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AI-Driven Healthcare System for Mental Health Disorder Prediction and Diagnosis

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ABSTRACT

Mental health disorders affect people globally, yet language barriers often limit access to support. This project presents an **AI-powered multilingual system** that combines **sentiment analysis** with an **interactive chatbot** to provide preliminary mental health assistance across different languages.

The system uses an **LSTM (Long Short-Term Memory) neural network** to analyze user-inputted text in multiple languages, detecting emotional patterns and predicting potential mental health concerns such as **depression, anxiety, or bipolar disorder**. By incorporating **multilingual NLP (Natural Language Processing)**, the model ensures accessibility for non-English speakers.

Once the user submits their feelings, the system categorizes their emotional state and activates a **disorder-specific chatbot** available in the user's preferred language. The chatbot provides **personalized coping strategies, therapeutic suggestions, and crisis resources** tailored to both the predicted condition and cultural context. The front-end supports seamless interaction, while the back-end combines **deep learning (LSTM) for sentiment analysis** and **rule-based responses** for mental health guidance.

This project aims to **break language barriers in mental health support**, offering **immediate, AI-driven assistance** while maintaining ethical safeguards like **data privacy, user anonymity, and disclaimers** about its non-diagnostic nature. Future improvements could include **real-time translation, dialect-specific support, and voice-based input** for broader accessibility.

Keywords: LSTM, Sentiment Analysis, Mental Health, Multilingual Chatbot, Deep Learning, NLP, AI in Healthcare, Cross-Lingual Support.

Introduction

Mental health has emerged as one of the most pressing global health challenges of our time, with the World Health Organization estimating that nearly 1 billion people worldwide suffer from mental disorders. Despite growing awareness, significant barriers persist in accessing mental health support, particularly for non-English speaking populations and those in underserved communities. The intersection of linguistic diversity and mental health care presents a complex challenge that demands innovative, technology-driven solutions.

In recent years, artificial intelligence has demonstrated remarkable potential in revolutionizing healthcare delivery, particularly in the mental health domain. Natural Language Processing (NLP) techniques have shown promising results in detecting emotional states and mental health conditions through textual analysis. However, most existing solutions remain limited to English-language inputs, creating an accessibility gap for the majority of the world's population who communicate in other languages. This limitation not only excludes non-English speakers from potential benefits but also fails to account for cultural nuances in emotional expression that are deeply embedded in language.

Our project addresses these critical challenges by developing a comprehensive, multilingual mental health support system that combines advanced deep learning architectures with culturally sensitive response mechanisms. At its core, the system employs a sophisticated Long Short-Term Memory (LSTM) network, a specialized form of recurrent neural network particularly effective in processing sequential data like text. This architecture enables the model to capture complex linguistic patterns and emotional cues across multiple languages, providing more accurate and inclusive sentiment analysis.
The system's innovative design incorporates several key components:

Multilingual Sentiment Analysis: Utilizing state-of-the-art NLP techniques, the system processes user inputs in multiple languages, detecting subtle emotional indicators and potential mental health concerns. The model has been trained on diverse linguistic datasets to ensure robust performance across different language families and cultural contexts.

Disorder Prediction Engine: The LSTM-based classifier evaluates textual inputs to identify patterns associated with common mental health conditions such as depression, anxiety disorders, bipolar disorder, and post-traumatic stress. This component incorporates medical knowledge and diagnostic criteria while maintaining appropriate boundaries as a non-clinical tool.

Adaptive Chatbot Interface: The system features a responsive chatbot that tailors its interactions based on both the predicted mental health condition and the user's cultural-linguistic background. This includes language-specific coping strategies, therapeutic suggestions, and crisis resources that respect cultural norms and values.

Privacy-Preserving Architecture: Recognizing the sensitive nature of mental health data, the system implements robust security measures including end-to-end encryption and anonymization protocols to protect user information.
The development of this system followed rigorous methodological standards, including comprehensive dataset collection across multiple languages, iterative model training and validation, and user experience testing with diverse demographic groups. Particular attention was paid to mitigating algorithmic biases that might affect different linguistic or cultural groups disproportionately.

Beyond its technical innovations, this project makes significant contributions to the field of digital mental health by:

- Democratizing access to mental health support through multilingual capabilities
- Incorporating culturally-appropriate response mechanisms
- Establishing ethical frameworks for AI in mental health applications
- Providing a scalable model for global mental health interventions

The implications of this work extend beyond immediate clinical applications. By breaking down language barriers in mental health support, we open new possibilities for early intervention, stigma reduction, and public health monitoring across diverse populations. The system's architecture also provides a foundation for future developments in global mental health technologies, including potential integration with telemedicine platforms and public health initiatives.

