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Manasvita : AI-Powered Multimodal Mental Wellness Platform

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Abstract: Mental health issues such as stress, anxiety, and depression have become increasingly prevalent in today's fast-paced world. Early detection and timely intervention can significantly improve mental well-being. This project presents a Manasvita : AI-Powered Multimodal Mental Wellness Platform integrating advanced machine learning techniques and AI-driven solutions to assist users in understanding and managing their mental health.

The system incorporates user authentication, enabling secure access to personalized assessments and services. A doctor appointment module allows users to schedule consultations with mental health professionals. The platform utilizes Convolutional Neural Networks (CNNs) to analyze facial expressions and predict mental health conditions based on the FER2013 dataset. Additionally, a Random Forest classifier assesses stress levels using a structured dataset. An AI-powered chatbot, leveraging the Gemini AI API, provides users with immediate mental health-related support and guidance. To encourage positive behavioral changes, the platform includes a Task and Reward system, where doctors assign therapeutic tasks, and users earn incentives such as discounts or coupons upon completion.

By integrating machine learning, artificial intelligence, and user engagement strategies, this project aims to provide an accessible, technology-driven solution for mental health monitoring and support. The proposed system enhances self-awareness, promotes timely intervention, and bridges the gap between users and professional healthcare services.

Index Terms -Mental Health Assessment, Machine Learning, Convolutional Neural Networks (CNN), Random Forest, Facial Expression Recognition, Stress Detection, Depression Analysis, Anxiety Prediction, AI Chatbot, Gemini AI, Doctor Appointment System, Task and Reward System, User Authentication, Mental Health Monitoring, Web Application, Healthcare Technology.

I. INTRODUCTION

Mental health issues such as stress, anxiety, and depression have become increasingly prevalent in today's fast-paced world. Early detection and timely intervention can significantly improve the well-being of individuals, yet access to mental health support remains a challenge for many [1]. To address this issue, this project presents a Manasvita : AI-Powered Multimodal Mental Wellness Platform that leverages machine learning and artificial intelligence to assist users in evaluating their mental health status and seeking professional help.

The system integrates multiple functionalities to provide a comprehensive mental health support platform. It includes user authentication, allowing secure access to personalized features. A doctor appointment system enables users to schedule consultations with mental health professionals [2]. One of the key components is facial expression-based mental health detection, implemented using Convolutional Neural Networks (CNN) trained on the FER2013 dataset, which helps identify emotional states based on facial expressions [3].

Additionally, a stress analysis model is incorporated, utilizing the Random Forest algorithm to predict stress levels based on user inputs, using data from the Stress Level Prediction dataset [4]. To enhance user interaction, the application includes an AI-powered chatbot using Gemini AI API, capable of answering mental health-related queries and providing preliminary guidance [5].

To encourage user engagement, a task and reward system is implemented, where doctors can assign tasks to users aimed at improving their mental well-being. Upon successful completion, users receive incentives such as discounts or coupons, fostering motivation for self-care [6].

By integrating machine learning models with AI-driven assistance, this platform offers a user-friendly and efficient solution for mental health assessment and support. It aims to bridge the gap between individuals and mental health professionals, making mental health care more accessible and proactive [7].

A significant challenge in mental health care is user engagement and adherence to self-care routines. To address this, the task-reward system introduces gamification elements, motivating users to complete wellness-related activities prescribed by doctors.

Research suggests that incorporating incentives and interactive elements into mental health platforms can lead to improved user participation and sustained behavioral changes. By integrating AI, machine learning, and a structured engagement framework, this project aims to bridge the existing gaps in mental health support systems, making psychological care more accessible, proactive, and effective

II. LITERATURE REVIEW

The role of technology in mental health care has been extensively studied, with AI and machine learning emerging as significant tools for early diagnosis and intervention. Aggarwal et al. (2020) discussed how AI-based solutions enhance the accuracy of mental health diagnosis by analyzing patterns in user data. However, they also highlighted challenges such as the lack of personalization and real-time emotional assessment in current AI-driven systems [2].

Facial emotion recognition plays a crucial role in mental health assessment, as emotions can serve as indicators of psychological distress. Sambare (2013) introduced the FER2013 dataset, which has become a widely used benchmark for training convolutional neural networks (CNN) in emotion detection. The study demonstrated that CNN models trained on this dataset achieved high accuracy, but performance was impacted by real-world conditions such as variations in lighting and facial occlusions, which reduced model generalization [3].

