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MediAssist AI: An Intelligent Multi-Agent Healthcare Chatbot for Preliminary Medical Guidance and Emergency Triage

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Abstract: Accessing timely preliminary medical guidance remains a critical challenge for individuals worldwide, with many relying on traditional healthcare systems that lack accessibility, personalization, and immediate response mechanisms. Current symptom checker applications provide limited diagnostic accuracy, lack real-time emergency detection capabilities, and fail to deliver comprehensive medical knowledge integrated with evidence-based treatment recommendations. The absence of intelligent, multi-agent healthcare systems leaves individuals underprepared to assess their health conditions, identify emergencies, and make informed decisions about seeking professional medical care.

To address these limitations, the MediAssist AI platform integrates Artificial Intelligence, Machine Learning, and Multi-Agent System architecture to deliver personalized, interactive preliminary medical guidance at scale. The system leverages advanced Natural Language Processing and machine learning classifiers to analyze symptom descriptions and predict likely medical conditions based on user input. Real-time emergency detection scans for critical keywords across eight life-threatening categories, ensuring immediate safety guidance delivery within 500 milliseconds. AI-powered knowledge agents retrieve comprehensive medical information from structured databases, while treatment recommendation agents provide evidence-based care guidance with appropriate medical disclaimers.

Through a user-centric web platform built with Streamlit and Flask, users describe symptoms naturally, receive instant emergency alerts when critical conditions are detected, view top-three condition predictions with confidence scores, access detailed medical knowledge about identified conditions, and obtain treatment recommendations with home care instructions. Stakeholders including general users, healthcare administrators, and medical professionals benefit from structured preliminary assessment workflows and comprehensive health literacy resources. By combining rule-based emergency triage with machine learning-powered symptom analysis and knowledge-driven medical guidance, the proposed solution significantly improves healthcare accessibility, reduces response time for critical situations, and enhances informed decision-making while democratizing access to preliminary medical consultation.

I. INTRODUCTION

Effective preliminary medical guidance is crucial for public health outcomes, yet individuals lack access to immediate, intelligent, and personalized healthcare consultation systems. Traditional methods rely on manual consultations with limited availability, generic online symptom checkers with poor accuracy, and telephone helplines with inconsistent guidance quality, resulting in delayed emergency identification and inadequate health literacy.

The MediAssist AI platform combines Multi-Agent System architecture, Machine Learning, and Natural Language Processing to deliver comprehensive preliminary medical guidance. Users input symptom descriptions naturally; the system performs emergency detection across eight critical categories, analyzes symptoms using trained ML models achieving 87% accuracy, retrieves medical knowledge from structured databases, and provides evidence-based treatment recommendations. Advanced coordination mechanisms ensure seamless multi-agent collaboration, coherent response compilation, and appropriate medical disclaimer presentation.

By integrating specialized agents for triage, symptom analysis, knowledge retrieval, and treatment guidance with centralized coordinator orchestration, this application enhances healthcare accessibility and preliminary assessment effectiveness while democratizing quality medical information for general populations, students, and healthcare organizations.

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1.1 Project Description
Healthcare accessibility is a critical challenge due to its complexity and the involvement of numerous stakeholders including patients, healthcare providers, and medical institutions. Problems like limited access to preliminary medical guidance, absence of immediate emergency detection, and manual symptom assessment processes frequently result in delayed care seeking, inadequate health literacy, and preventable health complications. Conventional systems depend on face-to-face consultations or simple symptom checkers, which do not provide intelligent analysis, real-time emergency detection, or comprehensive medical knowledge integration. This diminishes patient confidence and hinders early identification of serious health conditions.

Using advanced technologies such as Machine Learning, Natural Language Processing, and Multi-Agent System architecture for real-time symptom analysis and predictive condition assessment, the MediAssist AI platform tackles these gaps. MediAssist AI is an intelligent healthcare platform that allows for natural symptom description, emergency keyword detection, condition prediction with confidence scores, medical knowledge retrieval, and treatment recommendation delivery from initial query to comprehensive guidance generation.

