IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⋇ Peer-reviewed & Refereed journal ⋇ Vol. 15, Issue 1, January 2026

DOI: 10.17148/IJARCCE.2026.15121

AI-Based Health Monitoring System

Jagadevi Puranikmath[1], Harsha D V[2], Hemanth K[3], Mohammed Fida Moinuddin J[4], Kiran A[2]

Department of Computer Science and Engineering, Ballari Institute of Technology and Management Ballari, Karnataka, India[1-5]

Abstract: This paper presents a fully integrated AI-Based Health Monitoring System that performs natural-language symptom analysis, machine learning classification, severity estimation, multilingual recommendation delivery, personal health record management, and real-time emergency support aligned with UN SDG-3. The system accepts free-text symptoms, processes them through TF-IDF vectorization and Logistic Regression, and combines predictive results with rule-based severity logic to ensure medically responsible triage. To improve accessibility, the system provides multilingual outputs in English, Hindi, and Kannada using an offline translation dictionary. Emergency response capabilities include geolocation-based hospital discovery using OpenStreetMap APIs, prioritizing hospitals with verified contact details. Implemented with Python Flask, scikit-learn, SQLite/PostgreSQL, HTML, CSS, and JavaScript, the platform provides safe and reliable triage with intentional over-triage to reduce false negatives in critical conditions.

Keywords: AI Healthcare, Symptom Analysis, Logistic Regression, Multilingual Health System, Emergency Support.

I. INTRODUCTION

Artificial intelligence has significantly transformed modern healthcare by enabling rapid data analysis, scalable decision support, and personalized medical insights. With the increasing dependence on digital platforms for preliminary health information, there is a growing demand for intelligent systems that can safely analyze symptoms and provide context-aware guidance. Traditional symptom checker systems typically rely on fixed decision trees and structured questionnaires, which restrict their ability to understand free-text symptom descriptions and complex symptom combinations.

Natural Language Processing enables users to describe health concerns in their own words, allowing systems to extract meaningful medical information from unstructured text. Machine learning models trained on symptom-condition relationships provide consistent and repeatable predictions compared to rule-only approaches. However, safety remains a critical concern in digital triage systems, as incorrect severity assessment can delay medical intervention. Therefore, conservative triage strategies that prioritize over-triage are essential.

This work proposes an AI-based health monitoring system that integrates NLP-based symptom understanding, machine learning classification, severity-aware triage, multilingual recommendations, emergency response mechanisms, and personal health management. The system is designed using open-source technologies, ensuring affordability and scalability for deployment in resource-constrained environments while supporting proactive healthcare awareness.

II. LITERATURE SURVEY

Digital health research spans symptom checkers, telemedicine platforms, machine learning-based diagnosis, emergency response systems, and multilingual health interfaces. Several studies have evaluated existing online symptom checkers and reported inconsistent diagnostic accuracy, particularly for severe conditions. Many consumer-facing tools rely on decision-tree logic, limiting adaptability and personalization.

Telemedicine platforms enable remote consultations and chronic disease management, reducing hospital workload. However, most systems lack automated triage capabilities and depend on clinician availability. Natural Language Processing has been widely applied in clinical informatics to extract symptoms and diagnoses from medical text. TF-IDF and traditional machine learning models have shown reliable performance in clinical text classification tasks, particularly when datasets are limited.

Machine learning models such as Logistic Regression, Support Vector Machines, and Random Forests have been explored for disease prediction. Interpretable models are preferred in healthcare due to transparency and trust

DOI: 10.17148/IJARCCE.2026.15121

requirements. Emergency response research highlights the importance of geolocation-enabled hospital discovery and routing to reduce response time during critical cases. Additionally, multilingual interfaces significantly improve comprehension, trust, and adherence to medical guidance, especially in linguistically diverse populations.
These findings emphasize the need for a unified system that integrates NLP, machine learning, emergency support, multilingual communication, and structured health data management.

III. PROPOSED METHODOLOGY

The proposed system follows a multi-stage methodology combining artificial intelligence with rule-based medical safety logic. User symptoms are collected either through free-text input or predefined symptom selection. The input text undergoes preprocessing steps including lowercasing, tokenization, stop-word removal, and punctuation cleaning to ensure consistency.

Feature extraction is performed using Term Frequency–Inverse Document Frequency, which converts symptom text into weighted numerical vectors. Logistic Regression is then applied to predict probable medical conditions due to its low computational cost, interpretability, and suitability for real-time inference. Severity estimation uses a hybrid approach where machine learning confidence scores are combined with predefined red-flag symptom rules such as chest pain, breathing difficulty, confusion, or dizziness.

