iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 2026 **Issue:** Conference **Month of publication:** May 2026

DOI: https://doi.org/10.22214/ijraset.2026.82950

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue V May 2026- Available at www.ijraset.com
National Conference on Innovation in Engineering and Technology-(NCIET2026)

MediKitAI: A Multimodal Multi-Agent AI System for Intelligent Emergency Healthcare Assistance

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Abstract—Timely decisionmaking and immediate intervention are critical in medical emergencies to prevent severe complications or loss of life. However, in many real-world scenarios,particularly in rural areas of developing countries,the absence of prompt medical guidance and limited access to healthcare facilities often result in delayed or inappropriate responses. To address these challenges, this paper presents MedikitAI, an artificial intelligence–driven emergency healthcare assistance system designed to provide real-time first-aid guidance, emergency classification, and hospital recommendations prior to professional medical intervention.

The proposed system integrates Large Language Models, a multi-agent architecture, and computer vision techniques to deliver a comprehensive and intelligent emergency response framework. Users can input symptoms through natural language text or upload images depicting visible injuries such as burns or lacerations. Multiple specialized AI agents collaboratively process the input to analyze the condition, generate step-by-step first-aid instructions, and identify nearby hospitals and medical professionals using Global Positioning System-based services. Experimental results demonstrate that the proposed system achieves an average accuracy of approximately 85%, indicating its effectiveness in supporting timely and informed decisionmaking during critical situations.

Keywords— Artificial Intelligence, Emergency Healthcare, Large Language Models, Multi-Agent Systems, Computer Vision, First Aid

I. INTRODUCTION

In the modern era, characterized by rapid societal and technological advancements, medical emergencies require prompt decision-making and immediate intervention. Any delay in response can significantly hinder the delivery of appropriate healthcare services, particularly in cases involving severe complications or life-threatening conditions. However, a substantial number of reported incidents still lack timely access to essential first-aid guidance, information regarding nearby healthcare facilities, or consultation with medical professionals. Such delays often lead to the worsening of injuries, increased medical complications, and, in extreme cases, fatal outcomes. These challenges are particularly pronounced in rural and remote regions, where healthcare infrastructure remains underdeveloped and access to medical resources is limited. Recent breakthroughs in AI have immense potential to transform healthcare delivery, especially in emergency response systems [1].Someoftherecenttechnologiesthathaveenabled intelligentautomationareLargeLanguageModels,Computer Vision, and Multi-Agent Systems. These enable contextual understanding and real-time decision support, hence availing anopportunitytobridgethegapbetweentheoccurrenceof a medical emergency and the arrival of professional medical assistance.

To address these challenges, this paper proposes MedikitAI, an AI-enabled emergency healthcare assistance system designed to function as an intelligent virtual medical aid. MedikitAI serves as a real-time emergency support framework that leverages advanced artificial intelligence techniques to assist users during critical situations by AI. Using MedikitAI, patients are able to enter medical symptoms in natural text format or upload images of accidents to display images of injuries. Using patient input, AI entities work in unison to determine medical symptoms, which can be bleeding, burns, fractures, heart-related problems, or even general health symptoms and related questions.

In general, the role of MedikitAI is to serve as an AI help partner for the pre-hospital stage in critical situations. It assists users in making rapid and well-informed decisions in these situations.

II. RELATED WORK

Recent developments in AI and LLMs have marked significant influence in the healthcare domain, relating to medical diagnostics, data analytics, and intelligent decision support systems.

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Works have documented various uses of LLMs, multimodal AI, and machine learning in improving health outcomes, but also point at challenges on real-time applicability, scalability, and system complexity.

Wu et al. [1] presented a comprehensive survey on the use of LLMs for biomedical data analysis; discussed various model architectures, datasets, and application scenarios across healthcare domains. Although the survey gave good theoretical insights and future research directions, it lacks real-time system implementations which are required in emergency healthcare scenarios.

Chen et al. [2] presented an LLM-driven decoupled probabilistic prompt approach toward continual learning in medical image diagnosis. Their proposed method shows great adaptability for continuously evolving medical datasets, whereas computational complexity increases, and thus it is not much appropriate for real-time applications in emergency situations.