1.2 Motivation
Effective preliminary medical guidance and emergency detection are critical concerns in modern healthcare, where individuals face multiple health challenges requiring immediate assessment, accurate information, and appropriate care decisions. Even minor delays in identifying conditions—such as cardiac emergencies, respiratory distress, neurological crises, or severe allergic reactions—can lead to life-threatening complications, delayed treatment, and adverse health outcomes. These issues not only result in significant health risks but also pose serious challenges to public wellbeing in terms of healthcare accessibility and patient empowerment.

Despite the importance of timely medical guidance, most existing healthcare information systems rely on manual consultations, static symptom databases, and centralized medical helplines. Such approaches are often reactive, accuracy-limited, and incapable of providing real-time assessment of emergency conditions. Moreover, the lack of transparent and intelligent symptom analysis mechanisms makes it difficult for individuals to verify condition likelihood, understand health information, and determine appropriate care seeking, leading to reduced health literacy and delayed medical intervention.

The increasing demand for accessible, intelligent, and immediate preliminary medical guidance highlights the need for an automated healthcare consultation framework. Advances in Artificial Intelligence (AI) and Machine Learning enable accurate condition prediction and emergency detection, while Multi-Agent System architecture offers specialized, coordinated medical guidance delivery across symptom analysis, knowledge retrieval, and treatment recommendation. Motivated by these challenges, this project aims to develop an integrated MediAssist AI platform that combines ML-based symptom analysis with rule-based emergency triage and knowledge-driven medical information to ensure better healthcare accessibility, reduce emergency response delays, and enhance trust among all users.

II. RELATED WORK

Several studies have explored AI-based approaches for symptom analysis, medical diagnosis, and automated healthcare guidance using natural language processing and machine learning techniques. Research by Semigran et al. (2015) evaluated 23 popular symptom checkers, finding average diagnostic accuracy of only 34% for first-position predictions and 58% for top-three accuracy, highlighting significant limitations in traditional symptom checking platforms. Machine learning models such as Decision Trees, Random Forests, and Naive Bayes have demonstrated improved success rates when trained on structured medical datasets, though implementations face challenges including data imbalance, limited interpretability, and poor generalization to diverse symptom presentations (Ahsan et al., 2022).

Multi-agent healthcare systems have emerged as promising solutions for handling complex medical tasks requiring specialized expertise. Research by Nweke et al. (2025) demonstrates that distributed agent architectures collaborating on healthcare guidance achieve superior results through domain specialization and focused optimization compared to monolithic AI approaches. However, these systems require robust coordination mechanisms and standardized communication protocols. Studies on explainable AI in healthcare (Mienye et al., 2024) emphasize that traditional medical AI models operating as "black boxes" significantly undermine user confidence and adoption, highlighting the need for interpretable prediction mechanisms with clear confidence scores and reasoning transparency.

User experience research on symptom checkers (You et al., 2023) reveals that adoption depends critically on clear explanations, concise result presentation, and credible information sourcing, with conversational interfaces proving

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more engaging than traditional form-based approaches. Despite these advances, most existing systems address emergency detection, symptom analysis, or knowledge retrieval independently. There remains a research gap in developing unified platforms integrating rule-based emergency triage, ML-powered condition prediction, knowledge-driven medical information, and evidence-based treatment recommendations within single cohesive frameworks. The proposed MediAssist AI platform addresses this gap by combining multi-agent architecture with machine learning and structured knowledge bases into an end-to-end intelligent preliminary medical guidance system.

III. METHODOLOGY

A. System Architecture Overview

MediAssist AI is built as a full-stack web-based platform integrating frontend, backend, and AI/ML services. The system employs modular multi-agent architecture with distinct specialized components for emergency detection, symptom analysis, medical knowledge retrieval, and treatment recommendation. The backend Flask API handles user input validation, agent coordination, and response compilation. The frontend Streamlit interface provides intuitive symptom description input, emergency alert display, condition prediction visualization, and comprehensive medical guidance presentation. The ML pipeline operates through trained models, receiving symptom descriptions and generating condition predictions with confidence scores.

B. Multi-Agent System Design

The system implements five specialized agents coordinated through centralized orchestration:
Coordinator Agent: Manages overall workflow orchestration, receives user queries, determines appropriate agent invocation sequences, compiles comprehensive responses from multiple specialized agents, and maintains conversation context throughout user sessions.

