Mitram AI: An Intelligent Mental Wellness Monitoring and Support Platform

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***Abstract*—Mental wellness is becoming an important concern because many people face stress, emotional pressure, and loneliness in their daily life. Some people also hesitate to share their feelings and problems with others. This paper presents Mitram AI, a mental wellness monitoring and support platform designed to provide a simple and easy-to-use digital system. The platform includes a structured wellness assessment for users who may find it difficult to directly express their feelings and concerns in words. Based on the user's assessment responses related to feelings and daily routine, the system provides a wellness score, risk-related information, and personalized recommendations. Mitram AI also includes an AI-powered chatbot that allows users to interact with the system through text. Other features of the platform include wellness history, risk-related analytics, and downloadable report generation. The system combines machine learning, generative AI, and web technologies in a single platform that can be accessed using mobile and desktop devices. The main aim of Mitram AI is to help users monitor their wellness, understand their wellness-related information, and access supportive recommendations and conversational assistance through an easy-to-understand platform.**

***Index Terms*—Artificial Intelligence, Generative AI, Machine Learning, Mental Wellness, Wellness Assessment.**

I. INTRODUCTION

Modern lifestyles are changing rapidly, and people face different types of pressure in their daily life. Competition is increasing among students, working professionals, and employees. Financial pressure and a busy daily routine may also affect a person's mental wellness. At the same time, the increasing use of digital devices has changed how people communicate and spend their time. These changes show the need for simple and accessible mental wellness support.

Another problem is that some people hesitate to express their feelings and personal difficulties. They may not share their concerns even with family members or friends because they feel that others may not understand their situation. This hesitation can make it difficult for a person to openly discuss emotional concerns. Therefore, a simple digital platform can provide another way for users to reflect on their wellness and access supportive features.

A normal web-based assessment system can collect user responses, calculate a score, and provide fixed recommendations. However, it may have limited interaction with the user. Artificial intelligence can be used to process text input and provide interactive responses. For this reason, AI-based conversational support is included in Mitram AI along with structured wellness assessment and monitoring features.

This paper presents Mitram AI, a mental wellness monitoring and support platform that combines different features in a single system. The platform includes wellness assessment, wellness scoring, risk-related information, personalized recommendations, wellness history, analytics, report generation, and an AI-powered chatbot. These modules are connected with each other. Assessment responses are processed to generate the wellness score and related information, which are further used for recommendations and analytics. The chatbot provides an additional text-based interaction feature for users.

The main objective of Mitram AI is to provide a simple and easy-to-understand web platform that can be accessed through mobile and desktop devices. The system is developed for wellness self-monitoring and supportive interaction. It is not intended to replace professional mental health diagnosis or treatment.

II. RELATED WORK

Artificial intelligence is increasingly being studied for different applications in mental health and wellness. Recent studies have used machine learning, deep learning, natural language processing, and other AI techniques for mental health-related analysis and support. A systematic review of recent research showed that AI has been applied to different mental health problems, but the type and quality of data used by these systems can affect their results. The review also identified challenges related to data diversity and the development of AI-based mental health systems [1].

AI-supported assessment systems have also been explored to improve the collection of mental health-related information. Previous research on an AI-enabled self-referral system showed that structured collection of information can support the assessment process. However, generic information may not fully represent the specific problems experienced by every user. More personalized and detailed information may therefore be useful in such systems [2].

Conversational agents and AI chatbots are another important area of research in mental wellness. Earlier chatbot systems commonly used predefined responses or fixed rules, which could make conversations less flexible. Recent generative AI systems can generate responses in real time and provide more adaptive interaction based on user input [3].

MindLift is an AI-based mental health support system developed mainly for students. The system combines different inputs and uses AI techniques for mental health assessment. It also includes an integrated chatbot and personalized support features. This study shows how AI-based assessment and conversational support can be combined within a mental health platform [4].