Sharma et al. [3] proposed sentiment-based recommendation systems with LLM-based feature engineering for the analysis of drug reviews. Although the system has robust accuracy and interpretability, it is limited to text data and does not support multimodal data, which is necessary for emergencyhealthcare platforms.

Li et al. [4] proposed PhenoFlow, which is human–LLM collaboration based, caters to exploratory analysis of largescale and complex stroke data, enhances the overall interactive nature, and lessens the cognitive load, but lacking robust healthspecific metadata, it lacks scalability.

Mehta et al. [5] proposed MID-LLM, an approach that combines LLMs, federated learning, and the use of blockchain to ensure the security of medical image diagnostics in their paper “MID-LLM: A Framework for Secure Medical Image Diagnostics Using LLMs, Federated Learning, and Blockchain.” Though it offers data privacy and scalability, the use of blockchain makes it less practical for time-critical applications like emergency situations.

Patel et al. [6] have carried out a discussion on AI-based personalized diabetes treatment systems, focusing especially on multimodal treatment plans. This type of system is useful for chronic illness management but is not suitable for emergency response situations.

Parket al. [7] used explainable machine learning algorithms for predicting hospital stay duration. This enhances interpretability. Nevertheless, this research only concentrates upon in-hospital information without any consideration of emergency activities outside the hospital.

Ahmed et al. [8] proposed an intelligent multimodal AI system based on convolution neural networks for the assessment of the preoperative difficult airway. Although the system has high accuracy, the amount of labeled data required for the system to work is considerable, and the system’s scope of application remains limited to surgery/preoperative.

Zhao et al. [9] did a systematic review on optimization methods for large language models. Their work focused on the efficiency and optimization of the performances of models. The paper offers an insight into LLM optimization but lacks relevance to health and emergency-related tasks.

Liu et al. [10] introduced an LLM-based multi-agent system for simulating the influence and cooperation processes within complex systems. Their system conceptually fits the framework of coordinated systems for handling emergencies; the system has, however, never been tested or applied in a real medical or healthcare setting.

Overall, existing studies highlight the significant potential of Large Language Models (LLMs) and multimodal artificial intelligence in advancing healthcare applications. However, a critical gap persists in the development of real-time, multi-agent, and context-aware emergency healthcare systems capable of effectively integrating textual, visual, and geolocation data. The proposed MedikitAI system aims to bridge this gap by introducing an AI-driven pre-hospital emergency assistance framework that emphasizes rapid response, contextual understanding, and practical real-world deployment.

III. PROBLEM DEFINITION AND OBJECTIVES

In a medical emergency, first-aid care needs to be provided to the patient immediately to prevent serious health issues or loss of life. However, in practical life conditions, patients are not provided with first-aid care knowledge or correct hospital information.

A. Problem Definition

To design and implement MedikitAI, an AI-powered emergency healthcare assistant capable of providing instant first-aid guidance and recommending nearby hospitals using Large Language Models and a Multi-Agent AI framework.

B. Objectives

- To develop a multi-agent framework that collaboratively analyzes emergency situations in real time.

- To create intelligent agents capable of analyzing text-based and image-based symptoms using LLMs such as Mistral, TinyLlama, and Gemma.
- To design an AI-based first-aid guidance module that generates step-by-step emergency instructions using LLMs and LangChain orchestration.
- To implement a GPS-based system that instantly identifies nearby hospitals, clinics, and ambulance services.
- To enhance pre-hospital emergency response by reducing decision-making time and improving situational awareness.

IV. SYSTEM ARCHITECTURE

The proposed MedikitAI system follows a modular and layered multi-agent architecture designed to ensure real-time responsiveness, scalability, and efficient processing of medical emergency data. The architecture integrates Large Language Model technologies, Computer Vision techniques, and GPS- based services for the delivery of intelligent prehospital emergency health assistance. As illustrated in Fig. 1, the proposed MedikitAI system architecture is divided into three primary layers: Application Layer, Agent Layer, and Model and Ser- vice Layer.

