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Mental Health Monitoring Framework Using AI

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KEYWORD

Mental Health, Machine Learning, NLP, AI, Stress Prediction, MLOps.

ABSTRACT

Mental health issues such as stress, anxiety, and depression are increasing rapidly due to academic pressure, work stress, and lifestyle changes. Early detection of mental health conditions is important for providing timely support. Traditional mental health assessment methods rely on manual evaluation, which is time-consuming and inconsistent. This research proposes an AI-based mental health monitoring framework using Natural Language Processing (NLP) and machine learning techniques. The system collects user input in text format and predicts mental health condition using trained machine learning models. The system architecture includes React frontend, Flask backend, NLP vectorizer, machine learning model, SQLite database, and Docker deployment. The model processes text input and predicts mental health condition such as stress, anxiety, or normal. The proposed system provides real-time prediction and scalable architecture. Experimental results show improved performance and faster prediction time. This framework can help in early mental health detection and awareness.

1. Introduction

Mental health is a critical component of overall well-being and directly affects how individuals think, feel, and behave in daily life. In recent years, mental health problems such as stress, anxiety, and depression have increased significantly due to academic pressure, workload, social isolation, and lifestyle changes. Students and working professionals are particularly vulnerable to these conditions. However, many individuals hesitate to discuss their mental health issues openly because of social stigma, lack of awareness, or limited access to professional support. As a result, early detection of mental health problems becomes difficult, which may lead to serious consequences if left untreated.

Traditional mental health assessment methods rely on clinical interviews, questionnaires, and manual evaluation by mental health professionals. Although these methods are effective, they are time-consuming, subjective, and not always accessible to everyone. Moreover, continuous monitoring of mental health is challenging using traditional approaches. With the rapid advancement of Artificial Intelligence (AI) and Machine Learning (ML), automated systems can now analyze user behavior and textual data to detect patterns associated with mental health conditions. These technologies provide an opportunity to develop scalable and real-time mental health monitoring systems.

Natural Language Processing (NLP), a subfield of AI, plays an important role in analyzing textual input provided by users. Individuals often express their emotions and mental states through written text such as messages, journal entries, or feedback. NLP techniques can process this textual data, extract

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meaningful features, and classify mental health conditions using machine learning algorithms. By combining NLP with ML models, it becomes possible to predict whether a user is experiencing stress, anxiety, depression, or a normal mental state.

This research proposes an AI-based mental health monitoring framework that uses NLP and machine learning techniques to predict mental health conditions from user-provided text input. The system provides a user-friendly web interface where users can enter their thoughts or feelings. The backend process the input using a trained vectorizer and machine learning model to generate predictions in real time. The architecture includes a React-based frontend, Flask backend API, Scikit-learn model, SQLite database for storing prediction history, and Docker for deployment. This end-to-end MLOps pipeline ensures scalability, accessibility, and efficient performance.

The proposed system aims to assist users in identifying potential mental health issues at an early stage and encourage awareness. Although the system does not replace professional medical diagnosis, it serves as a supportive tool for preliminary mental health assessment. By integrating AI technologies with web-based deployment, the framework provides an accessible and practical solution for mental health monitoring.

2. Background

Mental health monitoring has become an important research area in recent years due to the increasing number of people experiencing stress, anxiety, and depression. Traditional mental health evaluation methods depend on clinical interviews, psychological tests, and expert observation. Although these approaches provide reliable results, they are time-consuming, costly, and not accessible to everyone. Moreover, continuous monitoring of mental health using manual methods is difficult. These limitations have encouraged researchers to explore automated solutions using Artificial Intelligence (AI) and Machine Learning (ML).

Machine learning techniques have been widely applied in healthcare for disease prediction and patient monitoring. Algorithms such as Logistic Regression, Support Vector Machine (SVM), Naive Bayes, Decision Tree, and Random Forest are commonly used for classification tasks. These algorithms can learn patterns from datasets and predict outcomes based on input features. In mental health prediction, datasets may include questionnaire responses, behavioral data, or textual inputs. Among these, textual data has gained popularity because individuals often express their emotions and mental states through written language.