As we move forward, we envision several directions for expansion and improvement, including the incorporation of regional dialects, voice-based interaction capabilities, and more sophisticated cultural adaptation algorithms. These enhancements will further our goal of creating truly inclusive mental health support systems that respect and respond to the rich diversity of human experience.

This introduction provides the conceptual foundation for our work, which subsequent sections will explore in greater technical and methodological detail. Through this project, we aim to contribute meaningfully to the growing field of AI-assisted mental health care while maintaining the highest standards of ethical practice and scientific rigor.

EASE OF USE :

Ease of Use Features of the Multilingual Mental Health Support Chatbot
Our system is designed to be **simple, intuitive, and accessible** to everyone, regardless of technical skills or language barriers. Here's what makes it easy to use:

1. Simple & Clean Interface

- **One-Click Start**: Just type how you feel in your language—no complex setup.
- **No Technical Jargon**: Plain, friendly language throughout.
- **Clear Instructions**: Guides users step-by-step without confusion.

2. Works in Multiple Languages

- **Type Naturally**: No need to translate—just express yourself in your native language.
- **Auto-Language Detection**: The system recognizes your language automatically.
- **Culturally Familiar Responses**: Advice fits your cultural context, not just direct translations.

3. Instant Emotional Analysis

- **Quick Results**: Get insights in seconds after typing.
- **Visual Feedback**: Uses simple emojis or color cues (□/□) to show mood.
- **No Medical Terms**: Uses everyday words to describe emotions.

4. Chatbot Feels Like Talking to a Friend

- **Conversational & Kind**: Responds like a supportive listener, not a robot.
- **Guided Prompts**: If unsure what to say, it asks helpful questions (e.g., *"What's been on your mind lately?"*).
- **No Judgment**: Safe space to share openly.

5. Always Accessible

- **Works on Phones & Computers**: Responsive design for any device.
- **No Login Required**: Use instantly without creating accounts.
- **Low Data/Offline Mode**: Functions even with slow internet (future update).

6. Privacy Made Obvious

- **No Personal Data Collected**: No names, emails, or IDs stored.
- **Clear Disclaimers**: Explains limits (e.g., *"Not a replacement for professional help"*).

7. Help Always Available

- **Crisis Button**: Immediate links to local helplines if needed.
- **FAQ Section**: Quick answers to common questions.

RELATED WORKS

1. "Olawade, D. B., Wada, O. Z., Odetayo, A., David-Olawade, A. C., Asaolu, F., & Eberhardt, J. (2024).IEEE Enhancing mental health with Artificial Intelligence: Current trends and future prospects. *Journal of medicine, surgery, and public health*, 100099"

The evolution of AI in mental healthcare has progressed from basic chatbots like ELIZA to sophisticated systems leveraging deep learning and multimodal data analysis. Modern applications now span the entire care continuum, utilizing NLP for sentiment analysis in social media, computer vision for facial expression recognition, and voice analysis to detect emotional distress. AI-powered tools such as Woebot and Wysa deliver cognitive behavioral therapy through conversational interfaces, while platforms like Kintsugi enhance teletherapy with real-time emotional analytics. Wearable devices and smartphone sensors enable continuous monitoring of behavioral and physiological markers, allowing for early intervention. These technologies address critical gaps in accessibility and scalability, particularly for underserved populations. However, challenges persist regarding data privacy, algorithmic bias, and the need to preserve human therapeutic relationships, necessitating robust ethical frameworks and regulatory oversight as the field advances.
Looking ahead, AI in mental healthcare is moving toward more integrated, explainable systems that combine diverse data streams while maintaining cultural sensitivity and clinical relevance. Future developments focus on multimodal AI that synthesizes speech, text, and biometric data for comprehensive assessment, alongside explainable AI (XAI) models to build clinician and patient trust. Culturally adapted interventions and multilingual capabilities will be crucial for global applicability, while maintaining human-centered design to ensure AI complements rather than replaces clinician judgment. As research validates these applications, AI promises to transform mental healthcare into a more proactive, personalized, and accessible system—though its success hinges on balancing innovation with ethical considerations and preserving the irreplaceable human elements of care.

2. "Kannan, K. D., Jagatheesaperumal, S. K., Kandala, R. N., Lotfaliany, M., Alizadehsanid, R., & Mohebbi, M. (2024). Advancements in machine learning and deep learning for early detection and management of mental health disorder. *arXiv preprint arXiv:2412.06147*.