A systematic review and meta-analysis of AI-based conversational agents examined 35 studies, including 15 randomized controlled trials. The study reported positive results for some mental health outcomes, while user experience was influenced by engagement, communication quality, and the relationship between users and AI systems. The authors also highlighted the need to study long-term effects and the safe integration of large language models in mental health applications [5].

User experience is also an important part of mental health chatbot design. A formative study of the rule-based conversational agent MYLO discussed common problems reported in mental health chatbot interaction, including repetitive content, users not feeling understood, inappropriate responses, and technical issues. The study also found that repetitive and generic questioning could disturb the flow of conversation and affect user engagement. These findings show the importance of careful conversational design in AI-based mental wellness systems [6].

Personalization and user engagement have also been studied in AI-supported mental health tools. A real-world observational study of a generative AI-enabled therapy support tool reported higher attendance and fewer treatment dropouts among users of the AI-supported tool. The study also highlighted personalized support as an important part of user engagement [7].

Existing research shows that AI can support assessment, conversational interaction, and personalized mental wellness features. However, AI-based mental health systems still require careful consideration of reliability, privacy, user engagement, and the limitations of automated support. Many existing studies focus on a particular task, condition, or specific group of users. These studies provide an important base for the development of Mitram AI, which combines structured wellness assessment, wellness scoring, recommendations, wellness history analytics, report generation, and AI-based text interaction in a single web platform.

III. PROPOSED SYSTEM AND METHODOLOGY

Mitram AI is designed as a web-based mental wellness monitoring and support platform. The main purpose of the proposed system is to combine different wellness-related functions in a single and easily understandable platform. The system integrates structured wellness assessment, wellness scoring, machine learning-based risk classification, condition-based recommendations and insights, wellness analytics, report generation, and AI-based conversational interaction.

The proposed system follows a frontend and backend architecture. The frontend is developed using React and provides interfaces for user registration, login, wellness assessment, dashboard visualization, and chatbot interaction. The backend is developed using

FastAPI and processes API requests and assessment-related operations. SQLAlchemy is used for database interaction, and the implemented authentication module uses bearer access tokens and password hashing for user login-related operations.

The wellness assessment contains questions from different categories, including stress, anxiety, burnout, loneliness, motivation, emotional fatigue, sleep, focus, social interaction, and neutral responses. Questions are selected from a predefined question bank. After the user submits the assessment, the responses are processed by the backend to calculate a wellness score. The implemented weighted scoring method starts from a base score and adjusts the score according to positive and negative wellness factors. The final score is limited to a range between 0 and 100.

For risk classification, the system uses a trained Random Forest classifier. The experimental dataset used for model development contains 2,000 synthetically generated records with ten assessment-related features. Risk labels in the dataset are generated using a predefined risk-scoring rule and are divided into High, Moderate, and Low categories. The dataset is divided into training and testing sets using an 80:20 split. The trained Random Forest model contains 100 estimators and is stored for use by the prediction module during assessment analysis.

After risk classification, the system generates wellness-related insights and recommendations using predefined conditional logic. Different assessment factors, including sleep, stress, anxiety, motivation, and emotional fatigue, are considered while selecting recommendations. Assessment information is stored and used to generate wellness history and analytical summaries, including average wellness score, total assessments, and counts of different risk categories.

Mitram AI also provides an AI-based text chatbot. The chatbot module is designed to send user text to a generative AI service and return a conversational response. The availability of generated responses depends on the configured external AI service and API access. This feature is intended to provide supportive text-based interaction and is not presented as a replacement for professional mental health diagnosis or treatment.

A PDF report generation module is also included in the system. It presents available wellness-related information in a structured report format. The overall platform is intended as an experimental wellness self-monitoring and supportive interaction system rather than a clinically validated diagnostic tool.

Fig. 1. Architecture of the Mitram AI System

A. Wellness Assessment and Scoring

The wellness assessment is used to collect structured self-reported responses from the user. The system maintains a predefined question bank containing questions related to different wellness factors. The assessment responses are provided as numerical values and are processed by the backend.