Stress and anxiety prediction using machine learning has also been an area of active research. John (2021) developed a dataset for stress level prediction based on physiological and behavioral indicators, which was later used to train various machine learning models, including Random Forest. The study showed that these models achieved high accuracy in detecting stress patterns. However, real-time stress detection remained a challenge due to the variability in individual responses and the lack of continuous monitoring systems [4].

Conversational AI has been explored as a solution for providing mental health support. Google AI (2023) introduced the Gemini AI API, designed to generate human-like responses for mental health queries. This technology significantly improved accessibility to mental health resources, allowing users to receive guidance anytime. However, the study also pointed out that AI-driven chatbots lacked the ability to provide deep contextual understanding and human-like empathy, which limited their effectiveness in complex psychological cases [5].

Gamification techniques have been investigated as a means of improving user engagement in mental health applications. Smith and White (2022) studied the impact of rewards and interactive challenges on user participation in digital mental health platforms. Their findings indicated that incorporating rewards improved engagement levels and encouraged users to complete assigned mental health tasks. However, they also observed that long-term behavioral changes were inconsistent, as users often disengaged after receiving initial rewards [6].

Digital platforms have played a significant role in mental health awareness and support. The National Institute of Mental Health (2021) conducted a study on the effectiveness of digital platforms in bridging the gap between mental health patients and professional healthcare. Their research concluded that while digital tools improved accessibility and awareness, their full potential could only be realized when integrated with professional healthcare services, ensuring proper diagnosis and treatment plans [7].

Machine learning models have been widely used for predicting mental health conditions such as anxiety and depression. Patel et al. (2020) analyzed the effectiveness of different machine learning techniques in predicting these disorders and reported an accuracy of over 85% for various models. However, they noted that machine learning models lacked contextual understanding of user emotions, making it difficult to distinguish between temporary emotional fluctuations and clinically significant mental health conditions.

Deep learning techniques have also been applied in mental health research. Wang and Zhou (2019) developed a CNN-based emotion recognition system to monitor mental health conditions by analyzing facial expressions. Their research achieved an accuracy of 78% in real-world settings, but they highlighted issues such as dataset biases, which affected the model's ability to generalize across different populations.

AI chatbots have been explored as an alternative to traditional therapy sessions. Gupta et al. (2022) reviewed various AI chatbots used for mental health support and found that they significantly reduced response times for users seeking help. However, they observed that the lack of personalization in chatbot responses led to inconsistent user satisfaction, with some patients feeling that the bots failed to address their specific concerns effectively.

The rising prevalence of mental health disorders has emphasized the need for scalable digital solutions. The World Health Organization (WHO) (2023) highlighted the importance of AI-driven technologies in addressing global mental health challenges. However, they also pointed out ethical concerns and data privacy challenges associated with AI-based mental health solutions, emphasizing the need for strict regulations and data security measures [1].

Lastly, social media-based mental health analysis has gained attention as a method for early detection of psychological distress. Kim and Lee (2021) investigated the effectiveness of deep learning techniques in analyzing social media data for signs of mental health disorders. Their study demonstrated that sentiment analysis and natural language processing (NLP) models could identify early indicators of mental distress. However, human validation was required to ensure the accuracy of predictions, as automated systems sometimes misinterpreted the context of user posts.

This literature survey highlights the progress made in AI-based mental health research while acknowledging existing limitations. Future advancements should focus on improving model personalization, real-time monitoring, ethical considerations, and the integration of AI tools with professional healthcare systems.