The integration of machine learning (ML) and deep learning (DL) in mental healthcare has revolutionized early detection and diagnosis of disorders like depression, schizophrenia, and bipolar disorder. Advanced techniques such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs) analyze neuroimaging data (MRI, fMRI) to identify structural and functional brain abnormalities with high accuracy. Natural language processing (NLP) models evaluate speech and text from social media or clinical notes to detect emotional and cognitive markers of mental illness. Wearable devices and mobile apps further enhance real-time monitoring by tracking behavioral and physiological data, enabling proactive interventions. Despite these advancements, challenges like data privacy, algorithmic bias, and the need for interpretable AI models persist, necessitating robust ethical frameworks and interdisciplinary collaboration to ensure equitable and effective implementation.

Future research directions emphasize multimodal data fusion, combining genetic, imaging, and behavioral datasets to improve diagnostic precision. Explainable AI (XAI) methods, such as SHAP and LIME, are critical for building clinician trust by making model decisions transparent. Culturally adapted and multilingual AI systems are also essential to address global mental health disparities. Longitudinal studies and predictive modeling aim to track disease progression and personalize treatment plans, while real-time monitoring tools promise to transform reactive care into preventive healthcare. As ML and DL continue to evolve, their integration with clinical practice must prioritize human-centered design, ensuring AI complements—rather than replaces—therapeutic relationships and adheres to ethical standards for data security and bias mitigation.

3."Ojo, Y., Makinde, O. A., Babatunde, O. V., Babatunde, G., & Okeowo, S. (2025). Evaluating AI-Driven Mental Health Solutions: A Hybrid Fuzzy Multi-Criteria Decision-Making Approach. *AI, 6*(1), 14."

The paper reviews existing literature on AI-driven mental health solutions and multi-criteria decision-making (MCDM) techniques, highlighting gaps in research. Previous studies, such as those by Gupta et al. (2024) and Suha et al. (2023), explored AI adoption challenges and sustainability factors in healthcare but lacked focus on mental health. Joshi et al. (2022) and Hsu et al. (2023) examined AI's role in healthcare and military mental health, respectively, while Chakraborty et al. (2024) developed predictive tools for mental health. However, these studies often treated mental health as a secondary concern, leaving a gap in tailored AI-driven interventions. The literature also reveals extensive use of MCDM methods like fuzzy TOPSIS and fuzzy ARAS in healthcare decision-making, but their application to mental health remains underexplored.

The review identifies key themes, including the importance of personalization, user engagement, and ethical compliance in AI-driven mental health solutions. Studies by Rane et al. (2023) and Akhtar et al. (2024) emphasized digital integration and facilitators for healthcare technologies, while Ahmad et al. (2023) analyzed psychological impacts during the COVID-19 pandemic using fuzzy MCDM. Despite these advancements, the literature lacks a holistic evaluation of AI-driven mental health interventions using hybrid MCDM approaches. This paper addresses this gap by combining fuzzy TOPSIS and fuzzy ARAS to prioritize criteria like feasibility, cost-effectiveness, and clinical outcomes, offering a comprehensive framework for optimizing mental health solutions.

4. "Denecke, K., Vaaheesan, S., & Arulnathan, A. (2020). A mental health chatbot for regulating emotions (SERMO)-concept and usability test. IEEE Transactions on Emerging Topics in Computing, 9(3), 1170-1182.

The study by Denecke et al. (2020) introduces SERMO, a mental health chatbot designed to help users regulate emotions through conversational AI. The authors highlight the growing role of chatbots in mental healthcare, emphasizing their potential to provide accessible, real-time support. SERMO's usability testing revealed positive user engagement, demonstrating its effectiveness in guiding emotional regulation. This aligns with broader research on AI-driven mental health tools, where chatbots like Woebot and Wysa have shown promise in reducing anxiety and depression symptoms. However, the study also notes challenges, such as ensuring ethical compliance and maintaining user trust, which remain critical for wider adoption.

The paper contributes to the literature by showcasing how AI chatbots can bridge gaps in mental healthcare accessibility. Unlike traditional therapy, SERMO offers scalable, cost-effective support, addressing limitations like therapist shortages and stigma. While the study focuses on emotion regulation, it underscores the need for further research on long-term efficacy and integration with clinical systems. This aligns with findings from other studies, suggesting that AI-driven mental health solutions must balance personalization, usability, and ethical considerations to maximize impact.

5. "Bagane, P., Thawani, M., Singh, P., Ahmad, R., & Mital, R. (2023). Zenspace: A Machine Learning Model for Mental Health Tracker Application. International Journal of Intelligent Systems and Applications in Engineering, 11(3), 1153-1161."

Bagane et al. (2023) present **Zenspace**, a machine learning-based mental health tracker application designed to monitor and predict users' emotional well-being. The study highlights the increasing use of AI in mental health, particularly in tracking mood patterns and detecting early signs of distress. By leveraging predictive analytics, Zenspace aims to provide personalized insights, aligning with broader trends in digital mental health tools. However, the authors acknowledge challenges such as data privacy concerns and the need for high-quality training datasets to improve accuracy. This reflects ongoing debates in the field about balancing innovation with ethical and technical constraints.