Natural Language Processing (NLP) is a subfield of AI that focuses on analyzing and understanding human language. NLP techniques such as tokenization, stop-word removal, stemming, and vectorization are used to convert text into numerical form. Methods like TF-IDF and Count Vectorizer help in extracting meaningful features from text. These features are then used to train machine learning models for classification of mental health conditions. NLP-based systems have shown promising results in detecting stress, depression, and anxiety from textual data.

Recent studies have also introduced web-based mental health prediction systems that provide user-friendly interfaces. These systems allow users to input text describing their mental state. The backend processes the input using trained models and provides predictions. Some research also integrates databases to store prediction history and track user behavior. However, many existing systems lack complete deployment pipelines and scalability.

The advancement of MLOps practices has enabled deployment of machine learning models into real-world applications. By integrating frontend frameworks such as React, backend APIs such as Flask, and containerization tools like Docker, AI-based systems can be deployed efficiently. This research builds upon these developments and proposes a complete AI-based mental health monitoring framework that uses NLP and machine learning with an end-to-end architecture.

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3. Identification of the Issue

Mental health problems are increasing rapidly, but there is still a lack of effective tools for early detection and monitoring. Many individuals hesitate to share their mental health concerns due to social stigma and lack of awareness. This makes it difficult to identify mental health conditions at an early stage. Traditional mental health assessment methods depend on psychologists and clinical evaluation, which are not always available and require significant time and cost.

Another major issue is the absence of automated systems that can continuously monitor mental health. Most existing approaches rely on manual questionnaires or periodic check-ups, which do not provide real-time analysis. In addition, people often express their emotions through text messages, social media posts, or personal notes, but these textual data sources are not effectively utilized in traditional systems.

Existing AI-based systems also face limitations such as small datasets, lack of deployment architecture, and limited accessibility. Many research models remain only at experimental stage and are not integrated with user-friendly interfaces. Some systems do not store prediction history, making it difficult to track changes in mental health over time. Furthermore, language dependency and privacy concerns also affect the performance and usability of these systems.

4. Drawbacks of Existing System

Existing mental health monitoring systems have several limitations that reduce their effectiveness and usability. Traditional systems mainly depend on manual evaluation by mental health professionals, which is time-consuming and not accessible to everyone. These systems require users to visit healthcare professionals, making continuous monitoring difficult.

Another major drawback is the lack of automated real-time prediction. Most existing systems use static questionnaires that provide only one-time analysis. They do not support continuous monitoring or instant feedback. This limits early detection of mental health conditions.

Many existing machine learning models are trained on small or limited datasets. This affects the accuracy and generalization capability of the model. If the dataset is not diverse, the system may produce biased or incorrect predictions for different users.

Some systems also lack a proper user interface. Research models are often not integrated with frontend applications, making them difficult for non-technical users. Without a user-friendly interface, users cannot easily interact with the system.

Another drawback is the absence of database integration. Many systems do not store user inputs and prediction history. This makes it impossible to track mental health trends over time. Continuous monitoring becomes difficult without data storage.

Language dependency is also a limitation. Most systems support only English text input. Users entering Hindi or mixed language text may receive inaccurate predictions. Additionally, privacy and security concerns arise when sensitive mental health data is stored without proper protection.

Finally, many existing systems are not deployed using scalable architectures. Lack of deployment tools such as Docker and cloud services makes the system difficult to use in real-world environments.

5. Proposed Framework

The proposed system presents an AI-based Mental Health Monitoring Framework that uses Natural Language Processing (NLP) and machine learning techniques to predict mental health conditions. The system is designed to provide real-time analysis of user input through a web-based interface. It follows an end-to-end architecture including frontend, backend, machine learning model, database, and deployment environment.

The framework allows users to enter text describing their mental state, thoughts, or feelings. The input text is sent from the frontend to the backend API. The backend processes the input using NLP techniques such as text cleaning, tokenization, and vectorization. The processed data is then passed to the trained machine learning model. The model predicts the mental health condition and returns the result to the user interface. The prediction is also stored in the database for future reference.

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The proposed framework consists of the following modules:

- User Interface Module
- Backend API module
- NLP Processing module
- Machine Learning model
- Database module
- Deployment module
- Working of proposed of framework
- User enters text input
- Frontend sends request to backend
- Backend preprocesses text
- Vectorizer converts text to numeric form
- Model predicts mental health condition
- Result stored in database
- Prediction displayed on UI.

