influence a user's mood. Recommendation systems help transform emotion detection results into practical support mechanisms, making the application more beneficial for users [15].

F. Emotional History Tracking Supports Self-Awareness

Maintaining records of user responses and emotional states over time helps users understand their emotional patterns. Historical data allows individuals to identify recurring stress factors, mood fluctuations, and behavioral trends. This promotes self-awareness and

enables users to take proactive steps toward improving their mental health.

G. Data Visualization Simplifies Mood Analysis

Graphical visualization of emotional trends helps users easily interpret their mental health status. Daily, weekly, and monthly mood charts provide clear insights into emotional changes over time. Visual analysis makes emotional data more understandable and supports informed decision-making regarding personal well-being.

H. Integrated Systems Provide Better Mental Health Support

The study found that combining AI, NLP, Machine Learning, recommendation systems, and visualization tools within a single platform provides a more comprehensive solution than standalone emotion detection systems. An integrated approach improves functionality, user engagement, and overall effectiveness in supporting emotional well-being.

I. Future Scope for Advanced Mental Health Applications

The findings suggest that future systems can be enhanced by incorporating advanced deep learning models, voice-based emotion recognition, facial expression analysis, chatbot support, and personalized mental health counseling features. Such improvements can further increase prediction accuracy and user support capabilities.

IV. PROPOSED SYSTEM ARCHITECTURE

The proposed AI-Powered Mental Health Monitoring and Recommendation System is designed as a web-based platform that integrates Artificial Intelligence, Machine Learning, Natural Language Processing, database management, and recommendation technologies to monitor and improve users' emotional well-being. The system follows a modular architecture where each component performs a specific task and communicates with other modules to provide accurate emotion prediction and personalized recommendations. The architecture is designed to ensure smooth data flow, efficient processing, secure data storage, and an interactive user experience. The overall architecture consists of several layers, including the User Interface Layer, Gemini API

Integration Layer, Data Collection Layer, NLP Processing Layer, Feature Extraction Layer, Machine Learning Prediction Layer, Recommendation Layer, Database Layer, Visualization Layer, and Dashboard Layer. These components work together to analyze user responses and generate meaningful outputs [16].

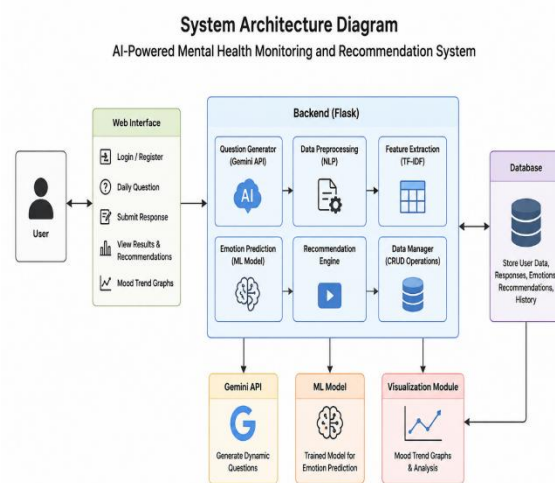


Fig 1. System Architecture Diagram

A. User Interface Layer

The User Interface Layer serves as the interaction point between the user and the system. It is developed using HTML, CSS, JavaScript, and Flask templates. Through this interface, users can register, log in, answer daily questions, view predicted emotions, access recommendations, and monitor their emotional history. A simple and user-friendly interface encourages regular user participation and improves overall usability [17].

B. Gemini API Integration Layer

This layer is responsible for generating dynamic daily questions related to emotional well-being. Instead of presenting fixed questionnaires, the Gemini API generates unique and engaging questions every day. Dynamic questioning helps collect more meaningful user responses and improves user engagement. The API communicates with the Flask backend and delivers AI-generated questions to users in real time [18].

C. Data Collection Layer

The Data Collection Layer receives responses submitted by users through the web interface. These

responses contain valuable emotional information that forms the basis for further analysis. The module validates the input data and forwards it to the preprocessing stage while ensuring data consistency and reliability.

D. NLP Processing Layer

The Natural Language Processing Layer prepares raw textual responses for machine learning analysis. Since user responses may contain unnecessary words, punctuation, and inconsistencies, preprocessing is required to improve data quality.

The preprocessing steps include:

1. Lowercase Conversion
2. Stopword Removal
3. Punctuation Removal
4. Tokenization
5. Text Cleaning

These techniques help transform unstructured text into a format suitable for emotion prediction and improve the overall performance of the Machine Learning model [19].