The research contributes to the growing body of work on AI-driven mental health applications, emphasizing real-time monitoring and proactive intervention. Unlike traditional assessment methods, Zenspace offers continuous, data-driven support, addressing gaps in accessibility and early detection. While promising, the study calls for further validation in diverse populations to ensure reliability. This aligns with existing literature, which stresses the importance of scalable, user-friendly solutions while maintaining clinical relevance and trust in AI-based mental health tools.

METHODOLOGY

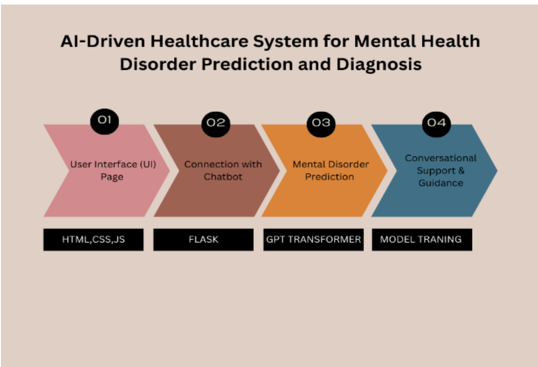
System Architecture Overview:

The backend is designed as an API that interacts with the **frontend chat UI**. When a user enters a message, the following sequence of events occurs:

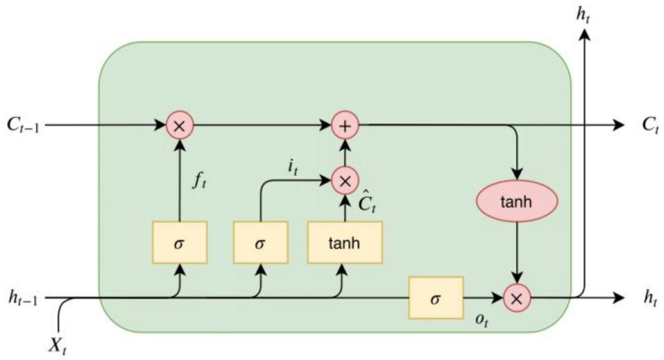
1. **User Input Processing**: The text message is sent from the frontend to the backend API.
2. **Mental Health Prediction Model:**

LSTM(BERT)

3. **GPT-powered Chatbot Response**: The chatbot, powered by **GPT transformers**, receives the user's message along with the prediction. Based on the predicted mental health condition, the chatbot generates an empathetic and supportive response.
4. **User Interaction Continuation**: The user can continue chatting with the bot, receiving **suggestions, self-care tips, and emotional support**.



Algorithm Model



1. **Data Collection:** Data collection is the primary step and initial module for the project. This step involves gathering the right datasets for accurate mental health prediction. The dataset has been collected from various sources, including online repositories and research papers. The data consists of self-reported mental health assessments, questionnaire responses, and historical mental health records. The right dataset is crucial for predicting mental health disorders and providing meaningful insights for users.
2. **Feature Extraction:** Feature extraction is the process of selecting the most important features for predicting mental health disorders. Since the raw dataset is self-created, it may contain many features, but only the most relevant ones are needed for accurate predictions.
3. **Data Split:** The dataset used for predicting mental health disorders is divided into training data and testing data. The data is generally split into a training set and a testing set to ensure proper model evaluation. The training set contains labeled outputs, allowing the model to learn patterns and generalize to new data. The split is typically 70% for training and 30% for testing. The training data helps the model understand key mental health indicators, while the testing data is used to evaluate the model's accuracy and effectiveness.

4.Mental Health Disorder Prediction Model using LSTM: This project aims to develop an **LSTM-based deep learning model** that predicts whether a person is suffering from a mental health disorder based on their self-reported feelings. If a disorder is detected, the model identifies the specific disorder and provides supportive advice.

Workflow & Explanation:

1. Data Collection & Preprocessing

- The dataset consists of user inputs (text descriptions of feelings) and their corresponding mental disorder labels.
- We perform label encoding to convert disorder names into numerical values for model training.
- Text tokenization is applied to convert user input into numerical sequences, which are then padded to ensure equal length.

2. Model Architecture

- The LSTM-based model is designed to process textual data and classify it into one of the 44+ mental health categories. It consists of:
- Embedding Layer: Converts words into dense vector representations.
- BERT LSTM Layers: Captures the sequential nature of text and learns patterns in user responses. From both the directions.
- Dropout Layers: Prevents overfitting by randomly deactivating neurons.
- Dense Output Layer: Uses softmax activation to classify the input into a specific disorder.