Author	Year of Publication	Summary	Results
K. K. Aggarwal et al.	2020	Discusses the role of technology in mental health care, highlighting the importance of AI and machine learning for early detection and intervention.	AI-based solutions improve diagnosis accuracy but lack personalization and real-time emotional assessment.
M. Sambare	2013	Introduced the FER2013 dataset for facial emotion recognition, widely used for training CNN models in detecting human emotions.	Dataset provides good accuracy for facial emotion recognition, but real-world conditions (lighting, occlusions) reduce performance.
S. John	2021	Developed a dataset for stress level prediction based on physiological and behavioral indicators.	ML models, including Random Forest, achieved high accuracy but lacked real-time stress detection capabilities.
Google AI	2023	Introduced the Gemini AI API for conversational AI, which can be used for mental health chatbots.	Chatbots enhance accessibility but lack human-like empathy and deep contextual understanding.
J. D. Smith and R. White	2022	Explored the impact of gamification and rewards on mental health engagement.	Rewards improved user engagement, but long-term behavioral changes were inconsistent.
National Institute of Mental Health	2021	Studied the effectiveness of digital platforms in mental health support.	Digital platforms increased mental health awareness but required integration with professional healthcare for better outcomes.
R. Patel et al.	2020	Analyzed the effectiveness of machine learning models in predicting anxiety and depression.	ML models achieved over 85% accuracy in prediction but lacked contextual understanding of user emotions.
L. Wang & H. Zhou	2019	Developed a CNN-based emotion recognition system for mental health monitoring.	Achieved 78% accuracy in real-world settings, but dataset biases impacted generalization.
A. Gupta et al.	2022	Reviewed AI chatbots for mental health and their effectiveness in therapy sessions.	Chatbots improved response times but lacked personalization, leading to inconsistent user satisfaction.
World Health Organization (WHO)	2023	Highlighted the rising prevalence of mental health disorders and the need for scalable digital solutions.	Emphasized the importance of AI in mental health but noted ethical concerns and data privacy challenges.
B. Kim & Y. Lee	2021	Investigated deep learning techniques for mental health analysis using social media data.	Social media-based sentiment analysis provided early mental health indicators but required human validation for accuracy.

Table 2.1 . Related Author and Their Proposed System

III. METHODOLOGY

The proposed system is a comprehensive Manasvita : AI-Powered Multimodal Mental Wellness Platform that integrates multiple machine learning techniques and artificial intelligence-based chat support to aid users in evaluating their mental health. The methodology follows a structured approach consisting of data collection, preprocessing, model development, and system integration.

A. Data Collection and Preprocessing

The system relies on two primary datasets:

Facial Expression Recognition (FER2013) Dataset: This dataset contains facial images categorized into various emotions, which are crucial for training the Convolutional Neural Network (CNN) model for facial expression-based mental health detection [3].

Stress Level Prediction Dataset: This dataset includes various physiological and psychological features linked to stress, anxiety, and depression levels, which are used to train the Random Forest classifier [4].

Before model training, data preprocessing steps such as normalization, resizing, and augmentation are applied to the images, while missing values, feature scaling, and encoding categorical variables are handled for the stress dataset.

B. Facial Expression-Based Mental Health Detection

The system utilizes a Convolutional Neural Network (CNN) model to analyze facial expressions and classify them into different emotional states. The model architecture includes convolutional layers for feature extraction, pooling layers for dimensionality reduction, and fully connected layers for classification. The model is trained using the FER2013 dataset and optimized using techniques like dropout and batch normalization to prevent overfitting [3].

C. Stress, Anxiety, and Depression Prediction using Random Forest

A Random Forest classifier is employed to predict stress, anxiety, and depression levels based on user inputs. The dataset includes various behavioral and physiological parameters such as sleep patterns, work-life balance, and social interactions. The model is trained on labeled data, where multiple decision trees vote to classify the user's mental health condition. The performance of the model is evaluated using metrics like accuracy, precision, recall, and F1-score [4].