6. Suggested System Architecture

The suggested system architecture describes the overall structure and working of the AI-based mental health monitoring framework. The architecture is designed to provide real-time prediction using a web-based interface integrated with machine learning and NLP processing. The system follows a layered architecture consisting of frontend, backend, machine learning model, and database components.

The architecture begins with the user interacting with the web interface. The user enters text describing their mental state. This input is sent to the backend server through an API request. The backend processes the input using NLP techniques and passes the processed data to the trained machine learning model. The model predicts the mental health condition and sends the result back to the frontend. The prediction is also stored in the database for tracking and analysis

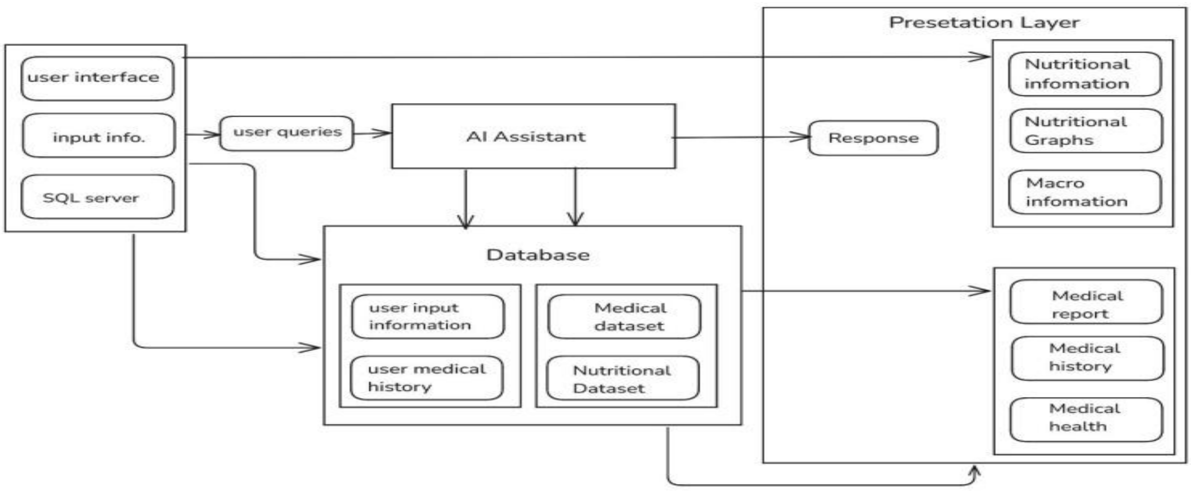

Figure 1: The System Architecture

The architecture starts with the user entering text describing their mental state. The frontend sends this data to the backend, where NLP preprocessing converts text into structured features. A trained machine learning model analyzes these features and predicts the mental health condition. The result is stored in a database and displayed to the user.

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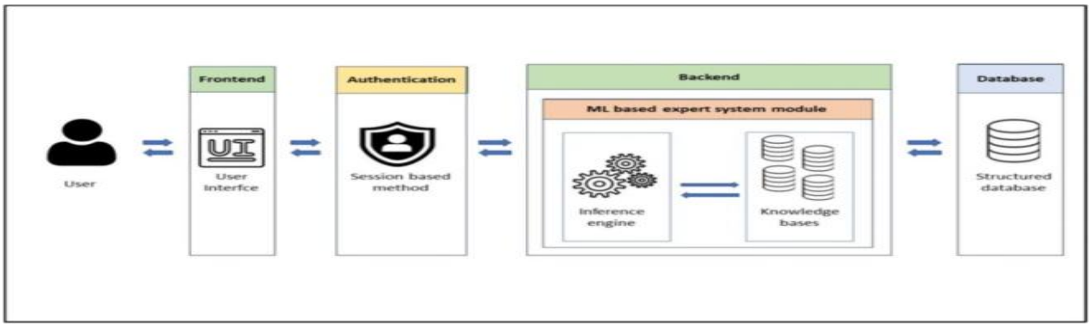

Figure 2: The Components Diagram

The Component Diagram illustrates the internal structure of the AI-based Mental Health Monitoring Framework and shows how different software components interact with each other. It focuses on the modular design of the system, where each component performs a specific task such as user interaction, data processing, prediction, and storage. This diagram helps in understanding how the frontend, backend, machine learning model, and database are connected.