E. Feature Extraction Layer

After preprocessing, the cleaned text is converted into numerical representations using TF-IDF (Term Frequency–Inverse Document Frequency). Machine Learning algorithms cannot directly process textual data; therefore, feature extraction converts user responses into numerical feature vectors. TF-IDF helps identify important words and assigns weights based on their significance within the text dataset.

F. Machine Learning Prediction Layer

The Machine Learning Prediction Layer is the core component of the system. The extracted features are provided to a trained Machine Learning model that analyzes the text and predicts the user's emotional state. The model classifies emotions into categories such as:

1. Happy
2. Sad
3. Stressed
4. Relaxed

The prediction results provide insights into the user's current emotional condition and form the basis for personalized recommendations [20].

G. Recommendation Layer

The Recommendation Layer generates suitable content based on the predicted emotion. The system maps emotional categories to different types of supportive videos and resources.

Examples include:

1. Happy → Entertainment Videos
2. Sad → Motivational Videos
3. Stressed → Meditation and Relaxation Videos
4. Relaxed → Wellness and Lifestyle Content

This module helps users improve or maintain their emotional well-being by providing relevant recommendations immediately after emotion detection.

H. Database Layer

The Database Layer stores all important information generated by the system. The database maintains:

1. User Registration Details
2. Login Credentials
3. Daily Responses
4. Predicted Emotions
5. Recommendation History
6. Date and Time Records

SQLite or MySQL databases can be used to ensure efficient storage, retrieval, and management of user data.

I. Visualization Layer

The Visualization Layer generates graphical representations of emotional trends. Mood tracking graphs allow users to monitor emotional changes over time and identify patterns in their behavior.

The system provides:

1. Daily Mood Analysis
2. Weekly Emotional Trends
3. Monthly Mood Reports

Visual representation of emotional data improves self-awareness and helps users understand their mental health more effectively.

J. Dashboard Layer

The Dashboard Layer acts as the central control panel of the application. It combines outputs from all modules and presents them in an organized manner. The dashboard displays:

1. Current Predicted Emotion
2. Daily Questions
3. Personalized Recommendations

4. Emotional History
5. Mood Trend Graphs

This layer provides users with a complete overview of their emotional well-being and system activities through a single interface.

V. RESULT AND DISCUSSION

The AI-Powered Mental Health Monitoring and Recommendation System was successfully developed and tested to evaluate its functionality, usability, emotion prediction capability, recommendation generation, and emotional history tracking. The system integrates Artificial Intelligence, Machine Learning, Natural Language Processing, and web technologies to provide an intelligent platform for mental health monitoring.

A. Home Page

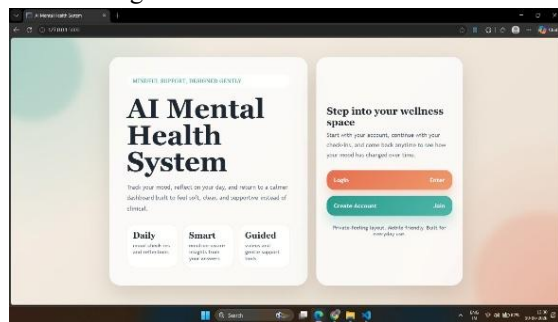


Figure 2. Home Page of AI Mental Health System

The home page serves as the entry point of the application. It provides users with options to log in or create a new account. The page introduces the major features of the system, including daily mood check-ins, emotion-aware insights, and personalized support recommendations. The clean and user-friendly interface encourages users to interact with the platform regularly.

B. User Dashboard

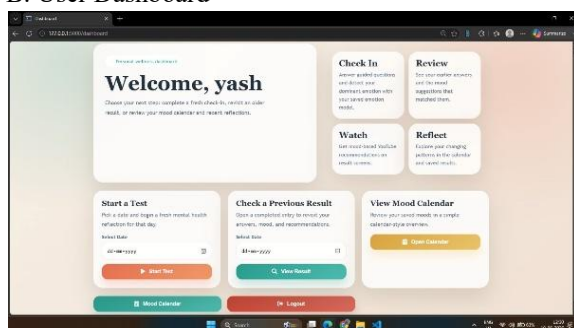


Figure 3. User Dashboard

After successful login, users are redirected to the dashboard. The dashboard acts as the central control panel of the application. It allows users to:

1. Start a new mental health assessment.
2. View previous emotional records.
3. Access mood calendar history.
4. Review emotional trends.

The dashboard provides quick navigation to all major functionalities of the system.