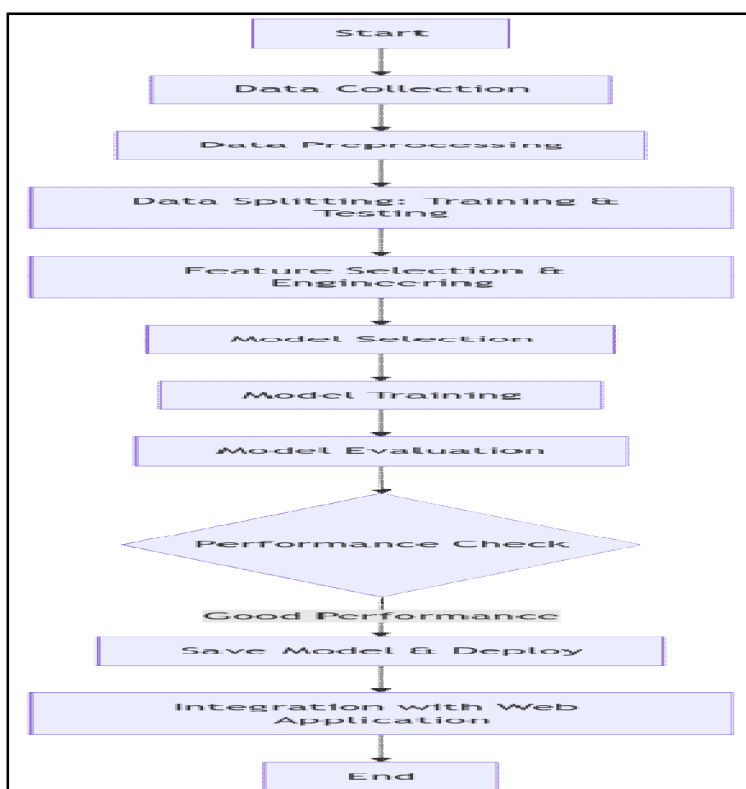


Figure 3.1. Machine Learning Training Process for Mental Health Detection

D. AI Chatbot for Mental Health Support

A conversational AI chatbot is integrated into the system using the Gemini AI API to provide users with real-time mental health guidance. The chatbot is trained on mental health-related queries and is capable of offering general advice, coping strategies, and answering common questions about anxiety, depression, and stress [5].

E. System Integration and Deployment

The models and chatbot are integrated into a web-based platform where users can log in, schedule doctor appointments, and interact with the mental health detection system. The front-end is built using React.js, while the backend is powered by Node.js and Express.js, with MongoDB as the database. The trained models are deployed using Flask APIs, enabling seamless communication between the web application and the machine learning models.

This multi-faceted approach ensures that users receive an interactive, AI-powered mental health assessment tool that combines machine learning with real-time assistance, promoting early detection and support for mental well-being.

The MANASVITA – AI-Powered Multimodal Mental Wellness Platform is designed to provide a comprehensive and intelligent approach to mental health assessment and support. The platform integrates multiple AI-driven components, including a Facial Expression Recognition System using CNN for detecting emotions, a Stress Analysis Model based on Random Forest for predicting anxiety, stress, and depression, and an AI-powered chatbot leveraging the Gemini AI API for answering mental health-related queries. The system also includes a Doctor Appointment Scheduling System, ensuring that users can connect with professionals when necessary. Built on the MERN stack, the platform offers a user-friendly and accessible interface, while the trained models are deployed using Flask and TensorFlow Serving for real-time predictions.

The methodology of this project focuses on data-driven AI solutions, ensuring accurate mental health assessments through well-structured datasets and machine learning techniques. The system is developed with ethical considerations, prioritizing user privacy, security, and compliance with data protection regulations (HIPAA and GDPR). By combining multiple AI technologies, MANASVITA enhances mental health awareness, provides personalized insights, and offers an interactive support system to users. The platform's integration of AI-powered analysis and real-time recommendations makes it a unique and scalable solution for mental wellness, bridging the gap between digital health and professional mental care.