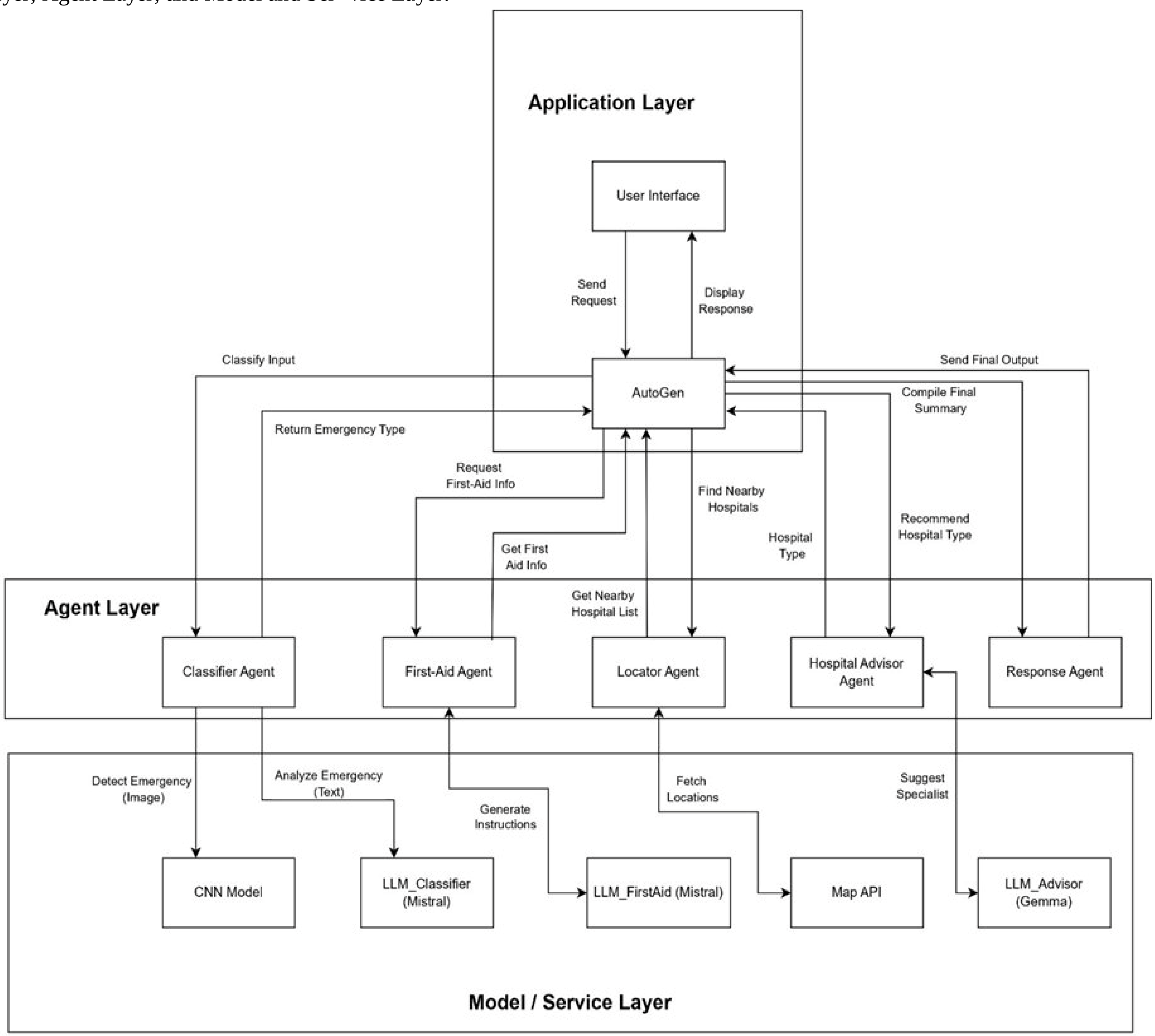

Fig. 1. Proposed MedikitAI System Architecture

A. Application Layer

This layer is the key interface between the user and the MedikitAI system. This interface enables the user to interact with the MedikitAI system by entering the symptoms using natural text or by using images of any injuries of the kind that are seen viz. burns, injuries, and fractures. This interface is designed to be very simple and user-friendly and can be used even when the user is under immense stress during the time of emergencies. This layer presents the final output, including the results of the emergencies and directions to the nearest hospital.