C. Mental Health Assessment Interface

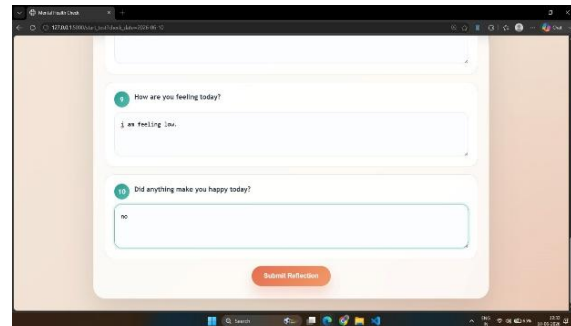


Figure 4. Mental Health Assessment Form

The assessment page displays dynamically generated questions related to the user's emotional well-being. Users provide text-based responses describing their feelings, experiences, and daily activities. These responses are collected and forwarded to the Machine Learning module for analysis. The interface is designed to make users comfortable while sharing their emotions.

D. Emotion Prediction Result

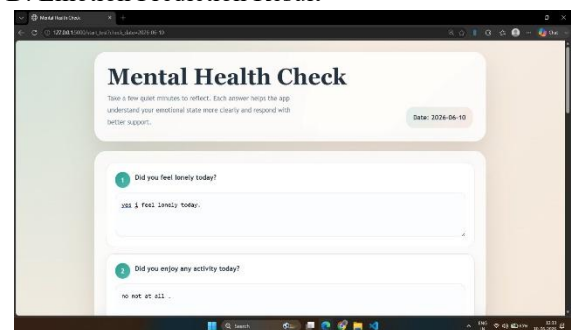


Figure 5. Emotion Prediction and Recommendation Screen

After submitting responses, the system performs text preprocessing, feature extraction, and emotion prediction. The detected emotion is displayed on the result page. In the example shown, the system successfully identified the user's mood as Sad. A supportive suggestion is also displayed to provide emotional guidance. The recommendation module

further suggests motivational and emotional support videos that may help improve the user's mood and mental state.

E. Personalized Video Recommendations

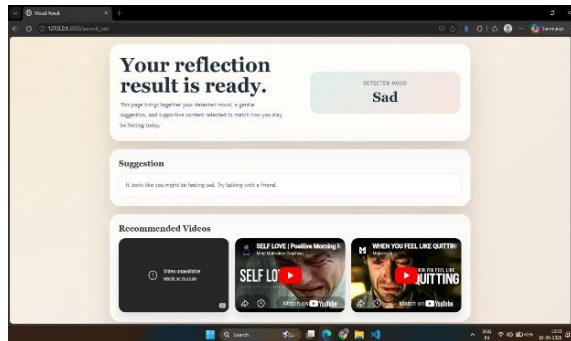


Figure 6. Recommended Videos Based on Emotion

The recommendation system provides emotion-based video suggestions. Depending on the predicted emotional state, users receive appropriate content such as:

1. Motivational videos
2. Meditation videos
3. Relaxation content
4. Entertainment videos

This feature transforms emotion detection results into practical emotional support.

F. Mood Calendar

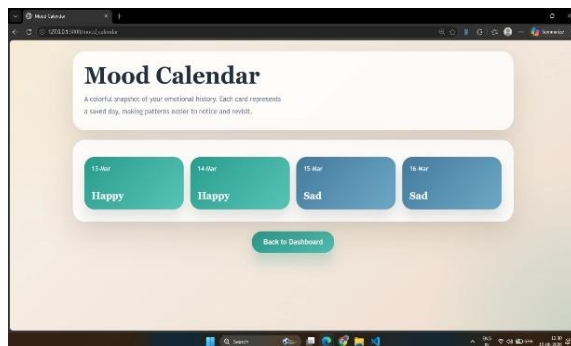


Figure 7. Mood Calendar View

The Mood Calendar stores historical emotional records and displays them in a calendar-style layout. Each entry represents a previously completed assessment along with its detected emotion. Users can quickly review their emotional history and identify recurring emotional patterns.

This feature helps improve self-awareness and long-term emotional monitoring.

G. Overall System Performance

The developed system successfully achieved its intended objectives:

1. Dynamic question generation using Gemini API.
2. Emotion prediction using Machine Learning.
3. Personalized recommendation generation.
4. Emotional history storage.
5. Mood trend tracking.
6. User-friendly interface.

The integration of Artificial Intelligence, Machine Learning, Natural Language Processing, and web technologies resulted in an efficient and practical mental health support platform.