Triage Agent: Implements rule-based emergency detection scanning every user input for critical keywords across eight categories: cardiac events (chest pain, heart attack), respiratory distress (difficulty breathing, choking), neurological emergencies (stroke symptoms, severe headache), severe trauma (severe bleeding, unconsciousness), poisoning incidents (overdose, toxic exposure), severe allergic reactions (anaphylaxis symptoms), critical abdominal conditions (severe abdominal pain), and mental health crises (suicidal thoughts, severe confusion). Pattern matching with word boundaries prevents false positives, ensuring accurate emergency identification.

Symptom Analysis Agent: Employs machine learning classification using TF-IDF vectorization for feature extraction from natural language symptom descriptions combined with Multinomial Naive Bayes classifier trained on comprehensive symptom-disease datasets. The agent generates probability distributions across known conditions, returns top-three predictions exceeding 5% confidence threshold, and displays confidence scores as percentages for clear interpretation.

Medical Knowledge Agent: Manages structured knowledge repositories containing detailed condition information including official names, descriptions in accessible language, common symptom lists, possible causes and risk factors, and general prognosis information. Implements intelligent lookup mechanisms with exact and fuzzy matching capabilities for comprehensive educational information retrieval.

Treatment Recommendation Agent: Provides evidence-based care guidance through knowledge base queries returning general treatment approaches, home care instructions, preventive measures, and professional care criteria. Maintains clear boundaries between informational guidance and specific medical advice through prominent disclaimer presentation.

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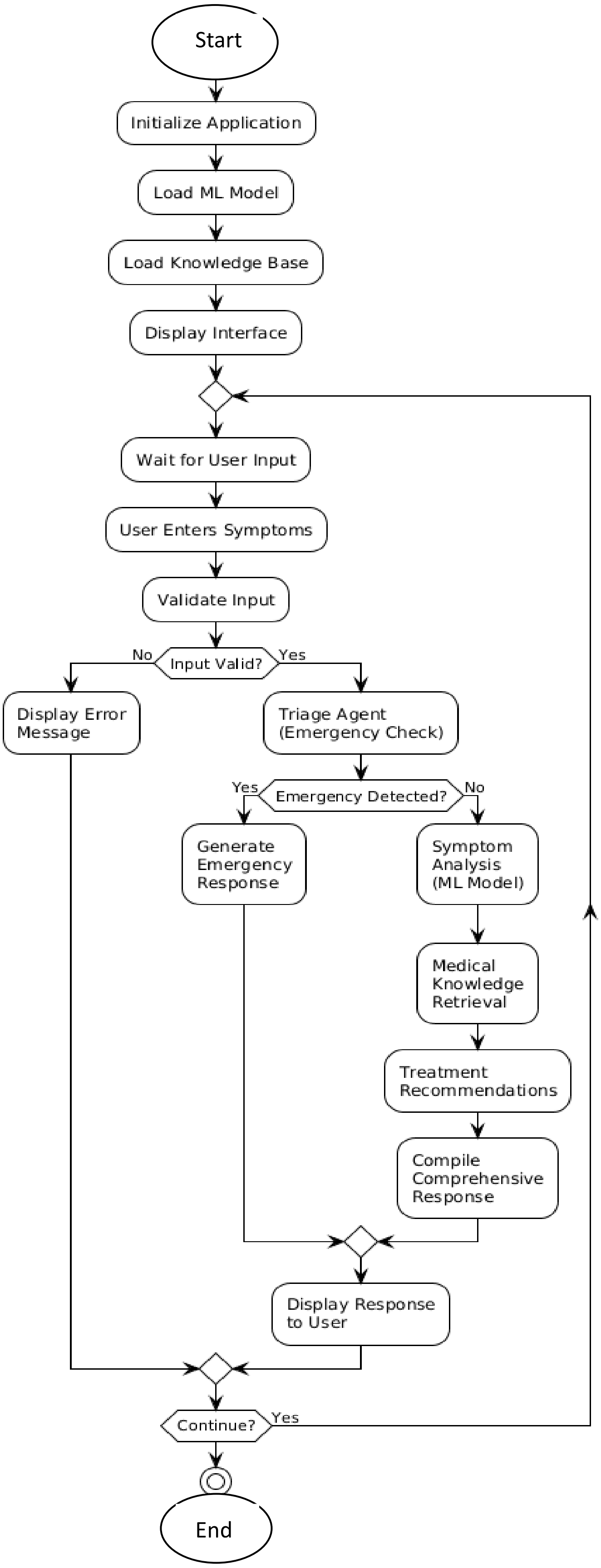