In this architecture, the User Component interacts with the system through a web interface. The Frontend Component (React) collects the user's text input and sends it to the backend server using API calls. The Backend Component (Flask) acts as the central controller that receives input, processes requests, and communicates with other components.

The NLP Processing Component handles text preprocessing. It cleans the text, removes stop words, converts text to lowercase, and prepares it for feature extraction After preprocessing, the Vectorizer Component converts the text into numerical features using.TF-IDF or Count Vectorizer. These numerical values are required by the machine learning model.

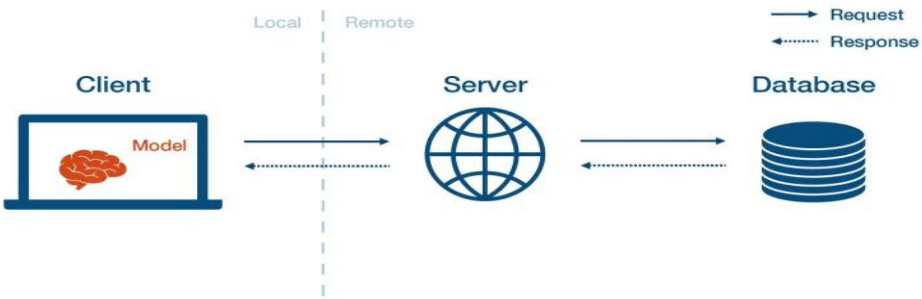

Figure 3: The Deployment Diagram

The Deployment Diagram shows how the AI-based mental health monitoring system is physically deployed on hardware and software environments. It explains where each component runs and how they communicate with each other during execution.

This diagram focuses on runtime environment instead of internal structure. It shows nodes such as user device, web server, backend server, machine learning model, and database.

6. Implementation

The proposed AI-based Mental Health Monitoring Framework is implemented using machine learning, natural language processing, and web technologies. The implementation phase involves dataset preparation, preprocessing, feature extraction, model training, and deployment of the prediction system. The system is designed to analyze user text input and predict mental health conditions such as stress, anxiety, depression, and normal state.

The first stage in implementing the prediction system is selecting an appropriate dataset. The dataset contains labeled text data representing different mental health conditions. These labels are used by machine learning algorithms to learn patterns and make predictions. The dataset is divided into training

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and testing sets to evaluate model performance. The training dataset is used to train the model, while the testing dataset is used to measure accuracy.

Data preprocessing is an important step for obtaining meaningful results from machine learning algorithms. The raw text data may contain noise such as punctuation, uppercase letters, and stop words. Therefore, preprocessing techniques such as lowercase conversion, punctuation removal, tokenization, and stop word removal are applied. These steps improve model performance and reduce unnecessary features.

After preprocessing, feature extraction is performed using vectorization techniques. The text input is converted into numerical format using TF-IDF vectorizer. Machine learning algorithms cannot process raw text directly, so converting text into feature vectors is necessary. The vectorizer is trained using the dataset and saved for future predictions.

To handle class imbalance in dataset, oversampling and undersampling techniques are used. Oversampling increases the number of samples in minority classes, while undersampling reduces the number of samples in majority classes. These techniques help in improving model accuracy and avoiding biased predictions.

The system uses supervised machine learning algorithms such as Logistic Regression, Naive Bayes, Support Vector Machine, and Random Forest. These algorithms are trained using the processed dataset. The model with the highest accuracy is selected for prediction. After training, the model is saved as a serialized file for deployment.

8.OUTCOME

The proposed AI-based Mental Health Monitoring Framework successfully predicts mental health conditions such as stress, anxiety, depression, and normal state using user text input. The system uses NLP techniques and machine learning models to analyze data and generate real-time results. The Support Vector Machine (SVM) model achieved the highest accuracy among all tested models. The system provides fast and reliable predictions through a simple web interface. All user inputs and results are stored in the database with timestamps for future analysis. Overall, the system is effective, scalable, and useful for early detection and awareness of mental health conditions.