VI. DISCUSSION

The experimental results indicate that the system can effectively analyze user responses and classify emotional states. The use of NLP preprocessing and TF-IDF feature extraction improved prediction quality. Dynamic question generation enhanced user engagement, while recommendation and visualization features increased the practical usefulness of the application. Overall, the proposed system provides a reliable foundation for intelligent mental health monitoring and can be further enhanced with advanced deep learning techniques and multimodal emotion recognition [25].

VII. FUTURE SCOPE

The AI-Powered Mental Health Monitoring and Recommendation System provides an effective platform for monitoring emotional well-being using Artificial Intelligence, Machine Learning, and Natural Language Processing techniques. Although the current system successfully predicts emotions and provides personalized recommendations, there are several opportunities for future enhancement and expansion. Future improvements can increase prediction accuracy, user engagement, system intelligence, and overall effectiveness in supporting mental health management.

A. Advanced Deep Learning Models

The current system uses Machine Learning techniques for emotion prediction. In the future, advanced deep learning models such as BERT, RoBERTa, LSTM, and Transformer-based architectures can be implemented to improve emotion detection accuracy. These models can better understand the context and

meaning of user responses, leading to more reliable emotional analysis.

B. Voice-Based Emotion Recognition

The existing system analyzes only textual input provided by users. Future versions can incorporate voice-based emotion recognition, where the system analyzes speech patterns, tone, pitch, and voice modulation to identify emotional states. This feature would provide a more natural and convenient user experience.

C. Facial Expression Analysis

Human emotions can also be identified through facial expressions. Future enhancements may include computer vision techniques that analyze facial features using webcams or mobile cameras. Combining facial emotion recognition with text analysis can significantly improve prediction accuracy and provide more comprehensive emotional assessment.

D. Personalized Recommendation Engine

The current recommendation module follows a rule-based approach. In future versions, intelligent recommendation algorithms can be implemented to provide highly personalized content based on user preferences, emotional history, viewing behavior, and interaction patterns. This would improve recommendation quality and user satisfaction.

E. Mental Health Chatbot Integration

An AI-powered chatbot can be integrated into the system to provide real-time emotional support and guidance. The chatbot can engage users in meaningful conversations, answer mental health-related questions, and offer motivational suggestions whenever needed. This feature can make the system more interactive and supportive.

VIII. CONCLUSION

The AI-Powered Mental Health Monitoring and Recommendation System successfully demonstrates how Artificial Intelligence, Machine Learning, and Natural Language Processing can be utilized to support mental health awareness and emotional well-being. In today's fast-paced world, many individuals experience emotional challenges such as stress, anxiety, sadness, and mood fluctuations, but often lack accessible tools for regular mental health monitoring.

The proposed system addresses this problem by providing a simple, intelligent, and user-friendly platform that enables users to monitor their emotional condition on a daily basis. The system effectively collects user responses through dynamically generated questions using the Gemini API and analyzes the responses using NLP techniques and Machine Learning algorithms. By processing textual data and predicting emotions such as Happy, Sad, Stressed, and Relaxed, the system helps users gain a better understanding of their emotional state. The integration of personalized video recommendations further enhances the usefulness of the application by providing supportive content that can help improve or maintain the user's mood.

Another important achievement of the system is its ability to store emotional history and present mood trends through graphical visualizations. This feature allows users to track emotional changes over time, identify recurring emotional patterns, and improve self-awareness regarding their mental health. The combination of emotion prediction, recommendation generation, historical record management, and mood visualization creates a comprehensive platform for emotional monitoring and support. The project also demonstrates the successful integration of multiple technologies, including Flask, Python, Machine Learning, Natural Language Processing, database management, and API services. The modular architecture ensures efficient system performance, scalability, and ease of future enhancement. The implementation confirms that AI-based systems can play an important role in assisting individuals with emotional self-monitoring and promoting mental health awareness. Although the system has certain limitations, such as support for a limited number of emotion categories and reliance on text-based input, it successfully achieves its primary objectives and provides a strong foundation for future development. With further enhancements such as deep learning models, voice and facial emotion recognition, intelligent recommendation engines, and mobile application support, the system can evolve into a more advanced and comprehensive mental health assistance platform.

In conclusion, the AI-Powered Mental Health Monitoring and Recommendation System offers an effective, practical, and innovative solution for monitoring emotional well-being. The project

highlights the potential of Artificial Intelligence in healthcare applications and contributes toward creating accessible digital tools that encourage emotional awareness, self-care, and improved mental health management.