Based on severity classification, the system generates personalized recommendations. Multilingual support is implemented using an offline translation dictionary to deliver advice in English, Hindi, and Kannada. Severe cases activate the emergency support module, which displays emergency contact options and locates nearby hospitals using geolocation services.

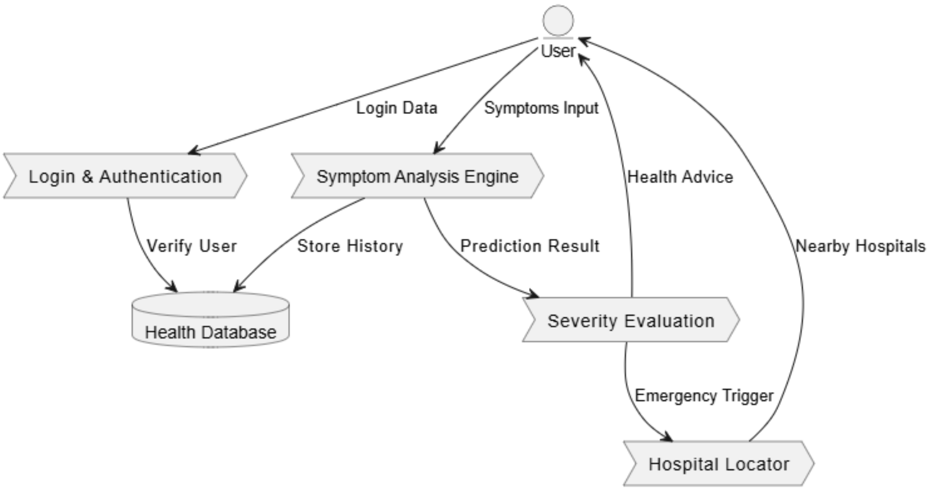

Fig. 1. Data Flow of the AI-Based Health Monitoring System

IV. SYSTEM ARCHITECTURE

The system architecture is organized into four primary layers. The front-end layer provides a responsive user interface developed using HTML, CSS, and JavaScript, enabling symptom entry, health record access, and emergency alerts. The back-end layer is implemented using Flask and handles user authentication, session management, API routing, and data validation.

The AI and NLP service layer manages text preprocessing, feature extraction, condition prediction, severity scoring, and recommendation generation. This layer ensures fast and interpretable inference suitable for low-resource systems. The data management layer uses SQLite for development and PostgreSQL for scalable deployment, storing user profiles, symptom histories, medications, appointments, and emergency contacts through structured relational schemas.
The overall layered architecture of the proposed AI-Based Health Monitoring System is illustrated in Fig. 1, highlighting the interaction between the client layer, application backend, AI service layer, data management layer, and external emergency services.

International Journal of Advanced Research in Computer and Communication Engineering
Impact Factor 8.471 ⁒ Peer-reviewed & Refereed journal ⁒ Vol. 15, Issue 1, January 2026
DOI: 10.17148/IJARCCE.2026.15121