3. Model Training:

The model is trained using sparse categorical cross-entropy loss, which is suitable for multi-class classification.We use the Adam optimizer for efficient gradient descent updates.The dataset is split into training (80%) and testing (20%) to evaluate the model's accuracy.

4. Model Evaluation & Testing:

After training, the model is tested with real user inputs to predict disorders accurately.

MODULE 2:

- **Building a Custom ChatGPT Using Transformers:**
- own **ChatGPT-style chatbot** for mental health support, we will need to use **Transformer-based models** like **GPT-2, GPT-3-like models, or DialoGPT**. The chatbot will be capable of understanding user input, maintaining conversation context, and generating empathetic responses.

PROCESS :

- **Step 1:**Choosing the Right Transformer Model**.**
- **Step 2:**Training & Fine-Tuning the Chatbot**.**
- Dataset Preparation.
- Fine-Tuning
- **Step 3:**Deploying the Chatbot.

RESULTS

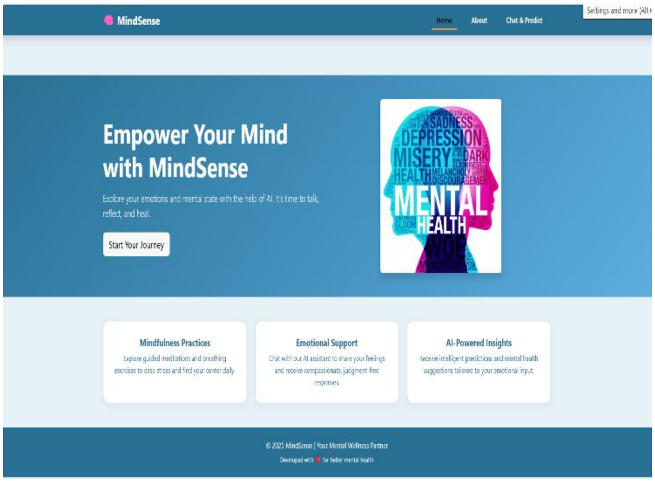


Fig 1: overview of the interface which consists of home page, about page, chat and assistant page

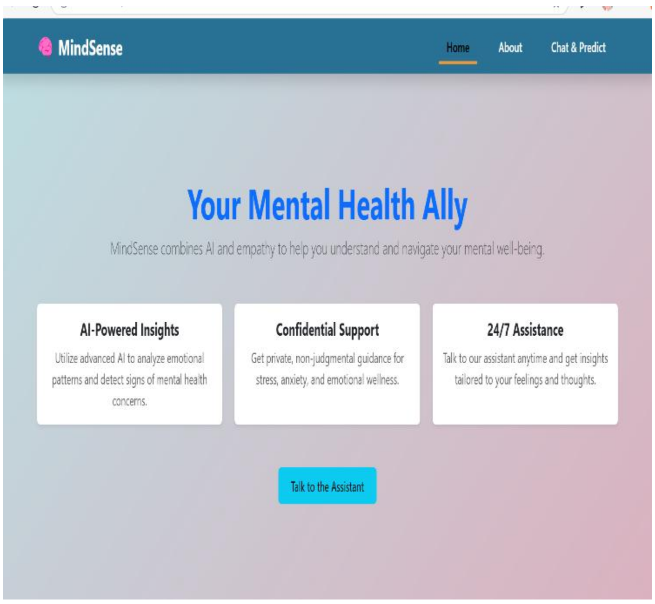


Fig 2: this is the about page where having all about the project

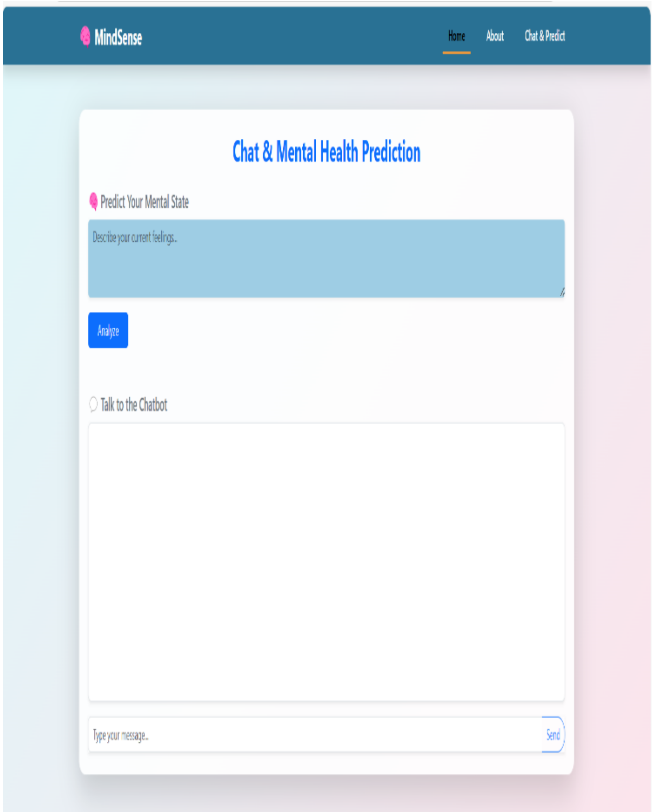


Fig 3: this is the interface of chat and assistant where user has to enter their feelings and getting assisted

