DOI: http://dx.doi.org/10.26483/ijarcs.v17i2.7427

ISSN No. 0976-5697

Volume 17, No. 2, March-April 2026

International Journal of Advanced Research in Computer Science

RESEARCH PAPER

Available Online at www.ijarcs.info

MINDVERGE: A HEALTH MONITORING SYSTEM USING SENTIMENT ANALYSIS WITH LLM

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Abstract: In the rapidly evolving digital healthcare ecosystem, individuals often face challenges in monitoring their emotional well-being and accessing timely medical support. Many existing healthcare platforms lack intelligent mechanisms to continuously analyze users' mental health conditions and provide real-time assistance based on their emotional state. To address this issue, this project proposes the development of an intelligent health monitoring system called **MindVerge**, which integrates advanced sentiment analysis techniques powered by Large Language Models (LLMs) to enhance user well-being and accessibility to healthcare services. The proposed system follows a structured and multi-functional approach that combines natural language processing and real-time data integration. It analyses user-generated text inputs such as chat messages or health logs to detect emotional states, including stress, anxiety, positivity, or negativity. The system utilizes NLP techniques such as contextual text analysis and deep learning-based language understanding to accurately interpret user emotions and identify potential mental health risks.

In addition to sentiment analysis, the system incorporates location-based healthcare support using Google Maps API to help users discover nearby hospitals and medical professionals. A distance calculation mechanism based on the Haversine formula ensures accurate recommendations of the nearest healthcare facilities. The platform also includes an appointment booking system that allows users to schedule consultations directly and receive real-time updates on appointment status. Furthermore, the system provides secure authentication, data privacy, and role-based access for users and hospital staff. Emotional data and appointment records are safely stored and managed within the database to ensure reliability and confidentiality. By integrating intelligent emotional analysis with real-time healthcare connectivity, Mind Verge offers a user-friendly, efficient, and proactive solution for continuous mental health monitoring and support.

Keywords: Health, Monitoring, System, MindVerge

INTRODUCTION

The rapid development of digital technology has significantly transformed the healthcare sector, especially in the way individuals monitor their mental and emotional well-being. In earlier times, people relied mainly on physical consultations, personal interactions, and manual assessments by healthcare professionals to understand their emotional health. These traditional methods were often time-consuming, less accessible, and lacked continuous monitoring capabilities.

With the advancement of web-based technologies and artificial intelligence, healthcare services have become more accessible, efficient, and user-friendly. Today, individuals can use digital platforms to track their health, communicate their concerns, and receive timely support without the need for frequent hospital visits. However, despite these advancements, there are still several challenges in effectively monitoring emotional health and providing real-time assistance. Many existing systems lack intelligent mechanisms to analyze user emotions accurately and fail to integrate healthcare services such as hospital discovery and appointment booking within a single platform.

Another major concern is the lack of continuous emotional monitoring and early detection of mental health issues. Emotional conditions such as stress, anxiety, and depression often go unnoticed until they become severe. Traditional systems do not provide real-time analysis or personalized insights based on user input, which limits their effectiveness. Additionally, users may face difficulties in finding nearby healthcare facilities quickly, especially during urgent situations.

The increasing reliance on digital platforms, especially after the COVID-19 pandemic, has further emphasized the need for intelligent healthcare solutions. During this period, remote monitoring and online healthcare services became essential. This shift created the demand for systems that can not only analyze user health data but also provide immediate support and connect users with healthcare providers.

Earlier systems mainly relied on basic data analysis techniques and simple rule-based approaches for monitoring health conditions. While these methods can process structured data, they lack the ability to understand the deeper meaning and context of user-generated text. As emotional health analysis requires understanding human language, tone, and context, traditional approaches are often insufficient.

To overcome these limitations, this project proposes **MindVerge**, an intelligent health monitoring system that utilizes advanced sentiment analysis powered by Large Language Models (LLMs). Unlike traditional methods, LLM-based models can understand both the context and semantics of user input, enabling accurate detection of emotional states such as stress, anxiety, positivity, and negativity. The system processes user-entered text through natural language processing techniques to generate meaningful emotional insights.