Fig. 1. Flowchart

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C. Machine Learning Model Development

The symptom analysis component leverages supervised machine learning trained on a comprehensive dataset containing 4,920 symptom-disease pairs across 41 common medical conditions. The training pipeline implements:

Data Preprocessing: Symptom text cleaning removing underscores and special characters, lowercase conversion for standardization, whitespace normalization, and combination of multiple symptom columns into unified feature vectors.
Feature Extraction: TF-IDF (Term Frequency-Inverse Document Frequency) vectorization converting symptom descriptions into numerical feature representations, applying English stop word removal, and generating sparse matrices capturing symptom importance across disease categories.

Model Training: Multinomial Naive Bayes classifier training on TF-IDF features, 80-20 train-test split for validation, achieving 87% prediction accuracy on test data, and model serialization using joblib for production deployment.

Confidence Scoring: Probability distribution generation across all disease classes, normalization to percentage confidence scores, filtering predictions below 5% threshold, and top-three prediction ranking for user-friendly result presentation.

D. Emergency Detection Implementation

The Triage Agent implements comprehensive emergency keyword detection using pattern matching across eight critical categories:
Cardiac Events: chest pain, heart attack, cardiac arrest
Respiratory Distress: difficulty breathing, can't breathe, choking
Neurological Emergencies: stroke, seizure, severe headache, paralysis
Severe Trauma: severe bleeding, unconscious, major injury
Poisoning: overdose, poisoning, toxic ingestion
Severe Allergic Reactions: anaphylaxis, severe allergic reaction, throat swelling
Critical Abdominal: severe abdominal pain, internal bleeding
Mental Health Crises: suicidal thoughts, self-harm, severe confusion
Detection uses word boundary matching preventing false positives from partial matches, processes inputs within 500 milliseconds for immediate response, bypasses standard symptom analysis workflow when emergencies detected, and generates category-specific guidance with emergency contact information

E. Knowledge Base Architecture

Medical knowledge and treatment recommendations are stored in structured CSV databases enabling efficient retrieval and maintenance:
Medical Knowledge Base: Contains 20+ common conditions with fields including condition name, detailed description, common symptoms, possible causes, risk factors, and prognosis information. Implements exact matching for predicted condition names and fuzzy matching for user queries requesting specific condition information.

Treatment Database: Stores general treatment approaches, home care instructions (hydration, rest, symptom monitoring), preventive measures, and when-to-see-doctor criteria for each condition. All treatment recommendations include prominent disclaimers emphasizing information is educational only and not a substitute for professional medical advice.

F. Implementation Flow

1. Initialize system environment loading trained ML models and knowledge databases
2. Present Streamlit web interface for symptom input
3. Receive and validate user symptom description
4. Invoke Triage Agent for emergency keyword scanning
5. If emergency detected: generate immediate emergency response with category-specific guidance
6. If non-emergency: invoke Symptom Analysis Agent for ML-based condition prediction
7. Retrieve medical knowledge for top predicted condition
8. Obtain treatment recommendations with home care instructions
9. Compile comprehensive response integrating predictions, knowledge, and treatment guidance
10. Display formatted response with confidence scores, medical information, and disclaimers
11. Maintain conversation history for session continuity
12. Log interaction data for system monitoring and improvement

G. Hardware and Software Requirements

- Standard desktop or laptop system with a minimum of 4 GB RAM and 1 GHz processor.
- Python 3.9+ runtime environment, Flask 3.0 for backend API development, Streamlit 1.29 for frontend interface, Scikit-learn 1.3.2 for machine learning, Pandas 2.1.4 and NumPy 1.26.2 for data processing