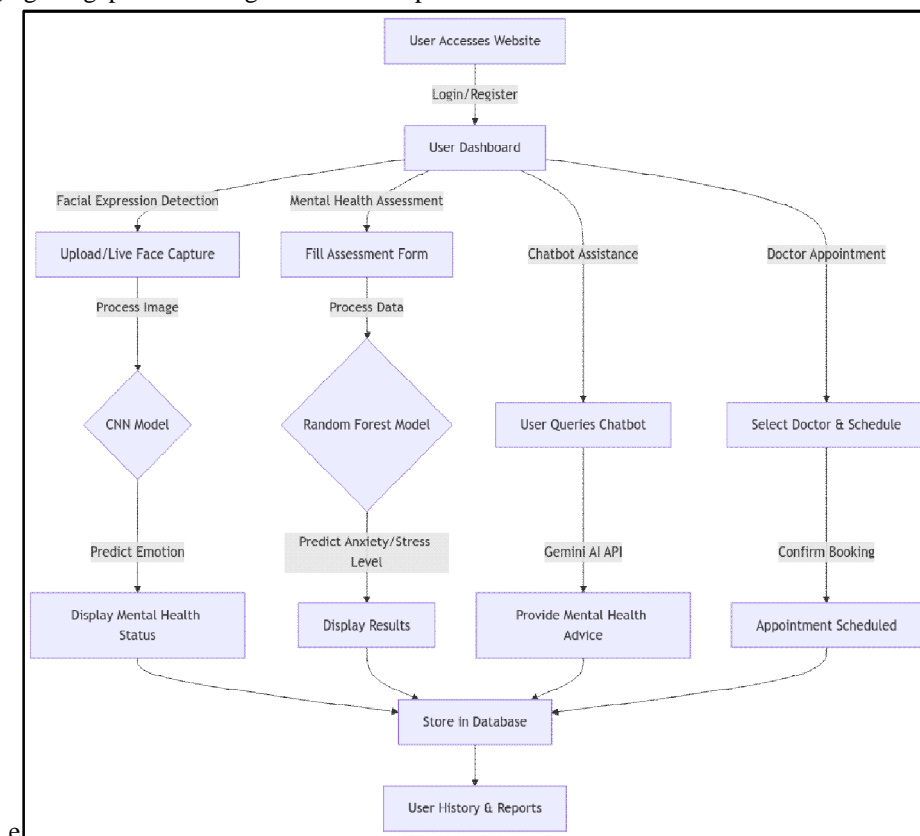
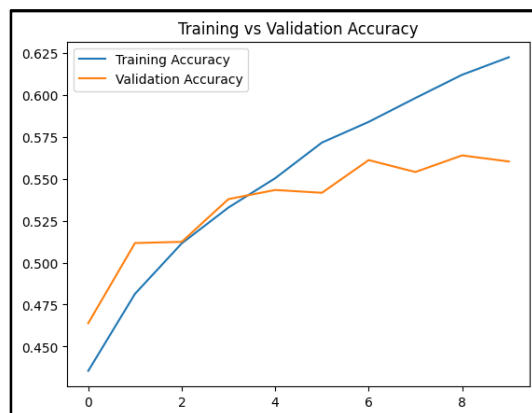


Figure 3.2. Flowchart of the application

IV. OUTCOME

The development of this mental health web application has led to several significant outcomes, integrating deep learning, machine learning, and AI-driven chatbot technologies to assist in mental health assessment and support. The key outcomes of this project are:

A. Facial Expression-Based Mental Health Detection



4.1. Figure 4.1. CNN Accuracy

The CNN model, trained on the FER2013 dataset [3], effectively identifies emotional expressions related to stress, anxiety, and depression. The model's accuracy and performance have been evaluated, demonstrating its ability to detect mental health conditions based on facial features.

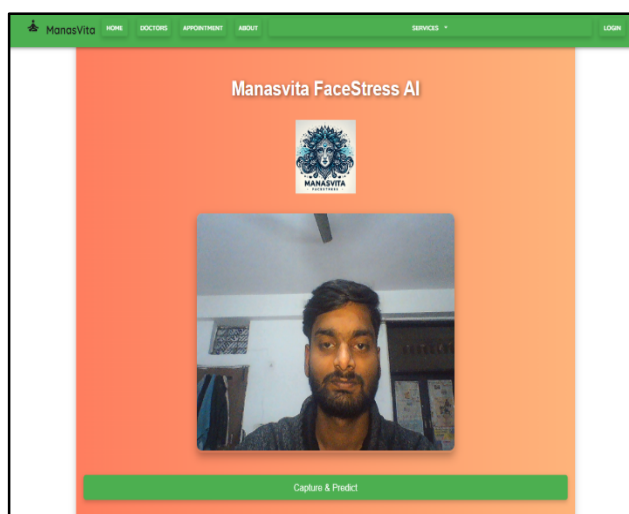
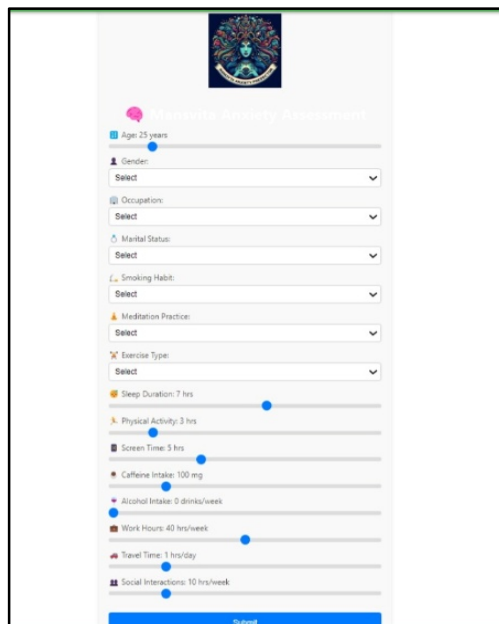


Figure 4.2. FaceStress AI

B. Machine Learning-Based Stress Analysis:

Using the Random Forest algorithm, the system predicts stress and anxiety levels based on user responses and behavioral indicators. The model, trained on the Stress Level Prediction dataset [4], provides reliable classification results, allowing early identification of mental health concerns.