In addition to emotional analysis, MindVerge integrates location-based services using Google Maps API to help users identify nearby hospitals and healthcare centres. The system uses the Haversine formula to calculate accurate distances and recommend the nearest healthcare facilities. Furthermore, users can book appointments directly through the platform, while hospital staff can manage requests by accepting or rejecting them.

The main objective of this project is to develop a scalable, intelligent, and user-friendly system that provides real-time emotional monitoring and seamless access to healthcare services. By combining LLM-based sentiment analysis with location-based hospital discovery and appointment management, MindVerge aims to improve early detection of mental health issues, enhance user support, and provide a comprehensive digital healthcare solution.

RELATED WORK

A. Background and Emergence of Digital Healthcare Systems

The rapid evolution of digital communication technologies has significantly transformed the healthcare sector. Modern healthcare systems increasingly rely on web-based platforms, mobile applications, and intelligent systems to provide accessible and efficient services. These technologies reduce geographical barriers and allow users to monitor their health remotely.

However, despite these advancements, several challenges remain in mental health monitoring. Traditional healthcare systems rely heavily on manual assessments and in-person consultations, which may not capture real-time emotional changes. Many digital health applications provide only basic tracking features and lack intelligent mechanisms to accurately analyze emotional conditions.

Emotional health issues such as stress, anxiety, and depression often go unnoticed due to the absence of continuous monitoring systems. Additionally, users may face difficulties in accessing nearby healthcare facilities quickly during emergencies. This highlights the need for intelligent systems that combine emotional analysis with real-time healthcare support.

B. Limitations of Traditional Approaches in Health Monitoring

Earlier healthcare monitoring systems relied on simple analytical methods and rule-based approaches that were not capable of understanding human emotions effectively. These approaches lacked the ability to interpret the context and meaning of user-generated text, which is essential for accurate emotional analysis.

Since mental health assessment depends heavily on understanding tone, context, and language patterns, traditional approaches are not sufficient to detect complex emotional states such as stress, anxiety, or depression. This limitation reduces the effectiveness of conventional systems in real-world healthcare applications.

C. System Expansion and Integration Challenges

As healthcare technologies evolved, researchers began integrating multiple data sources such as emotional logs, patient records, and behavioural data. This improved the ability of systems to analyze user conditions more effectively.

However, challenges still exist in terms of data diversity and generalization. Emotional expressions vary across individuals, languages, and cultural contexts, making it difficult to design a universal model. Additionally, many systems lack integration with real-time services such as hospital discovery and appointment booking, limiting their practical usability.

D. Challenges in Real-Time Monitoring

One of the major challenges in health monitoring systems is detecting critical emotional conditions in real time. Most user inputs represent normal emotional states, while high-risk conditions such as severe stress or anxiety occur less frequently.

This makes it difficult for systems to identify critical cases effectively. Therefore, healthcare systems must focus on timely detection and continuous monitoring to ensure early intervention and prevent serious consequences.

E. LLM-Based Approaches in Healthcare Systems

Recent advancements in artificial intelligence have introduced Large Language Models (LLMs), which provide powerful capabilities for natural language understanding. Unlike traditional approaches, LLMs analyze both the context and semantics of user input, enabling accurate detection of emotional states.

In healthcare applications, LLMs can process user-generated text such as chat messages and health logs to identify subtle emotional patterns. These models are capable of understanding complex language structures and long textual inputs, making them highly effective for sentiment analysis.

In the MindVerge system, sentiment analysis is performed using an Ollama-based LLM (LLaMA model), which directly analyses user input and provides emotional insights without relying on traditional feature extraction methods.

F. Integration of Location-Based Services

Modern healthcare systems require integration with real-world services to provide complete support. Location-based technologies such as Google Maps play a crucial role in connecting users with nearby healthcare facilities.

By integrating Google Maps API, systems can identify nearby hospitals, display their locations, and provide navigation support. This improves accessibility and ensures that users can quickly find medical assistance when needed.

In MindVerge, Google Maps integration combined with distance calculation using the Haversine formula enables accurate and efficient hospital recommendations.

II. METHODOLOGY

The proposed MindVerge Health Monitoring System follows a structured methodology that integrates LLM-based sentiment analysis using Ollama, Google Maps-based hospital discovery, and real-time appointment management. The goal is to design a system that is intelligent, scalable, and practical for real-world healthcare applications.

