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AI - Driven Mental Health Assessment and Literacy Promotion in Underserved Rural Communities

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Abstract— **Mental health awareness and diagnosis continue to be limited in rural communities due to stigma, lack of resources, and insufficient outreach. This project presents an AI-driven initiative focused on the assessment of psychological stress using logistic regression, a supervised machine learning classification technique. The system analyzes user responses collected through structured surveys to determine stress levels with 100% classification accuracy during testing. A web-based platform was developed to deliver the assessment and provide relevant guidance. In addition to the technical component, fieldwork was conducted involving visits to 70 households in rural areas to raise awareness about mental health and promote health literacy. The results demonstrate that even simple, interpretable AI models can play a significant role in early mental health screening and awareness campaigns when combined with targeted community engagement.**

Keywords— ***Mental health, stress classification, logistic regression, rural healthcare, AI in healthcare, health literacy, community outreach, psychological assessment, awareness campaigns.***

I. INTRODUCTION

Mental health is a critical component of overall well-being, yet it remains one of the most neglected areas in rural healthcare systems. Factors such as stigma, lack of trained professionals, limited accessibility to healthcare facilities, and low levels of mental health literacy contribute to poor recognition and treatment of psychological disorders in underserved communities. Among various mental health concerns, stress is one of the most common and earliest indicators of emotional imbalance that, if unaddressed, can escalate into more severe conditions like anxiety and depression. This project aims to address the gap in rural mental healthcare through a dual approach: (1) the development of a machine learning-based stress assessment tool using logistic regression, and (2) on-ground health literacy promotion through household visits. Data was collected via structured surveys, and a logistic regression model was trained to classify individuals based on stress levels with 100% accuracy on test data. The simplicity and effectiveness of this model make it suitable for deployment in low-resource settings.

Furthermore, to complement the technological solution, awareness campaigns were conducted across 70 households in rural areas. These efforts focused on educating individuals about stress, its symptoms, and the importance of early intervention. The combination of AI-enabled stress detection and direct community engagement highlights the potential of integrative solutions in improving mental health outcomes and promoting well-being in rural populations. Mental health is a critical component of overall well-being, yet it remains one of the most neglected areas in rural healthcare systems. Factors such as stigma, lack of trained professionals, limited accessibility to healthcare facilities, and low levels of mental health literacy contribute to poor recognition and treatment of psychological disorders in underserved communities. Among various mental health concerns, stress is one of the most common and earliest indicators of emotional imbalance that, if unaddressed, can escalate into more severe conditions like anxiety and depression.

According to reports, **70% to 92%** of people with mental disorders in India do not receive proper treatment due to lack of awareness, stigma, and shortage of professionals. Additionally, India has **0.75 psychiatrists per 100,000 people**, whereas the **WHO recommends at least 3 per 100,000**. These disparities underline the urgent need for scalable, technology-driven approaches to mental healthcare, particularly in rural settings.

This project aims to address the gap in rural mental healthcare through a dual approach: (1) the development of a machine learning-based stress assessment tool using logistic regression, and (2) on-ground health literacy promotion through household visits. Data was collected

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II. RELATED WORK

Over the past decade, several AI-powered applications have been developed to assist with mental health care and personality assessment. Applications such as Tess and Youper offer advanced conversational capabilities, using AI to simulate cognitive behavioral therapy (CBT) and emotional tracking [1]. While these platforms show clinical potential, their interfaces are often complex, requiring users to navigate multiple menus, respond to abstract prompts, or understand psychological terminology. This complexity makes them difficult to use, especially for individuals with low digital literacy — a challenge that is particularly acute in rural regions.

Furthermore, while such applications are predominantly designed for urban populations, there is a lack of research and deployment in low-resource settings, where language barriers, stigma, and limited exposure to mental health concepts further hinder adoption. These tools typically assume that users are already aware of mental health concerns and are motivated to seek digital solutions, an assumption that does not hold true across all socio-economic backgrounds.