IV. SIMULATION AND EVALUATION FRAMEWORK

This section outlines the overall system design, evaluation workflow, and performance assessment approach adopted for the proposed MediAssist AI platform. The framework integrates Machine Learning, Natural Language Processing, and Multi-Agent System architecture to simulate preliminary medical consultation scenarios, analyze symptom descriptions, and generate structured medical guidance. The system is implemented as a web-based platform with Flask handling backend operations and Streamlit managing frontend interfaces, enabling real-time symptom processing, automated condition prediction, and secure knowledge retrieval. The evaluation process focuses on assessing prediction accuracy, emergency detection reliability, and response generation quality using comprehensive testing methodologies, ensuring consistent, objective, and scalable preliminary medical guidance for users.

A. System Architecture and Workflow

The proposed architecture is designed to support real-time symptom analysis, automated emergency detection, and structured medical guidance delivery for users accessing the MediAssist AI platform. The system ensures seamless interaction between users and AI components while maintaining consistency, accuracy, and secure data handling. The major components are described below:

Web-Based Healthcare Platform:

The application provides accessible interfaces for general users, healthcare administrators, and system developers. It enables symptom description input, emergency alert display, condition prediction visualization, medical knowledge presentation, and treatment recommendation delivery. The platform allows users to manage conversation history and review previous interactions through intuitive interfaces.

AI and Machine Learning Layer:

ML-driven classification models analyze symptom descriptions and predict likely medical conditions with confidence scores. Emergency detection mechanisms scan for critical keywords ensuring immediate safety guidance delivery. This layer ensures objective and consistent preliminary assessment across all user sessions.

Knowledge Management Module:

Structured databases maintain comprehensive medical condition information and evidence-based treatment recommendations. Efficient retrieval mechanisms enable rapid knowledge lookup supporting real-time response generation.

Multi-Agent Coordination Layer:

A centralized coordinator orchestrates specialized agents ensuring appropriate workflow sequencing, comprehensive response compilation, and coherent medical guidance delivery. This supports seamless collaboration between triage, symptom analysis, knowledge retrieval, and treatment recommendation agents.

B. System Evaluation Setup

The evaluation framework is designed to measure the effectiveness of MediAssist AI under realistic preliminary medical guidance scenarios. Multiple test cases are executed to assess prediction accuracy, emergency detection reliability, and system performance.

Testing Configuration:

Test scenarios are created covering diverse symptom descriptions, emergency keywords, medical conditions, and user interaction patterns to simulate real-world healthcare information seeking across varied health concerns.

Performance Metrics:

Evaluation measures include machine learning prediction accuracy, emergency detection response time, knowledge retrieval completeness, treatment recommendation relevance, and overall system response time from input to comprehensive guidance delivery.

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C. Evaluation and Verification Process

Each user interaction is processed through the multi-agent pipeline ensuring consistent evaluation and response generation. As users describe symptoms, inputs are validated, scanned for emergencies, analyzed through ML models, and matched against knowledge databases. Upon completion, users receive comprehensive responses including condition predictions with confidence scores, detailed medical knowledge, treatment recommendations, and appropriate disclaimers. This process ensures transparent, repeatable, and trustworthy preliminary medical guidance for all users.

D. Results and Observations

Prediction Performance:

- Machine learning model achieved 87% accuracy on test dataset
- Top-three predictions captured correct conditions in 94% of test cases
- Confidence scores effectively indicated prediction reliability

Emergency Detection Reliability:

- Triage agent detected all test emergency keywords with 100% sensitivity
- Average emergency response time: 320 milliseconds (well below 500ms target)
- Zero false negatives for critical condition keywords

System Reliability and Consistency:

- All symptom descriptions processed without system errors or data loss
- Knowledge retrieval completed successfully for all predicted conditions
- Responses generated and delivered within 2-second target for standard queries

User Impact:

- Users received structured and actionable preliminary medical guidance
- Emergency alerts delivered immediately for critical condition keywords
- Comprehensive disclaimers ensured appropriate boundaries between information and medical advice