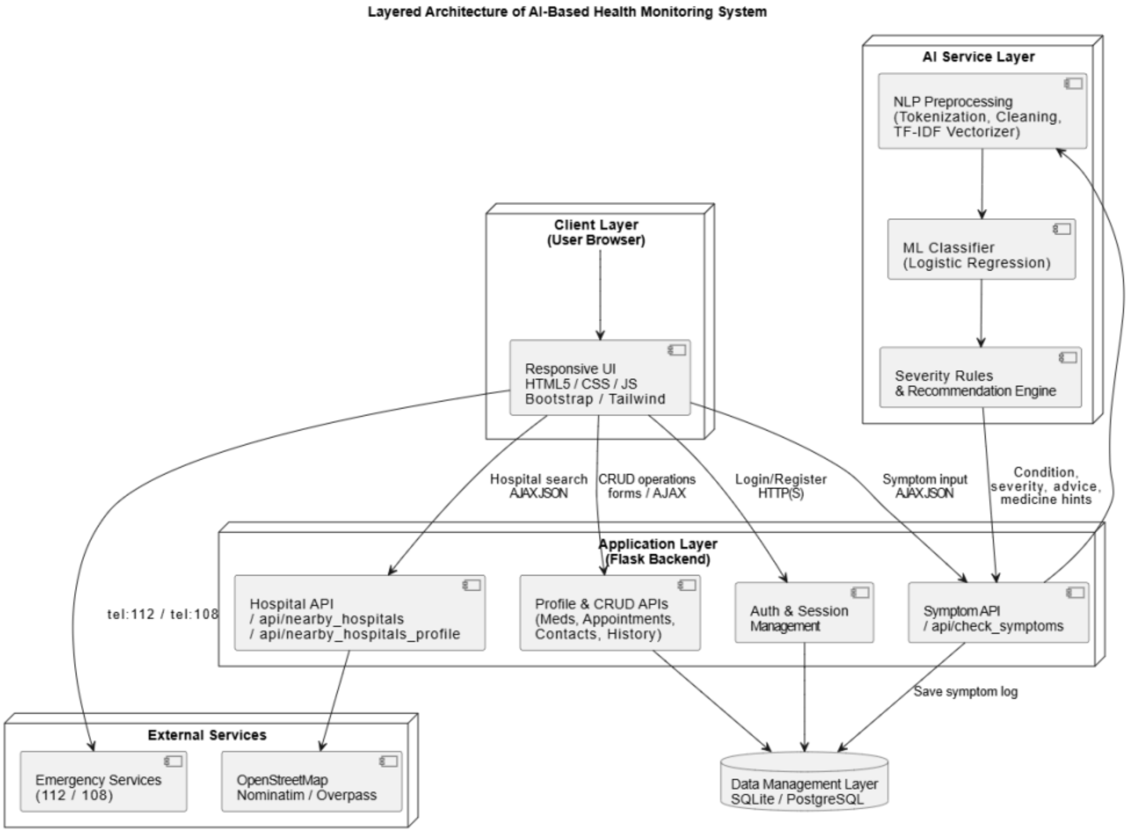

Fig. 2. System Architecture of the AI-Based Health Monitoring System

V. IMPLEMENTATION DETAILS

The system is implemented using Python Flask for backend services and scikit-learn for machine learning operations. User authentication is secured through password hashing and session-based login management. The symptom checker module accepts user inputs and performs real-time inference to generate condition predictions and severity classifications.

The emergency module activates for severe conditions, displaying emergency numbers and nearby hospitals prioritized by verified contact information. The personal health management module enables users to maintain medication schedules, appointment records, symptom histories, and emergency contacts with full create, read, update, and delete functionality. Multilingual recommendations are generated offline to ensure consistent medical phrasing without reliance on external APIs.

VI. RESULTS AND DISCUSSION

The system was evaluated across multiple functional modules including user registration, symptom analysis, severity classification, hospital discovery, and health record management. Results demonstrate accurate classification of mild, moderate, and severe conditions with high recall for critical cases. The hybrid severity logic successfully identifies emergency scenarios even when machine learning confidence is moderate.

User interface testing confirmed intuitive navigation and clear presentation of health insights. Hospital discovery results prioritized facilities with verified phone numbers, improving emergency usability. The results validate the system's effectiveness in providing safe, accessible, and responsive digital triage support.