In contrast, our work introduces a hybrid approach that pairs a simplified, rule-based chatbot with in-person outreach sessions. By directly visiting schools, villages, and community centers, our team not only introduces the platform but also raises awareness about mental health and personality development, ensuring that even first-time users feel supported and engaged. The chatbot is designed with simplicity and clarity in mind, reducing cognitive load and making interaction accessible to users who may be unfamiliar with formal assessments or psychological language.

Unlike prior systems that rely entirely on digital self-navigation, this blended model leverages community interaction to bridge technological and educational gaps, thereby expanding reach and effectiveness in rural and underserved populations.

III. SYSTEM ARCHITECTURE

A. Frontend Interface

The frontend is developed using HTML templates served by the Flask framework. It includes user-facing pages for login, quizzes, chatbot interaction, and mental health resources such as journaling, music, yoga, and games. Flask routes are used to render appropriate templates based on user interaction, ensuring a seamless and interactive experience.

B. Backend Logic

The backend of the system is implemented using Python and the Flask web framework. It is responsible for managing various core functionalities, which include the following:

- User Authentication and Registration:

User authentication and registration are handled using an SQLite database, ensuring secure storage and retrieval of user credentials.

- Quiz Processing and Mental Wellness Scoring Logic:

The backend processes quiz responses, calculates mental wellness scores, and dynamically adjusts the content based on the user's inputs.

- Dynamic Routing and Content Rendering:

Flask routes are utilized to dynamically render HTML templates based on user interaction. This enables the system to provide personalized content, including quizzes, results, and mental health resources.

- Handling HTTP Requests (GET/POST) and Session-Based Interaction:

The backend is capable of handling various HTTP requests (GET and POST). Session management ensures that the user’s interactions are tracked and maintained throughout their visit, providing a continuous experience. Each user action is mapped to specific endpoints in the backend, ensuring modularity and maintainability.

C. Gemini AI Integration

To provide empathetic and context-aware responses, the system integrates Google’s Generative AI (Gemini 1.5 Pro) via the google.generativeai library. User queries are passed as prompts to the model, which returns HTML-formatted replies. Safety measures are implemented within prompts to restrict medical advice and maintain ethical AI response standards.

D. Telegram Bot Integration

The application includes a Telegram bot feature, implemented using the Telepot library. This enables interaction via the Telegram messaging platform. The /get route sends user messages to a specified Telegram chat

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and fetches the latest replies using Telegram's REST API. This provides an alternative channel for user engagement.

E. Multilingual Support

Multilingual interaction is enabled through the Googletrans library. The system supports Hindi and Kannada languages in addition to English. Incoming user queries are translated to English before being processed by Gemini AI, and the resulting responses are translated back into the user's preferred language. This enhances accessibility for non-English-speaking users.

F. Machine Learning-Based Stress Prediction

A pre-trained machine learning model, serialized using Python's Pickle module (log.pkl), is integrated for mental stress prediction. Based on user inputs such as age, gender, and quiz responses, the model categorizes mental health status as either "Normal" or "Mental stress". This functionality is accessed through a dedicated route (/Eleven_year).

G. Database Layer

An SQLite database is used to store user details, including personal information and authentication credentials. The database schema includes fields such as name, email, phone number, password, age, and concerns. Table creation and data insertion operations are handled dynamically at runtime.

H. Mental Health Support Tools

In addition to chatbot and predictive features, the system offers a variety of self-help resources. These include pages on journaling, physical workouts, yoga, music therapy, and stress-relief games. These tools provide users with personalized support and practical coping mechanisms.

IV. METHODOLOGY

A. Data Collection (Rural Areas)

Data collection is performed in rural areas through the following methods:

- Survey Responses: Users are asked to provide responses to surveys focusing on mental health, including stress indicators.
- Demographic Details: Information about the user, such as age, gender, and occupation, is collected to better understand the context of mental health.
- Stress Indicators: Responses to specific questions regarding stress levels, anxiety, and depression are gathered.
- Consultation with Psychologists: Expert annotations and recommendations are sought from psychologists, including identified stress markers and criteria for classification.