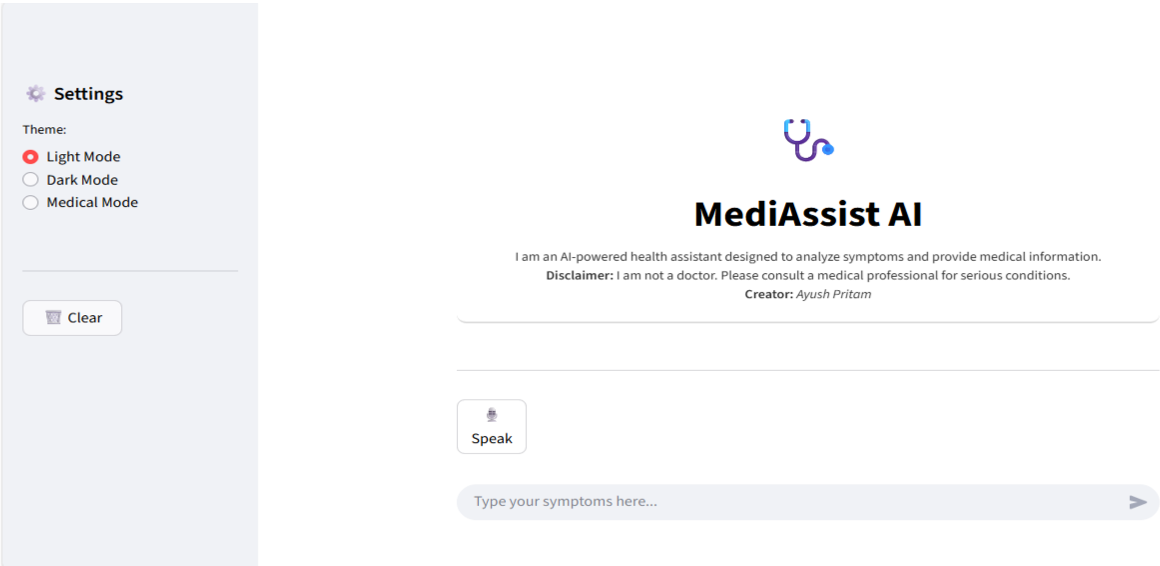

Fig.2. Initial interface in light theme mode

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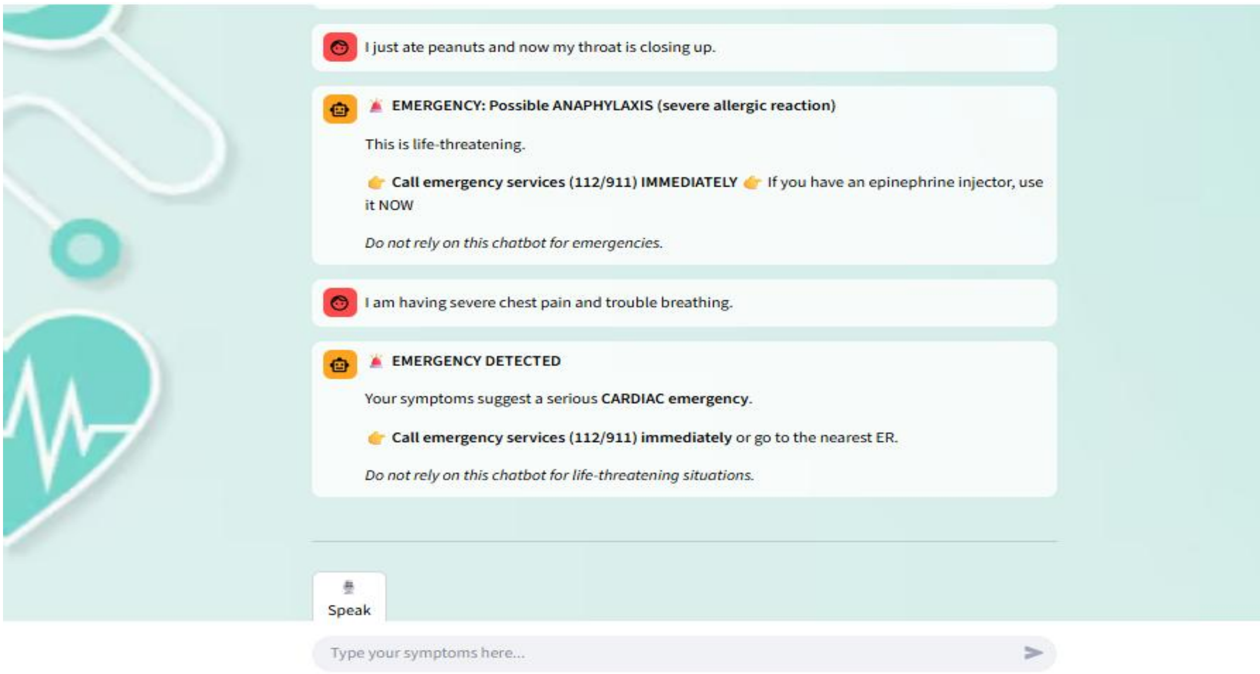