The wellness score is calculated using a weighted scoring method. The calculation begins with a base score of 50. Negative wellness factors such as stress, anxiety, burnout, loneliness, and emotional fatigue reduce the score, while positive factors such as motivation, sleep, focus, and social interaction increase the score. Different factors are assigned different weights according to the implemented scoring logic. After calculation, the final wellness score is restricted to the range of 0 to 100.

B. Machine Learning-Based Risk Classification

The system uses a Random Forest classifier for wellness risk classification. An experimental synthetic dataset containing 2,000 records is used for model development. Each record contains ten assessment-related input features. The risk categories are High, Moderate, and Low, and the target labels are generated using a predefined risk-scoring rule.

The dataset is divided into training and testing data using an 80:20 split. A Random Forest model with 100 estimators and a fixed random state of 42 is trained and stored as a serialized model file. During assessment analysis, the prediction module loads the trained model and processes the user's assessment responses to generate a risk category. The classification output is used as wellness-related risk information and is not intended as a clinical diagnosis.

C. Insights and Recommendation Generation

After the wellness score and risk category are obtained, the system generates wellness-related insights and recommendations using predefined conditional logic. The insight module uses the predicted risk category and compares the latest wellness score with the previous average score to generate wellness-related observations.

The recommendation module checks assessment factors such as sleep, stress, anxiety, motivation, and emotional fatigue. Based on these conditions and the predicted risk category, the system provides supportive suggestions related to sleep routine, stress management, relaxation, daily goals, recovery, and general wellness practices. The recommendations are intended to help users reflect on their current wellness-related responses.

D. Wellness History and Analytics

Assessment results are stored so that previous wellness information can be used for history and analytics. The analytics module processes stored assessment records and calculates information such as the average wellness score, total number of assessments, and counts of different risk categories.

The dashboard uses assessment history to present wellness score information and risk progression over multiple assessments. This allows the user to review changes in recorded wellness-related results over time.

E. AI-Based Conversational Interaction

Mitram AI includes a text-based chatbot for conversational interaction. The user enters a text message through the chatbot interface, and the message is sent to the backend chatbot API. The chatbot uses an external generative AI service and its availability depends on API access.

The chatbot is included as a supportive conversational feature of the platform. It is separated from the machine learning risk classification process and does not generate the assessment risk category. The conversational feature is not intended to replace professional mental health diagnosis or treatment.

F. Report Generation

The system includes a PDF report generation module for presenting wellness-related information in a structured format. The report generation service uses available assessment and analytics information to create a downloadable report. The generated report can contain the wellness score, risk information, insights, recommendations, analytics summary, and wellness history.

IV. RESULTS AND DISCUSSION

The implemented Mitram AI system was examined using the machine learning classification results and the outputs of the integrated wellness modules. The machine learning evaluation was performed using the synthetically generated experimental dataset described in the methodology. Therefore, the obtained results represent the behavior of the implemented model on the generated dataset and should not be interpreted as clinical validation.

A. Random Forest Model Evaluation

The Random Forest classifier used in the implemented system was evaluated on the testing portion of the experimental dataset. The model obtained an overall classification accuracy of 81.25%.