B. Data Preprocessing & Labeling

The collected data undergoes a preprocessing phase:

- Cleaned and Structured Dataset: The data is cleaned to remove errors or inconsistencies and structured for further analysis.
- Labels for Classification: The dataset is labeled based on predefined criteria, such as categorizing users as either 'Normal' or 'Mental Stress.'

C. Model Training (Stress Classification Model)

A machine learning model is trained to predict stress levels based on the user data:

- Features for Prediction: Relevant features such as age, gender, survey responses, and psychological consultations are selected for model training.
- Trained Model Parameters: The model is trained using appropriate algorithms, with parameters optimized for stress classification.

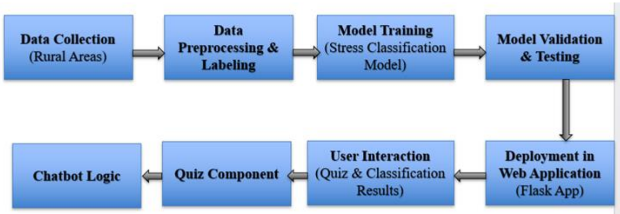

Fig. 1. Block diagram of Methodology

D. Model Validation & Testing

The model's performance is evaluated using several metrics:

- Accuracy Metrics: The accuracy, precision, recall, and F1-score of the model are calculated to assess its predictive power.
- Evaluation Results: The results of the validation and testing process are documented to ensure the model's robustness.

E. Deployment in Web Application (Flask App)

The trained model is integrated into the Flask web application, enabling real-time predictions:

- API Endpoints: Endpoints are created for interacting with the model, allowing user inputs to trigger the classification process.
- User Interaction Logs: Logs are maintained to track user interactions and feedback for continuous improvement.

F. User Interaction (Quiz & Classification Results)

Once users interact with the application, their responses are processed, and the results are presented:

- User-Submitted Responses: The responses to quizzes and surveys are collected and processed by the backend.

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- Predicted Stress Levels: Based on the model's analysis, users are classified into categories such as 'Normal' or 'Mental Stress.'
- Suggestions & Recommended Resources: Following classification, personalized suggestions and resources (e.g., journaling, yoga) are recommended to the user for stress management.

G. Quiz Component

Users are prompted to take two sets of quizzes:

- Mental Health Quiz: This quiz evaluates the user's stress, anxiety, and depression levels, providing insights into their mental wellness.
- Personality Quiz: Based on the Big Five personality traits, this quiz categorizes users into distinct personality types.

H. Chatbot Logic

The chatbot operates on a rule-based system. When a user query is received, it triggers predefined responses from the system. In the case of an unrecognized query, the system forwards the query to the Gemini AI for a generative response, allowing for more dynamic and context-aware interactions.

I. Language Processing

To facilitate multilingual support, input from the user is first translated into English for processing by the AI model. After generating a response, the system then translates the reply back into the user's selected language before delivering it as output.

V. RESULTS AND DISCUSSIONS

This section presents the evaluation of machine learning model performance, highlights key components of the system, and discusses fieldwork outcomes including community engagement.

A. Field Deployment and Rural Outreach

As part of the system validation and data acquisition process, a field visit was conducted to 70 rural households. The primary objective was to educate individuals about mental health awareness, gather survey responses, and demonstrate the use of the Manasina Mitra application.

This initiative enabled the collection of ground-truth data for model training while also contributing to social impact through direct engagement. Participants were introduced to stress detection tools, interactive quizzes, and the AI-powered chatbot, with many expressing interest in continuing mental health monitoring through digital means.