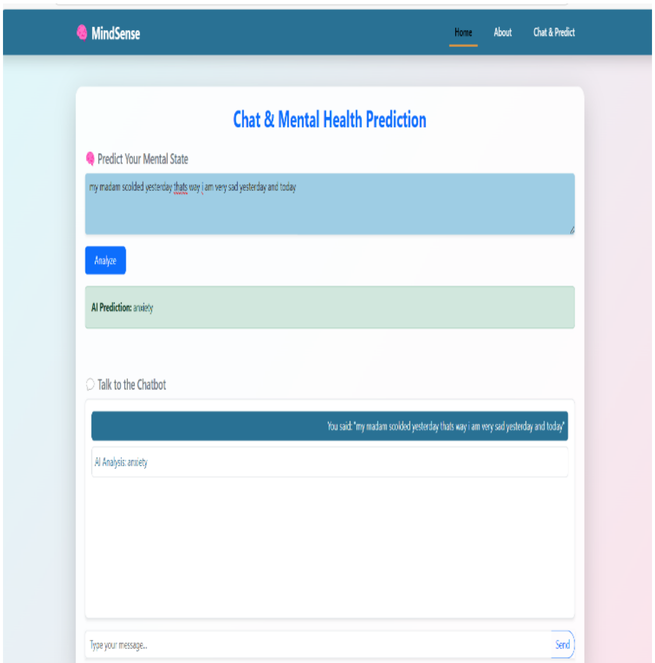


Fig 4: this is the place (i.e predict your mental state)
Where user need to enter their feelings