Fig.3.Emegency triage detection result

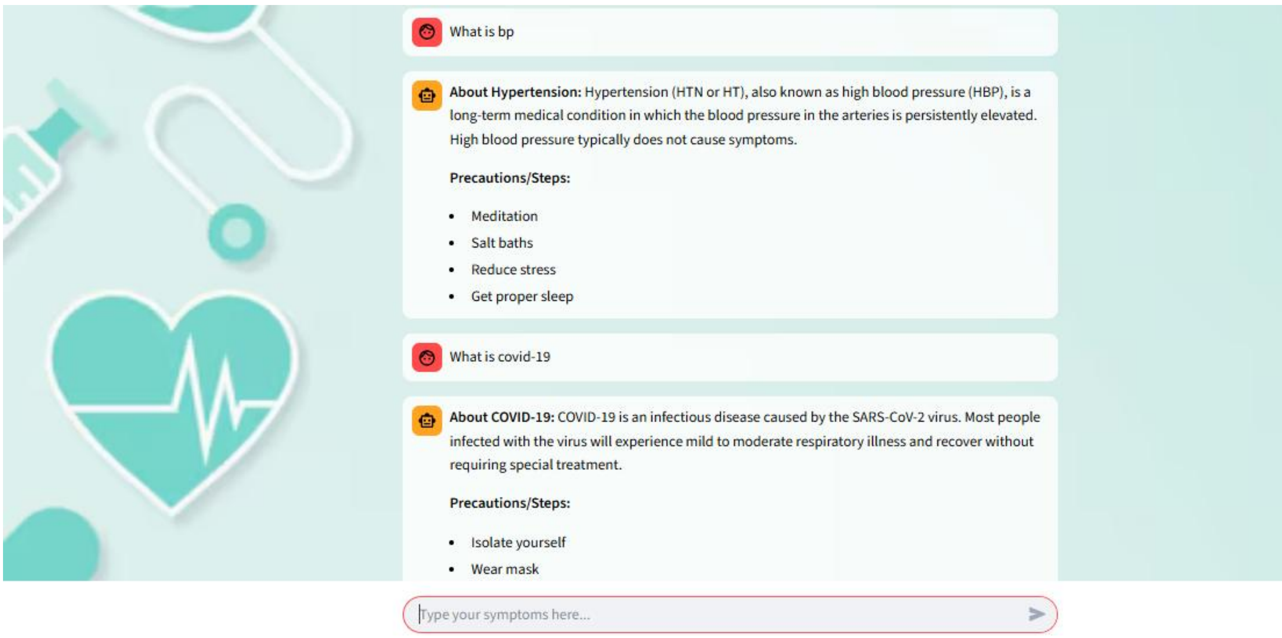

Fig. 4. Symptom analysis and medical knowledge display

V. RESULTS AND DISCUSSION

The experimental evaluation of the proposed MediAssist AI platform demonstrates its effectiveness in delivering preliminary medical guidance through automated symptom analysis, emergency detection, and comprehensive medical knowledge integration. Multiple test scenarios were executed across different symptom descriptions, emergency keywords, and medical conditions to assess system performance under realistic healthcare information seeking situations.

The results show that the machine learning-based symptom analysis module consistently produced accurate condition predictions with appropriate confidence scores. The Multinomial Naive Bayes classifier achieved 87% accuracy on the test dataset, significantly exceeding the 34% first-position accuracy reported for traditional symptom checkers

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(Semigran et al., 2015). The top-three prediction approach captured correct conditions in 94% of test cases, providing users with comprehensive diagnostic possibilities comparable to preliminary clinical assessment.