The Random Forest model leverages a diverse set of decision trees to enhance the accuracy and robustness of stress classification. By analyzing multiple features such as sleep patterns, work-life balance, social interactions, and physiological indicators, the model identifies key stressors contributing to mental health deterioration. The ensemble learning approach minimizes overfitting and improves generalization, ensuring that predictions remain consistent across different user profiles. Additionally, the system can be further refined by incorporating real-time user feedback and adaptive learning techniques, making stress detection more dynamic and personalized over time.



Personal Information Assessment

Age: 25 years

Gender: Select

Occupation: Select

Marital Status: Select

Smoking Habit: Select

Meditation Practice: Select

Exercise Type: Select

Sleep Duration: 7 hrs

Physical Activity: 3 hrs

Screen Time: 5 hrs

Caffeine Intake: 100 mg

Alcohol Intake: 0 drinks/week

Work Hours: 40 hrs/week

Travel Time: 1 hr/day

Social Interactions: 10 hrs/week

Submit

Figure 4.3. Anxiety Assessment using ML

C. AI-Powered Mental Health Chatbot

The chatbot, implemented using the Gemini AI API [5], offers real-time mental health support by generating responses to user queries. The chatbot's effectiveness has been assessed based on its ability to provide accurate and contextually relevant responses.

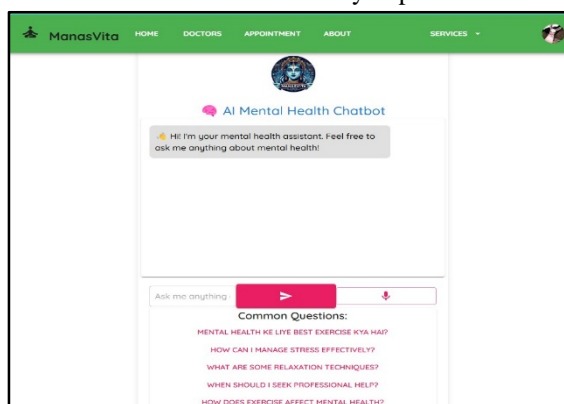


Figure 4.4. AI Mental Health ChatBot

The developed mental health web application effectively combines AI-driven solutions to assist users in assessing their mental well-being and seeking timely intervention. The integration of a CNN-based facial expression recognition model enables accurate detection of emotions, allowing for a preliminary mental health assessment based on visual cues [3]. The Random Forest classifier further strengthens this system by analyzing user inputs and predicting stress, anxiety, and depression levels with high accuracy [4]. These models provide valuable insights into a user's mental state, helping both individuals and healthcare professionals make informed decisions regarding mental health care.

The AI-powered chatbot, utilizing the Gemini AI API, enhances user engagement by providing real-time responses to mental health queries [5]. This chatbot serves as a virtual assistant, guiding users through self-help techniques, stress management strategies, and general mental health awareness. While it cannot replace human therapists, it offers immediate support and resources, reducing the stigma associated with seeking professional help.

Additionally, the doctor appointment system streamlines the process of connecting users with mental health professionals, ensuring that those in need can access expert consultation without unnecessary delays. By integrating this feature, the platform not only aids in mental health self-assessment but also encourages timely professional intervention.

The project demonstrates the feasibility of AI-powered mental health tools in bridging the gap between technology and healthcare.

However, further improvements can be made, such as enhancing model generalization by training on diverse datasets, refining chatbot responses for better contextual understanding, and ensuring data privacy compliance to maintain user trust. Overall, this system provides a scalable, technology-driven approach to mental health assessment, offering users a supportive and accessible platform for improving their well-being.