The system adopts a streamlined approach that focuses on deep language understanding and real-time service integration. This ensures accurate emotional analysis, efficient hospital discovery, and seamless appointment handling.

The process begins with user input, where users provide health-related text such as chat messages or logs. This input is directly processed by the Ollama-based LLM, which analyses the context and meaning of the text to determine the user's emotional state. The model generates outputs such as emotional category, sentiment score, and personalized suggestions.

The analysed emotional data is stored in the database to maintain user history and track emotional trends over time. This helps in providing continuous monitoring and early detection of mental health conditions.

To provide real-time healthcare support, the system integrates Google Maps API to fetch nearby hospitals based on the user's location. The Haversine formula is used to calculate the distance between the user and hospitals, ensuring accurate recommendations of the nearest healthcare facilities.

Users can then select a hospital and book appointments directly through the system. Hospital staff can manage these requests by accepting or rejecting appointments, and the updated status is communicated to users in real time.

The system also ensures security through JWT-based authentication, secure data storage, and role-based access control. Overall, this methodology combines intelligent emotional analysis with location-based healthcare access, providing a complete and efficient health monitoring solution.

PHASE 1: DATA COLLECTION AND PREPROCESSING

Dataset Acquisition:
The dataset used in this research is the MindConnect Integrated Healthcare & Assessment Dataset, collected from Kaggle and other healthcare-related sources. The initial dataset consists of 30,000 records, and after preprocessing, 10,000 records were retained for system implementation and analysis. The dataset is primarily used for nearby hospital filtering and healthcare recommendation based on geographical distance and service relevance.

The hospital dataset contains structured healthcare information with attributes such as hospital name, address, latitude, longitude, rating, specialization, consultation fee, and slot availability. These attributes help the system recommend suitable healthcare facilities to users based on their location and needs. The dataset size is 9.68 MB, and it supports real-time hospital discovery using map-based integration.

Feature Description:
The processed dataset contains important features required for hospital recommendation and user support. These include:

- hospital_id – Unique identifier for each hospital
- hospital_name – Official name of the hospital or clinic
- address – Physical location of the hospital
- latitude – Geographic coordinate used for distance calculation
- longitude – Geographic coordinate used for distance calculation
- rating – Average user rating of the hospital
- specialization – Mental health services offered such as CBT, counseling, and psychiatry
- consultation_fee – Cost of consultation for booking filter
- slot_availability – Available appointment slots for booking

Data Preprocessing:
Raw healthcare and hospital data often contain inconsistencies such as missing values, duplicate records, invalid coordinates, inconsistent specialization names, and unnecessary formatting issues. To improve data quality, a preprocessing pipeline is applied.
The preprocessing steps include removal of null values, elimination of duplicate entries, normalization of hospital names and specialization fields, correction of coordinate formats, and validation of latitude and longitude values. Records with incomplete or invalid information are filtered out. After this cleaning process, the dataset is reduced from 30,000 records to 10,000 records, ensuring better consistency and reliability for system usage.
In addition to hospital data preprocessing, user health-related text input is also prepared before sentiment analysis. The text is cleaned and formatted so that it can be effectively processed by the Ollama-based LLM for emotional evaluation.

PHASE 2: MODEL DEVELOPMENT AND ANALYSIS:

A. LLM-Based Sentiment Analysis Model:
The proposed system uses an Ollama-based Large Language Model (LLaMA model) for emotional analysis. Unlike traditional machine learning approaches, this model directly understands the context and meaning of user-generated health text.
When a user enters health-related text, the system sends it to the Ollama LLM, which analyses the content and identifies the emotional condition of the user. The output includes emotional indicators such as stress level, anxiety level, positivity, negativity, and overall risk level. This helps in understanding the user's current emotional state in a more accurate and meaningful way.

B. Emotional Risk Identification:
The system specifically focuses on identifying stress and anxiety levels, since these are important indicators in mental health monitoring. Based on the input text, the model categorizes user emotions into different levels such as:

- Low Stress / Low Anxiety
- Moderate Stress / Moderate Anxiety
- High Stress / High Anxiety

These emotional levels are stored in the database and can be used to track the user's mental health trend over time. If the detected emotional risk is high, the system can provide recommendations and guide the user towards nearby healthcare support.