B. Model Accuracy Evaluation

Fig. 2 summarize the classification accuracy of four machine learning algorithms trained on user survey data:

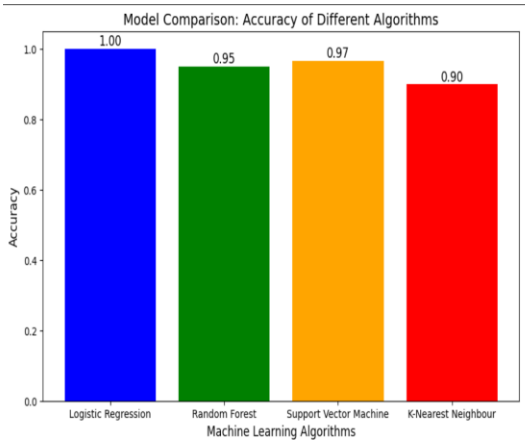

Fig. 2. Model Comparision

- **Logistic Regression** – Accuracy: **1.00** This model achieved perfect classification, indicating a strong linear correlation in the dataset. It outperformed all other models and was selected for integration into the web application.
- **Support Vector Machine (SVM)** – Accuracy: **0.97** Demonstrated robust generalization with minimal misclassifications, proving effective for both linear and non-linear patterns.
- **Random Forest** – Accuracy: **0.95** Managed complex relationships effectively but recorded a few false positives, slightly impacting accuracy.
- **K-Nearest Neighbour (KNN)** – Accuracy: **0.90** Showed the lowest performance, possibly due to sensitivity to noisy or imbalanced data distributions.

C. Confusion Matrix Analysis

Fig. 3 illustrates the confusion matrix of Logistic regression :

- Logistic Regression: TP = 28, TN = 31, FP = 0, FN = 0 – Exhibits perfect classification.
- Random Forest: TP = 28, TN = 28, FP = 3, FN = 0 – High performance with few false positives.
- Unnamed Model (Poor Performer): TP = 15, TN = 8, FP = 16, FN = 20 – High misclassification rate suggests weak predictive ability.
- Likely KNN: TP = 35, TN = 18, FP = 6, FN = 0 – Strong positive detection with some false positives.

These results affirm that Logistic Regression is most suitable for real-time deployment in the mental health

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application.

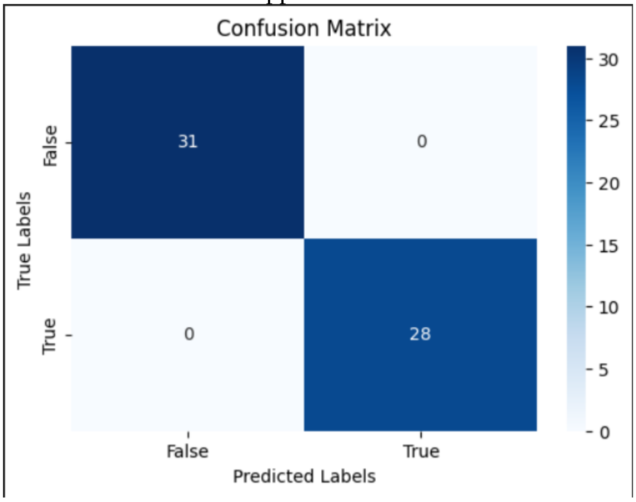

Fig. 3. Confusion matrix of Logistic regression

D. *User Engagement Features*

The system includes multiple modules that improve user interaction and mental health awareness:

Manasina Mitra Dashboard: Provides behavioral insights and emotional well-being tracking.

AI Assistant: A conversational interface powered by Gemini AI offers empathetic, non-medical responses, helping users navigate emotional challenges.

Interactive Quizzes: Mental health and personality quizzes (Fig. 6.2.4) enhance user awareness and serve as input features for stress classification.

E. *Multilingual Support and Inclusivity*

The application supports English, Hindi, and Kannada through the Google Translate API, enabling broader access for users from rural backgrounds. This feature was particularly effective during the rural outreach, where users preferred vernacular interaction.