REFERENCES

- [1] R. A. Calvo and S. K. D'Mello, "Affect Detection: An Interdisciplinary Review of Models, Methods, and Their Applications," *IEEE Transactions on Affective Computing*, vol. 1, no. 1, pp. 18–37, Jan.–Jun. 2010.
- [2] J. Devlin, M. W. Chang, K. Lee, and K. Toutanova, "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding," in *Proc. NAACL-HLT*, Minneapolis, MN, USA, 2019, pp. 4171–4186.
- [3] S. M. Mohammad and P. D. Turney, "Crowdsourcing a Word-Emotion Association Lexicon," *Computational Intelligence*, vol. 29, no. 3, pp. 436–465, Aug. 2013.
- [4] P. T. Nguyen, T. N. Nguyen, and H. V. Tran, "Emotion Recognition Using Machine Learning Techniques: A Review," *IEEE Access*, vol. 9, pp. 102274–102289, 2021.
- [5] A. Khaleghi, A. Aghaei, and M. R. Kamalabadi, "Emotion Detection Using Text Classification: A Survey," *IEEE Transactions on Affective Computing*, vol. 13, no. 1, pp. 1–15, 2022.
- [6] K. S. Hasan, M. A. Rahman, and M. A. Hossain, "Sentiment Analysis Using Machine Learning Approaches," *IEEE Access*, vol. 8, pp. 112289–112302, 2020.
- [7] M. Alhuzali and S. Ananiadou, "SpanEmo: Casting Multi-label Emotion Classification as Span Prediction," in *Proc. ACL-IJCNLP*, 2021, pp. 1573–1584.
- [8] D. Jurafsky and J. H. Martin, *Speech and Language Processing*, 3rd ed. Stanford, CA, USA: Stanford Univ., 2021.
- [9] S. B. Baker and W. Xiang, "Internet of Things for Smart Healthcare: Technologies, Challenges, and Opportunities," *IEEE Access*, vol. 5, pp. 26521–26544, 2017.
- [10] H. A. Schwartz et al., "Personality, Gender, and Age in the Language of Social Media: The Open-Vocabulary Approach," *PLOS ONE*, vol. 8, no. 9, pp. 1–16, 2013.
- [11] Y. LeCun, Y. Bengio, and G. Hinton, "Deep Learning," *Nature*, vol. 521, no. 7553, pp. 436–444, May 2015.
- [12] A. Vaswani et al., "Attention Is All You Need," in *Proc. Advances in Neural Information Processing Systems (NeurIPS)*, 2017, pp. 5998–6008.
- [13] T. Mikolov, K. Chen, G. Corrado, and J. Dean, "Efficient Estimation of Word Representations in Vector Space," in *Proc. ICLR Workshop*, 2013.
- [14] S. Hochreiter and J. Schmidhuber, "Long Short-Term Memory," *Neural Computation*, vol. 9, no. 8, pp. 1735–1780, 1997.
- [15] C. Cortes and V. Vapnik, "Support-Vector Networks," *Machine Learning*, vol. 20, no. 3, pp. 273–297, 1995.
- [16] T. Joachims, "Text Categorization with Support Vector Machines: Learning with Many Relevant Features," in *Proc. European Conf. Machine Learning*, 1998, pp. 137–142.
- [17] F. Pedregosa et al., "Scikit-learn: Machine Learning in Python," *Journal of Machine Learning Research*, vol. 12, pp. 2825–2830, 2011.
- [18] S. Bird, E. Klein, and E. Loper, *Natural Language Processing with Python*. Sebastopol, CA, USA: O'Reilly Media, 2009.
- [19] J. Brownlee, *Machine Learning Mastery with Python*. Melbourne, Australia: Machine Learning Mastery, 2016.
- [20] A. Géron, *Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow*, 3rd ed. Sebastopol, CA, USA: O'Reilly Media, 2022.
- [21] T. Mitchell, *Machine Learning*. New York, NY, USA: McGraw-Hill, 1997.
- [22] World Health Organization, "Mental Health," Geneva, Switzerland, WHO, 2023.
- [23] Google, "Gemini API Documentation," Google AI for Developers, 2025.
- [24] M. F. Porter, "An Algorithm for Suffix Stripping," *Program*, vol. 14, no. 3, pp. 130–137, 1980.
- [25] G. Salton and C. Buckley, "Term-Weighting Approaches in Automatic Text Retrieval," *Information Processing & Management*, vol. 24, no. 5, pp. 513–523, 1988.