C. Hospital Recommendation using Google Maps:
To provide immediate healthcare support, the system integrates Google Maps API for real-time hospital discovery. Based on the user's location, nearby hospitals are fetched and displayed.
The Haversine formula is used to calculate the distance between the user and available hospitals using latitude and longitude values. This ensures accurate ranking of hospitals based on proximity. Hospitals are then recommended according to nearest distance, specialization, and availability.

PHASE 3: SYSTEM INTEGRATION AND IMPLEMENTATION:

The trained emotional analysis model and healthcare services are integrated into a web-based application. The system follows a layered architecture consisting of a user interface layer, application logic layer, LLM analysis layer, map integration layer, and database layer.
The user interface allows users to:

- Register and log in securely
- Enter health-related text
- View emotional analysis results
- Search nearby hospitals
- Book appointments

The application logic layer handles user requests, authentication, and communication between components. The LLM analysis layer processes user input using Ollama and returns emotional insights such as stress and anxiety levels. The Google Maps integration layer retrieves nearby hospitals and supports distance-based filtering. The database layer stores emotional history, hospital details, and appointment records securely.

WORKING PROCESS FLOW:

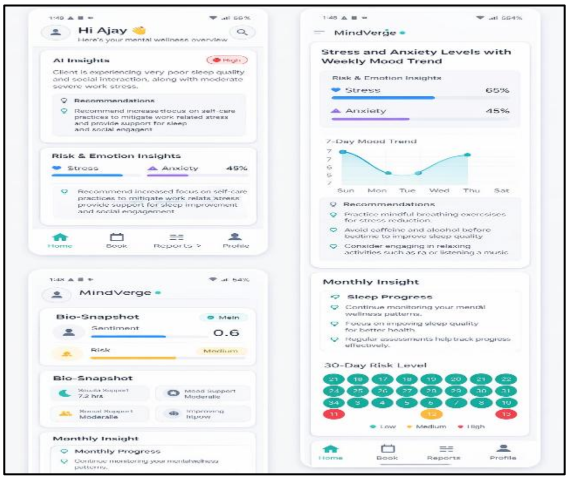
The system operates through a structured workflow. First, the user logs into the application and enters health-related text. The text is sent to the Ollama LLM, which performs sentiment analysis and identifies emotional indicators such as stress level and anxiety level.
If the detected emotional condition is normal or moderate, the system displays the results and stores them in the database for future tracking. If the emotional risk is high, the system suggests immediate consultation.
Next, the system fetches the user's current location and uses Google Maps API to identify nearby hospitals. The Haversine formula is applied to calculate accurate distances between the user and hospitals. Based on this, the nearest and most relevant hospitals are recommended.
The user can then select a hospital and book an appointment. The booking details are stored in the database, and hospital staff can accept or reject the request. The updated appointment status is displayed to the user in real time.

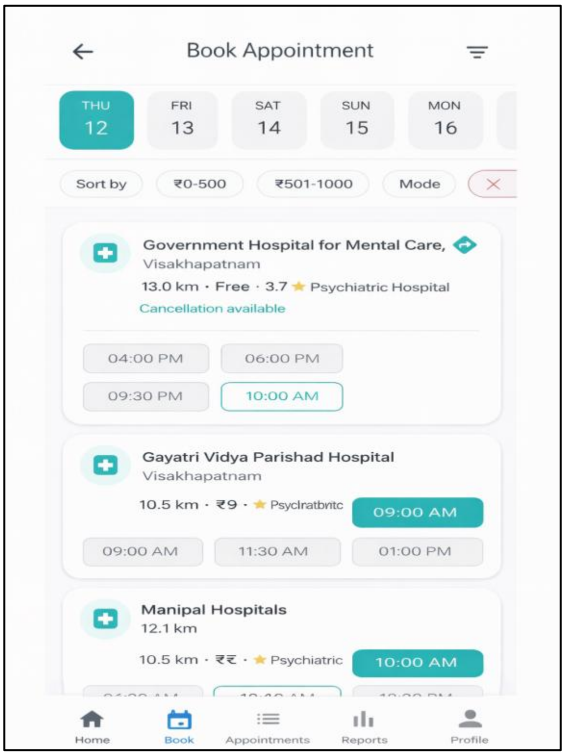
III. RESULTS:

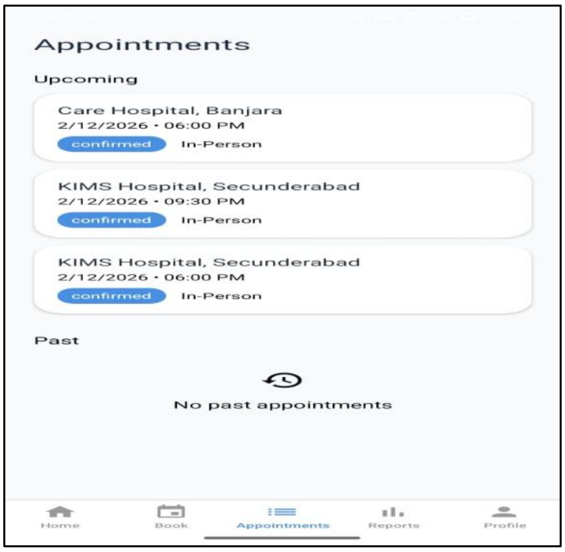
The experiments for the MindVerge system were performed using the MindConnect Integrated Healthcare & Assessment Dataset. The original dataset contains 30,000 records, and after preprocessing, 10,000 records were retained for implementation. The dataset includes structured hospital-related data with healthcare attributes required for hospital recommendation and appointment booking.
The system was evaluated based on its ability to perform two main tasks:

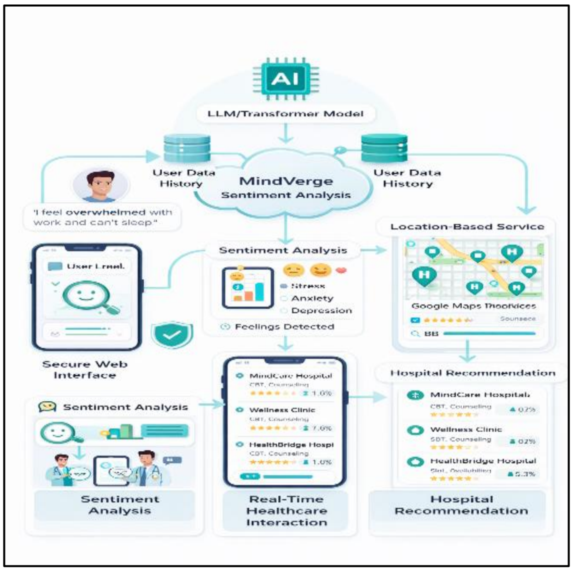
1. Emotional analysis using Ollama LLM
2. Nearby hospital recommendation using Google Maps and Haversine distance calculation

The sentiment analysis module successfully identified emotional conditions such as stress, anxiety, positive mood, and negative mood from user text. The model provided meaningful summaries and suggestions, enabling effective mental health monitoring.
The hospital recommendation module successfully fetched nearby hospitals based on the user's current location. Using the Haversine formula, the system accurately ranked hospitals according to distance. The integration with Google Maps improved accessibility and helped users locate appropriate healthcare services quickly.
The appointment booking module also functioned effectively by allowing users to select hospitals, book available slots, and receive real-time status updates. Overall, the system demonstrated strong usability, timely response, and effective integration of emotional analysis with healthcare accessibility.









IV. CONCLUSION:

The proposed MindVerge Health Monitoring System provides an intelligent and user-friendly solutkion for emotional health monitoring and healthcare support. By integrating Ollama-based LLM sentiment analysis with Google Maps hospital discovery, the system bridges the gap between emotional well-being assessment and real-world medical access. The use of the MindConnect Integrated Healthcare & Assessment Dataset, consisting of 30,000 records and 10,000 processed entries, supports accurate hospital recommendation and efficient appointment management. The system effectively identifies emotional indicators such as stress and anxiety levels, stores emotional history, and provides timely recommendations to users.

By combining advanced language understanding, map-based healthcare support, and secure appointment booking, MindVerge offers a practical, scalable, and efficient healthcare solution. It improves accessibility, promotes early intervention, and supports continuous monitoring of mental and emotional well-being.

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