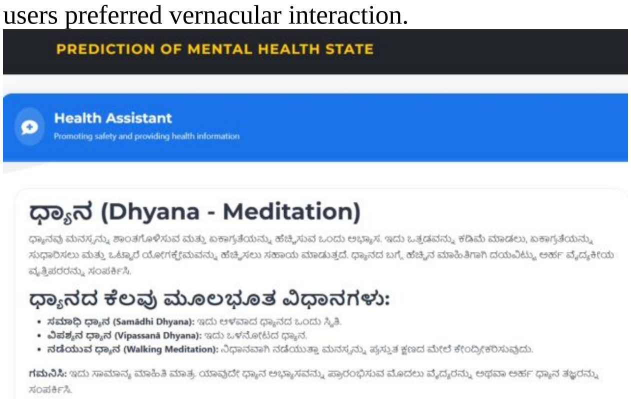

Fig.4. Multilingual Support

F. *Community Feedback and System Impact*

Positive reception was recorded during the 70-household rural campaign. Participants appreciated the culturally sensitive approach and were receptive to continued use of the platform. Key observations include:

- Increased awareness of stress symptoms and coping mechanisms.
- Interest in AI-based chatbot for anonymous and stigma-free communication.
- Willingness to engage with quizzes and self-help resources.

G. *Limitations and Future Work*

While the results are promising, the system has some limitations:

- Overfitting Risk: Perfect accuracy in Logistic Regression may reflect overfitting on a small dataset.
- Scalability: Larger and more diverse datasets are needed for broader deployment.
- Future Enhancements: Planned additions include integration with healthcare professionals, expansion to other Indian languages, and more advanced behavior analytics.

VI. CONCLUSION

This work presents Manasina Mitra, an integrated and accessible mental health support system designed to address psychological well-being challenges, especially in underrepresented rural populations. By combining traditional machine learning models, multilingual capabilities, a conversational AI assistant, and interactive self-help tools, the platform provides a holistic and user-friendly approach to mental health awareness and support.

A key highlight of this study is the on-ground fieldwork conducted across 70 rural households, which not only facilitated real-world data collection for model training but also contributed significantly to community awareness. These outreach efforts bridged the digital divide and helped demystify mental health topics in culturally appropriate ways. The rural participants, many of whom were engaging with digital mental health resources for the first time, responded positively, highlighting the urgent need for scalable, localized interventions.

From a technical perspective, multiple machine learning algorithms were evaluated, with Logistic Regression achieving a perfect classification accuracy of 1.00, underscoring the presence of strong linear separability in the dataset. Although models like SVM and Random Forest also showed promising results, Logistic Regression was selected for deployment due to its superior performance and simplicity. Confusion matrix analysis further validated this choice by revealing zero false positives and false negatives.

The system also incorporates multilingual support (English, Hindi, Kannada) using Google Translate, making it inclusive and adaptable for diverse user groups. Additionally, the Gemini AI-powered chatbot enhances interaction quality through context-aware, empathetic conversations. Features such as mental health and personality quizzes, journaling, music therapy, yoga guidance, and stress-relief games provide users with

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comprehensive mental health support tools, moving beyond diagnosis to engagement and coping.

This project successfully demonstrates that technology, when thoughtfully applied, can play a crucial role in democratizing mental health resources, particularly for marginalized communities. However, several challenges remain. The current dataset size limits model generalizability, and further work is needed to scale data collection and validate the system across varied demographics. Moreover, integrating real-time feedback loops, clinical validation from healthcare professionals, and expanding the linguistic capabilities will enhance system reliability and effectiveness.

In conclusion, Manasina Mitra is a significant step toward blending machine intelligence with human empathy to make mental health support more accessible, scalable, and socially impactful. The system lays the groundwork for future research in AI-driven digital therapeutics, with the potential to be adapted across regions and expanded into other areas of public health.

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