9.SCREENSHOT

9.1 Homepage:

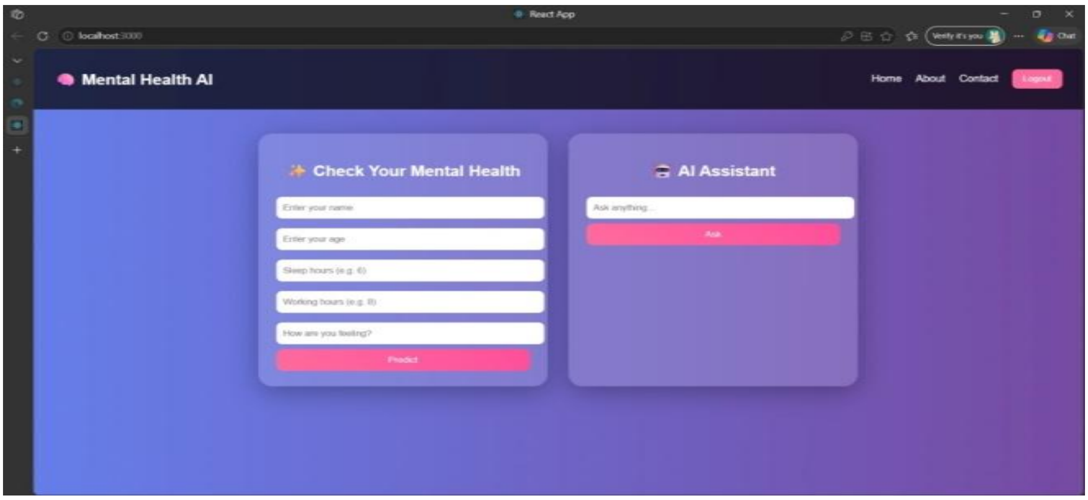

Figure 4: Home page

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9.2 Signup Screen:

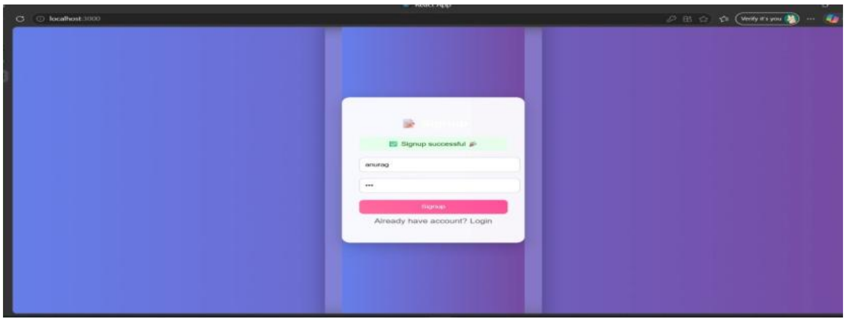

Figure 6:Signup Screen

9.3 Login Screen:

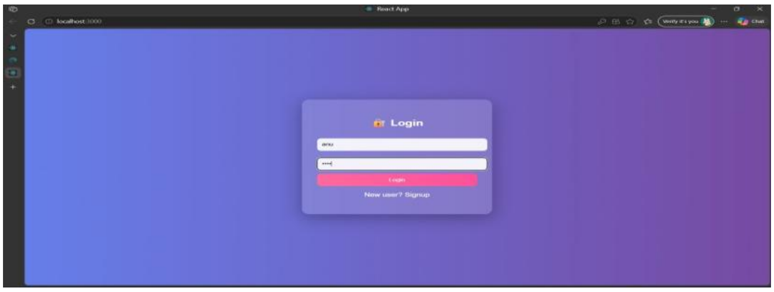

Figure 6: Login Screen

9.4 Mental Health Prediction:

Figure 7: Mental Health Prediction

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10.CONCLUSION

The AI-based Mental Health Monitoring Framework successfully demonstrates how machine learning and natural language processing can be used to detect mental health conditions from text input. The system provides an efficient and automated approach for early identification of stress, anxiety, depression, and normal mental states.

The proposed system integrates frontend, backend, machine learning model, and database into a complete end-to-end solution. It offers real-time prediction, easy accessibility, and storage of prediction history for future analysis. Among all tested models, Support Vector Machine (SVM) showed the best performance in terms of accuracy and reliability.

Although the system performs well, there is still scope for improvement in terms of dataset size, language support, and model optimization. Future enhancements can include deep learning models, multilingual support, and deployment on cloud platforms for wider accessibility.

Overall, this framework proves that AI can play a significant role in mental health monitoring and can assist in early detection and awareness, helping users take timely action for better mental well-being.

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