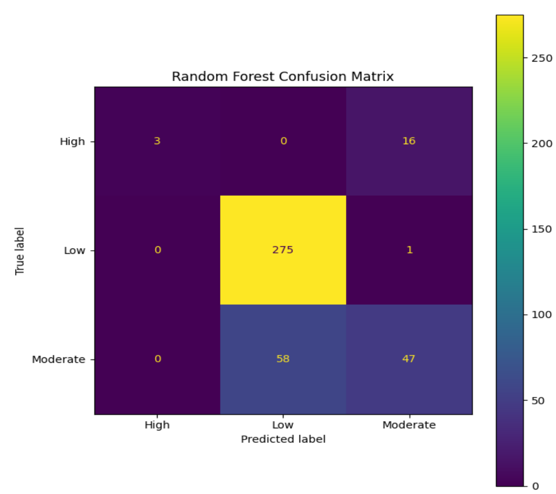

Fig. 2. Random Forest Confusion Matrix

The confusion matrix of the classifier is shown in Fig. 2. The confusion matrix shows that the model correctly classified most Low-risk records. However, classification performance was weaker for Moderate- and High-risk records. In particular, several High-risk records were classified as Moderate. The experimental dataset contains an unequal distribution of risk categories, with a larger number of Low-risk records than Moderate- and High-risk records. This class imbalance may influence the overall accuracy and classification behavior of the model.

These results indicate that overall accuracy alone is not sufficient to evaluate wellness risk classification. The obtained results are limited to the synthetically generated and rule-labeled dataset used in this work. Further evaluation using more balanced and appropriately validated data would be required before considering the model for real-world mental health assessment.

B. Integrated System Output

Mitram AI combines different wellness-related features in a single web-based system. When a user completes the wellness assessment, the submitted responses are processed by the backend. The system then calculates the wellness score and predicts a risk category. Based on the assessment result, the system also provides wellness-related insights and supportive recommendations.

The assessment results are stored so that the user can view previous wellness information. The dashboard uses this information to show details such as the average wellness score, number of completed assessments, and risk-related history. In this way, the user can observe previous assessment results instead of seeing only the latest result.

Fig. 3. Wellness Analytics Dashboard

The system also includes a chatbot interface for text-based interaction. The chatbot module is designed to send user messages to a generative AI service and return conversational responses. However, the availability of generated responses depends on the configured external AI service and API access. In addition, the report generation feature allows wellness-related information to be presented in a downloadable PDF report. By combining these features, Mitram AI provides assessment, risk prediction, wellness analytics, conversational interaction, and report generation within one platform.

V. LIMITATIONS AND FUTURE WORK

The current implementation of Mitram AI has some limitations. The machine learning model was developed and evaluated using a synthetically generated dataset with predefined risk-labeling rules. The dataset also contains an unequal distribution of risk categories. As observed from the confusion matrix, the Random Forest classifier shows weaker performance for some Moderate- and High-risk records. Therefore, the present model results cannot be considered as clinical validation of the system.

The chatbot feature depends on the availability and configuration of an external generative AI service. API access and service availability can affect the conversational feature. In addition, the current system has not been evaluated through clinical trials or large-scale studies with real users. The platform is designed for wellness self-monitoring and supportive interaction and not for medical diagnosis or treatment.

In future work, the machine learning component can be evaluated using more balanced and appropriately validated datasets. Different classification methods and class-balancing techniques can also be studied to improve risk classification, especially for less represented risk categories. The chatbot can be further improved by adding stronger safety mechanisms and more reliable service integration. Future studies may also include user-based evaluation and collaboration with mental health professionals to examine the usefulness and safety of the platform in practical settings.

VI. CONCLUSION

This paper presented Mitram AI, a web-based mental wellness monitoring and support platform that combines wellness assessment, weighted wellness scoring, machine learning-based risk classification, supportive recommendations, wellness analytics, conversational interaction, and report generation in a single system. The main purpose of the platform is to provide an easily understandable way for users to reflect on their wellness-related responses and review their previous assessment information.

The implemented system uses a Random Forest classifier for risk prediction. Experimental evaluation on the synthetically generated dataset produced an overall classification accuracy of 81.25%. The confusion matrix also showed limitations in the classification of some Moderate- and High-risk records, indicating the need for further improvement of the machine learning component.

Mitram AI demonstrates how structured wellness assessment, machine learning, analytics, and AI-based interaction can be integrated into one web platform. However, the current system is intended for wellness self-monitoring and supportive interaction rather than clinical diagnosis or treatment. Further work with appropriately validated data, improved risk classification, stronger chatbot safety mechanisms, and user-based evaluation can help in studying the practical usefulness of the proposed platform.

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