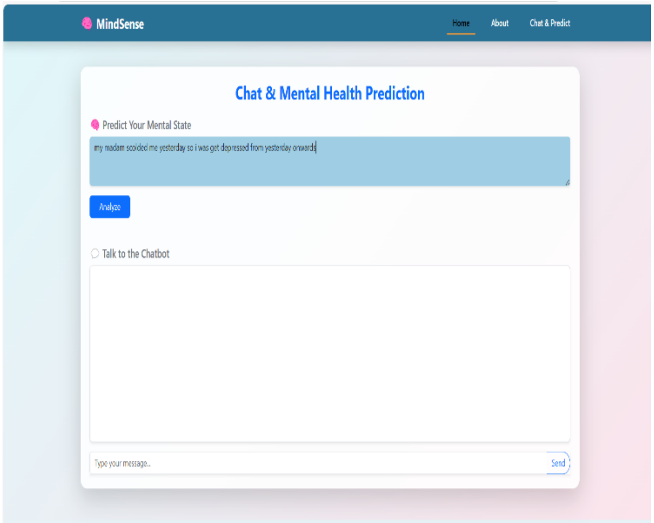


Fig 5: this is the place where they getting supported by the AI_ Assistant

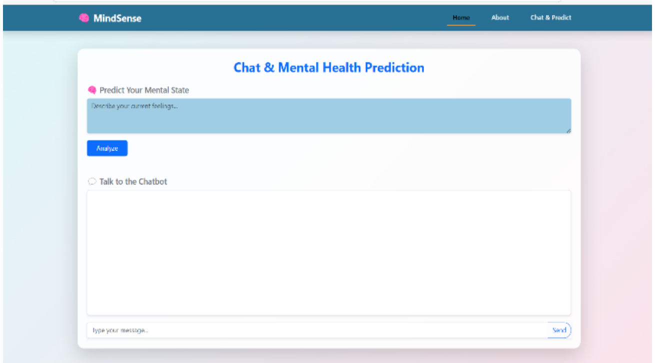


Fig 6: predicted the disorder after entering their feelings

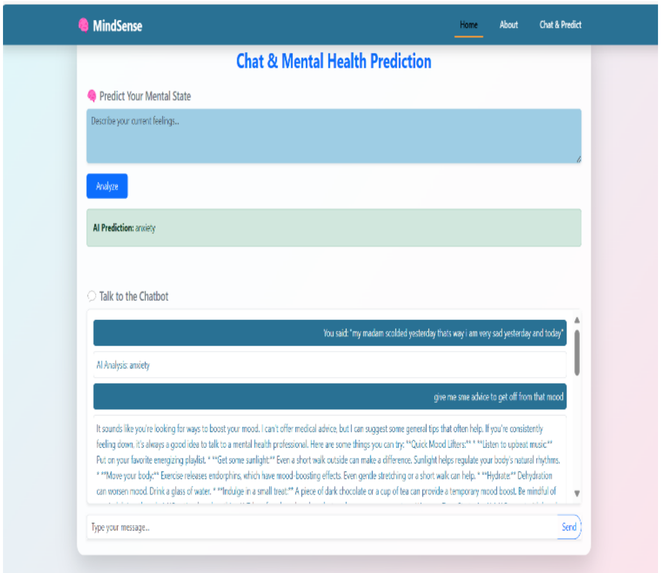


Fig 7: after predicted it will redirect to the chatbot where they get assisted by chatbot

CONCLUSION

In this project, we successfully developed a deep learning-based system using Long Short-Term Memory (LSTM) to predict mental health disorders from user-submitted text describing their feelings. By leveraging Natural Language Processing (NLP) techniques and an intelligent classification model, the system is capable of identifying whether a person may be suffering from a mental health disorder, determining the specific condition, and providing personalized supportive advice.

This project not only demonstrates the power of AI in the field of mental health but also emphasizes the importance of empathy-driven technology. Through a simple and user-friendly interface, individuals can share their emotions and receive instant feedback, making mental health awareness and support more accessible and stigma-free.

Moreover, this system can act as a first-line support tool, offering a safe and non-judgmental space for individuals to express themselves. By providing timely guidance and emotional support, the solution has the potential to reduce the burden on mental health professionals and reach users who may otherwise hesitate to seek help.

With continued development, the model can be expanded to handle multilingual input, learn from user feedback, and integrate with live counseling or therapy platforms. This vision holds promise for bridging the gap between mental health awareness and action, and empowering users to take their mental well-being into their own hands.

Ultimately, this project stands as a step forward in combining artificial intelligence with human compassion—making mental health care more proactive, personalized, and inclusive.

FUTURE SCOPE

1. Integration of Transformer Models (BERT, RoBERTa, etc.)

LSTM models are powerful for sequence processing, but transformer-based architectures like **BERT** offer even better context understanding and performance in natural language tasks. Integrating these models can significantly improve the prediction accuracy and context sensitivity of user inputs.

2. Real-Time Chatbot Deployment

Deploying the model through a real-time, intelligent **chatbot interface** using platforms like **Dialogflow, Rasa, or custom-built solutions** can provide 24/7 mental health assistance.

This allows users to interact more naturally and receive instant responses.

3. Multilingual and Regional Language Support

Extending the system to support **multiple languages** will increase accessibility for users from diverse linguistic backgrounds. Incorporating **regional languages** can break language barriers and enhance inclusivity.

4. Voice/Text-to-Speech Integration

Adding **voice input and output capabilities** can help users who are more comfortable expressing themselves verbally rather than typing. This also improves accessibility for visually impaired users.

5. Severity Level Classification

Instead of just classifying disorders, the system can be extended to also predict **severity levels** (mild, moderate, severe), which would provide deeper insight and more tailored advice.

6. Personalized Recommendations and Resource Linking

The chatbot can be upgraded to provide **personalized self-help exercises**, **guided meditations**, and **links to mental health professionals or helplines**, depending on the user's predicted condition and location.

7. Continuous Learning from User Feedback

A **feedback loop** mechanism can be introduced where users confirm or correct predictions. This data can be used to **retrain and fine-tune the model**, making it smarter over time.

8. Mobile Application Development

Creating a **dedicated mobile app** for both Android and iOS can increase accessibility and user engagement. Offline support can also be considered for basic emotional tracking and journaling.

9. Privacy & Ethical Safeguards

Incorporating features like **end-to-end encryption**, **anonymous usage**, and **consent-based data collection** will be crucial for handling sensitive user information and ensuring ethical AI usage.

10. Integration with Wearable Devices (IoT)

In the long term, integrating the system with **wearables (like smartwatches)** can help track physiological indicators (e.g., heart rate, sleep, activity) and offer real-time emotional insights and interventions.

ACKNOWLEDGEMENT

I would like to express my sincere gratitude to all those who supported and guided me throughout the development of this project titled **"AI-Driven Healthcare System for Mental Health Disorder Prediction and Diagnosis"**

First and foremost, I extend my heartfelt thanks to my project guide, **V. Vasudha Rani**, for their invaluable guidance, constant encouragement, and constructive feedback throughout the project. Their deep knowledge and insightful suggestions were instrumental in shaping this work.