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 15, Issue 1, January 2026

DOI: 10.17148/IJARCCE.2026.15121

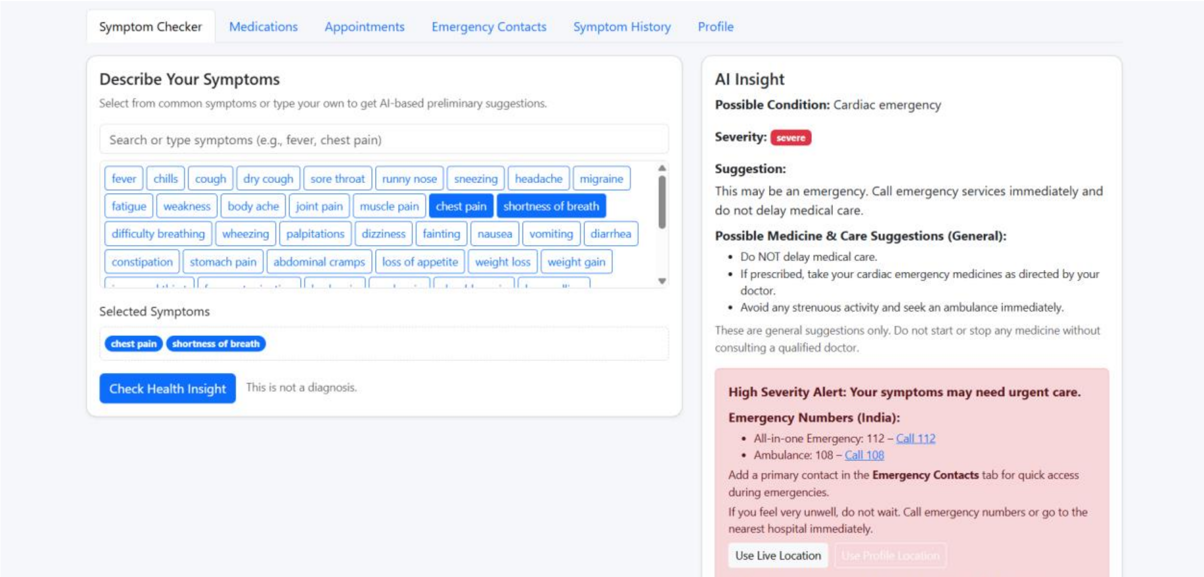

Fig. 3. AI-Based Symptom Analysis and Severity Classification Result

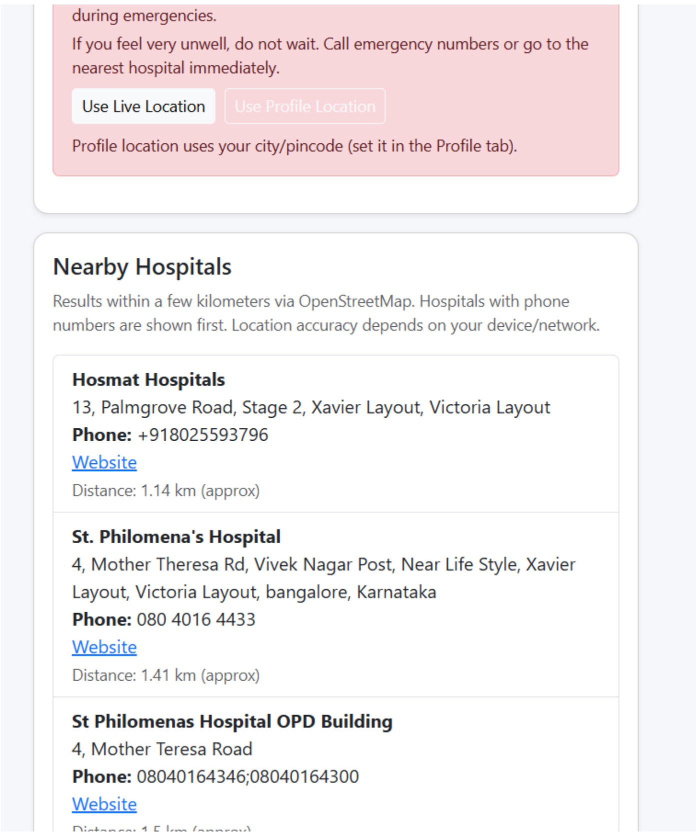

Fig. 4. Nearby Hospital Discovery Based on User Location

VII. FUTURE SCOPE

Future enhancements include integration with wearable devices for continuous vital monitoring and early risk detection. Advanced transformer-based NLP models such as ClinicalBERT can be incorporated to improve contextual understanding of long symptom descriptions. A dedicated doctor portal may allow clinicians to review patient histories and validate predictions. Additional language support and mobile application deployment can further improve accessibility. Aggregated, anonymized health data can also support public health analytics and outbreak monitoring.

DOI: 10.17148/IJARCCE.2026.15121

REFERENCES

[1]. R. Winn, T. Pogrebnyakov, and P. Ball, "Artificial Intelligence in Healthcare: Past, Present, and Future," IEEE Engineering in Medicine and Biology Magazine, vol. 40, no. 5, pp. 58–68, 2021.

[2]. A. White and S. Hassan, "Evaluating the Reliability of Digital Symptom Checkers," Journal of the American Medical Association, vol. 324, no. 4, pp. 398–404, 2020.

[3]. S. Semigran, A. Linder, and K. Cardozo, "Evaluation of Symptom Checkers for Self-Diagnosis and Triage," BMJ, vol. 351, pp. 1–8, 2015.

[4]. A. Névéol, K. Roberts, and T. Demner-Fushman, "Clinical Natural Language Processing: State of the Art," Journal of Biomedical Informatics, vol. 92, pp. 103–121, 2018.

[5]. K. Liao and F. Chen, "Symptom-Based Disease Classification Using Machine Learning," IEEE Access, vol. 8, pp. 110–123, 2020.

[6]. P. Narayan and S. Bhat, "Designing Multilingual Health Applications for Rural Communities," IEEE Global Humanitarian Technology Conference, pp. 912–918, 2020.