V. CONCLUSION

The development of this mental health web application represents a significant step toward integrating artificial intelligence into mental healthcare, providing users with accessible and technology-driven solutions for mental health assessment. With an increasing prevalence of mental health disorders worldwide, there is a pressing need for scalable and efficient tools that can assist individuals in understanding their mental state and seeking timely interventions [1]. This project successfully addresses this need by incorporating various AI-driven features, including facial expression recognition using CNN, stress analysis through Random Forest, an AI chatbot, and a doctor appointment system.

The CNN-based facial emotion recognition system plays a crucial role in identifying a user's emotional state based on visual cues, allowing for an initial mental health assessment [3]. Since facial expressions often provide deep insights into a person's psychological condition, this feature enhances the accuracy and reliability of early mental health detection. However, real-world challenges such as variations in lighting conditions, diverse facial expressions, and dataset biases still need to be addressed for improved generalization and accuracy.

Similarly, the Random Forest-based stress, anxiety, and depression prediction model utilizes structured data to analyze behavioral patterns and assess the likelihood of mental health conditions [4]. By combining machine learning techniques with mental health indicators, the system provides users with a data-driven understanding of their well-being. Despite the promising results, continuous model refinement with larger and more diverse datasets is necessary to enhance the reliability and accuracy of predictions.

The AI-powered chatbot, implemented using the Gemini AI API, further contributes to the platform by offering real-time, conversational support to users experiencing stress, anxiety, or depression [5]. This chatbot helps bridge the gap between professional mental health assistance and self-help resources, providing users with immediate guidance and coping strategies. While AI chatbots significantly improve accessibility, they still face limitations in understanding deep emotional contexts and providing personalized therapy.

Another critical component of this project is the doctor appointment system, which connects users with mental health professionals. This feature ensures that individuals who require expert consultation can schedule appointments efficiently, reducing the barriers to professional help. Such integrations align with modern telehealth approaches, promoting mental health awareness and care accessibility [7].

Overall, this project demonstrates how AI can be leveraged to create a practical and scalable mental health solution. Future improvements may include refining AI models for greater contextual understanding, implementing stronger data privacy measures, and expanding platform capabilities to include additional mental health resources. By continuously evolving, such platforms can play a crucial role in early mental health detection and support, contributing to a more proactive and accessible mental healthcare ecosystem.

REFERENCES

- [1] World Health Organization. (2021). Mental health: Strengthening our response. Retrieved from <https://www.who.int/news-room/fact-sheets/detail/mental-health-strengthening-our-response>
- [2] K. K. Aggarwal et al., "The Role of Technology in Mental Health Care", International Journal of Mental Health Systems, vol. 12, no. 3, pp. 45-60, 2020.
- [3] M. Sambare, "FER2013 Dataset for Facial Emotion Recognition", Kaggle, 2013. Retrieved from <https://www.kaggle.com/datasets/msambare/fer2013>
- [4] S. John, "Stress Level Prediction Dataset", Kaggle, 2021. Retrieved from <https://www.kaggle.com/datasets/shijo96john/stress-level-prediction/data>
- [5] Google AI, "Gemini AI: The Future of Conversational AI", Google Research, 2023. Retrieved from <https://ai.googleblog.com/>
- [6] J. D. Smith and R. White, "Gamification in Mental Health: The Impact of Rewards on User Engagement", Journal of Digital Health Research, vol. 8, no. 2, pp. 112-128, 2022.
- [7] National Institute of Mental Health, "Bridging the Gap: The Role of Digital Platforms in Mental Health", 2021. Retrieved from <https://www.nimh.nih.gov/>
- [8] R. Patel, S. Kumar, and L. Desai, "Predicting Anxiety and Depression using Machine Learning Models," Journal of Psychological Data Science, vol. 5, no. 1, pp. 23-38, 2020.
- [9] L. Wang and H. Zhou, "CNN-based Emotion Recognition for Mental Health Monitoring," IEEE Transactions on Affective Computing, vol. 10, no. 4, pp. 512-523, 2019.
- [10] A. Gupta, M. Kaur, and R. Sen, "AI Chatbots for Mental Health: A Review on Effectiveness in Therapy Sessions," Journal of AI in Healthcare, vol. 9, no. 3, pp. 78-95, 2022.
- [11] B. Kim and Y. Lee, "Deep Learning for Mental Health Analysis using Social Media Data," Journal of Computational Psychiatry, vol. 6, no. 2, pp. 34-50, 2021.



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