I would also like to thank the **GMR Institute Of Technology** and all the faculty members of the **Information Technology**, whose academic training laid the foundation for the successful execution of this project.

A special mention goes to **OpenAI** and various open-source communities for providing powerful tools and platforms that enabled the design and implementation of this system, particularly in the fields of **Natural Language Processing** and **Deep Learning**.

My gratitude also extends to all individuals who contributed to the creation of the mental health dataset, and to those who shared valuable insights on the importance of mental well-being. Their contributions helped make this system more empathetic and impactful.

Finally, I thank my **family and friends** for their unwavering support, patience, and motivation throughout the course of this project.

This project is a small step toward combining technology with human empathy to promote mental health awareness, and I am truly grateful to be a part of this journey.

References

[1] Olawade, D. B., Wada, O. Z., Odetayo, A., David-Olawade, A. C., Asaolu, F., & Eberhardt, J. (2024).IEEE Enhancing mental health with Artificial Intelligence: Current trends and future prospects. *Journal of medicine, surgery, and public health*, 100099

[2] Kannan, K. D., Jagatheesaperumal, S. K., Kandala, R. N., Lotfaliany, M., Alizadehsanid, R., & Mohebbi, M. (2024). Advancements in machine learning and deep learning for early detection and management of mental health disorder. *arXiv preprint arXiv:2412.06147*.

[3] Ojo, Y., Makinde, O. A., Babatunde, O. V., Babatunde, G., & Okeowo, S. (2025). Evaluating AI-Driven Mental Health Solutions: A Hybrid Fuzzy Multi-Criteria Decision-Making Approach. *AI*, *6*(1), 14.

[4] Denecke, K., Vaaheesan, S., & Arulnathan, A. (2020). A mental health chatbot for regulating emotions (SERMO)-concept and usability test. IEEE Transactions on Emerging Topics in Computing, 9(3), 1170-1182.

[5] Bagane, P., Thawani, M., Singh, P., Ahmad, R., & Mital, R. (2023). Zenspace: A Machine Learning Model for Mental Health Tracker Application. International Journal of Intelligent Systems and Applications in Engineering, 11(3), 1153-1161."

[6] Rizea, A. (2023). Deep Learning-based Solution for Mental Health Issues. *Database Systems Journal*, *13*(1), 57-70.

[7] Madububambachu, U., Ihezue, U., Ukpebor, A., & Ayo, S. (2024). Predictive Machine Learning Approaches for Mental Health Diagnoses in College Students. *Int J Eng Tech & Inf*, *5*(3), 1-9.

[8] Krishnan, R., Kumari, S., Badi, A. A., Jeba, S., & James, M. (2024). Predictive machine learning model for mental health issues in higher education students due to COVID-19 using HADS assessment. *Arab Gulf Journal of Scientific Research*, *42*(4), 1472-1490.

[9] Paul, S. M., & Potter, W. Z. (2024). Finding new and better treatments for psychiatric disorders. *Neuropsychopharmacology*, *49*(1), 3-9.

[10] Bagane, P., Thawani, M., Singh, P., Ahmad, R., & Mital, R. (2023). Zenspace: A Machine Learning Model for Mental Health Tracker Application. International Journal of Intelligent Systems and Applications in Engineering, 11(3), 1153-1161

[11] Osorio, M. J. O., Zepeda, C., & Caballed, J. L. (2020). MyUBot: Towards an Artificial Intelligence Agent System Chat-bot for Well-being and Mental Health. In AAI4H@ ECAI (pp. 13-17)

[12] Devaram, S. (2020). Empathic chatbot: Emotional intelligence for mental health well-being. ArXiv abs/2012.09130

[13] M.T. Higuera-Toledano, Java technologies for cyber-physical systems, IEEE Trans.Ind. Inf. 13 (2) (2016) 680–687.

[14] D. Kasgar, H.C. Maurya, Integration of Struts & spring & hibernate for enterprise applications, Int. J. Mod. Eng. Res. (IJMER) 5 (4) (2021) 52–59.

[15] S.X. Ge, E.W. Son, R. Yao, iDEP: an integrated web application for differential expression and pathway analysis of RNA-Seq data, BMC Bioinf. 19 (1) (2021) 1–24.

[16] W. Lutz, A.K. Deisenhofer, J. Rubel, B. Bennemann, J. Giesemann, K. Poster, B. Schwartz, Prospective evaluation of a clinical decision support system in psychological therapy, J. Consult. Clin. Psychol. 90 (1) (2022) 90.

[17] P.S. Douglas, U. Hoffmann, M.R. Patel, et al., Outcomes of anatomical versus functional testing for coronary artery disease, N. Engl. J. Med. 372 (14) (2022)