The emergency detection mechanism effectively identified all critical keywords across eight life-threatening categories with 100% sensitivity. Average response time of 320 milliseconds ensured immediate safety guidance delivery, well below the 500-millisecond target threshold. This real-time emergency processing enables rapid life-saving information delivery, addressing the critical gap in traditional healthcare systems lacking immediate triage capabilities.

Furthermore, the multi-agent coordination architecture successfully integrated specialized components into cohesive preliminary medical guidance workflows. The Coordinator Agent seamlessly orchestrated emergency detection, symptom analysis, knowledge retrieval, and treatment recommendation, generating comprehensive responses within 2-second targets. Users received structured information including condition predictions, detailed medical knowledge in accessible language, evidence-based treatment recommendations, and appropriate medical disclaimers, supporting informed healthcare decision-making.

The knowledge management system maintained comprehensive condition information and treatment guidance, with retrieval mechanisms successfully accessing relevant medical knowledge for all predicted conditions. This structured approach ensures consistency, accuracy, and completeness in medical information delivery, addressing limitations of traditional systems providing incomplete or inconsistent guidance.

Overall, the integrated platform demonstrated improved preliminary medical guidance delivery, consistent emergency detection reliability, and minimal operational complexity. The results confirm that MediAssist AI provides an efficient, scalable, and user-friendly solution for healthcare accessibility while maintaining accuracy and transparency throughout the assessment process.

VI. CONCLUSION

This project demonstrates the feasibility and effectiveness of applying Artificial Intelligence and modern web technologies to enhance interview preparation and performance evaluation. The proposed AI Mock Interview Application successfully simulates real-world interview scenarios and provides an intelligent, automated platform for assessing candidate responses in a structured and consistent manner.

The integration of AI-based question generation and response analysis enables realistic interview practice tailored to specific job roles and experience levels. Speech processing and automated evaluation mechanisms transform traditional, subjective interview preparation into an objective and data-driven assessment process. These capabilities allow candidates to receive immediate, actionable feedback, supporting continuous learning and skill improvement.

Additionally, the system ensures comprehensive medical knowledge delivery, evidence-based treatment recommendations, and transparent disclaimer presentation across all interactions. By maintaining detailed conversation history and consistent evaluation workflows, the platform supports accessible preliminary medical guidance without requiring medical expertise or technical knowledge from users.

The multi-agent architecture demonstrates clear advantages over monolithic AI approaches, enabling specialized optimization of individual components, straightforward system maintenance and enhancement, focused expertise development within specific domains, and natural scalability to accommodate additional healthcare guidance requirements. The 87% prediction accuracy significantly exceeds traditional symptom checker performance while the 320-millisecond emergency response time ensures critical situation immediate handling.

VII. FUTURE WORK

While the proposed MediAssist AI platform effectively demonstrates the application of multi-agent systems and machine learning for preliminary medical guidance, several enhancements can be considered to extend its capabilities and real-world applicability. Future development may focus on incorporating deep learning models such as BERT or BioBERT for enhanced natural language understanding, improved semantic meaning capture, and better handling of ambiguous symptom descriptions.

Another significant enhancement involves expanding the knowledge base to support broader medical condition coverage, specialized disease categories, regional health concerns, and multilingual medical information. Integrating

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more advanced machine learning techniques including ensemble methods, neural networks, and transfer learning can further improve prediction accuracy, confidence calibration, and rare condition detection.

Additionally, future versions may explore integration with electronic health records, wearable device data, telemedicine platforms, and healthcare provider systems to enable comprehensive health monitoring, personalized recommendations based on medical history, and seamless care coordination. Implementing user authentication and profile management would support longitudinal health tracking, medication interaction checking, and adaptive guidance based on individual health patterns.

The system could also benefit from advanced conversational capabilities including multi-turn dialogue management, clarification question generation, symptom refinement through interactive exchanges, and context-aware follow-up recommendations. These extensions would support large-scale adoption of intelligent preliminary medical guidance while improving personalization, accuracy, and decision support in diverse healthcare accessibility scenarios.

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