B. Agent Layer

The Agent Layer is the main intelligence part of the system, comprising a set of specialized AI agents that work together using a multi-agent orchestration framework. The Classifier Agent determines the nature and level of emergencies based on the results of text as well as image analysis. The First- Aid Agent develops a set of first-aid procedures corresponding to established medical protocols. The Locator Agent relies on GPS-related services for the purpose of detecting nearby hospitals, dispensaries, as well as emergency response centers. Thirdly, the Hospital Advisor Agent suggests a list of required medical professionals according to the identified emergency category, while the Response Agent combines all results to produce a response for the user.

C. Model and Service Layer

The Model and Service Layer is home to the machine learning models, as well as the services, which are necessary for the functionality of the system. There exists an injury detection model based on CNN for examining the images released by the user to detect injuries. There are also LLM-based classifiers, namely Mistral and TinyLlama, for examining the symptoms to arrive at emergency categories. There are advisory LLMs, such as Gemma, for specialist suggestions. Map APIs are used to obtain location-specific information about hospitals.

D. Data Flow Description

Inputs from the user begin at the Application Layer and progress to the Agent Layer for the distribution of duties to various specialized agents. Processing of text and image information occurs simultaneously at the Model and Service Layer. Results from the various agents are shared to promote uniform decision-making. The final response, developed by the Response Agent, is received at the Application Layer to relay to the user. All this occurs through the efficient structure of the various layers.

V. SYSTEM METHODOLOGY AND COMPONENTS

The structured methodology adopted in the MedikitAI system integrates multimodal data processing, multi-agent collaboration, and intelligent decision-making to offer real-time emergency healthcare assistance. The methodology is designed to ensure rapid response, accurate emergency classification, and reliable first-aid guidance during critical situations.

A. System Methodology

1)Data Acquisition: The system initiates by acquiring inputs provided by the users through the application interface. The users describe the medical symptoms in natural language text and upload images of visible injuries like burns, wounds, or fractures. It also captures geolocation data with user consent in order to support location-based hospital and ambulance recommendations.

2) Input Processing: The text inputs can be processed by LLMs like Mistral and TinyLlama for relevant medical extraction, symptoms, and contexts. The image inputs can be evaluated by the Convolutional Neural Network (CNN) developed and trained on medical datasets for injuries. Text and image pre-processing steps like text normalization, image resizing, and extraction of features can be done for accurate inference.

3) Emergency Classification: The processed text and image features are passed through the Classifier Agent, which identifies the nature and gravity of the medical emergency. To eliminate any doubts, multimodal fusion techniques are used to combine the findings of the text analysis and image analysis techniques.

4) Response Generation: Once the emergency has been identified, pre-stored medical protocols are retrieved, and the First-Aid Agent generates step-by-step first-aid instructions through the use of LLM-based reasoning. Concurrently, the Locator Agent identifies nearby hospitals, clinics, and ambulance services using GPS-based APIs while the Hospital Advisor Agent recommends suitable medical specialists. The Response Agent compiles these outputs into one unified, actionable response to be delivered back to the user.

B. System Components

- User Interface: Users can enter their symptoms, upload pictures, and display emergency information and hospital advice.
- Multi-Agent Orchestration Module: Handles coordination of AI agents through the use of AutoGen and LangChain frameworks.
- Text Analysis Module: Applies the text symptom descriptions to LLM models.
- Image Analysis Module: Utilizes the CNN-based injuries detection model for image analysis.
- Emergency Classification Module: Determines the emergency category and severity based on multimodal inputs.
- First-Aid Guidance Module: Produces informed, sequential first-aid guidelines.
- Location and Advisory Services: Provides location identification of neighboring healthcare institutions and indicates appropriate medical specialists by means of GPS services and advisory LLMs.

VI. IMPLEMENTATION AND DEPLOYMENT PLAN

The design and implementation of the MedikitAI system is done through a modular and iterative development methodology. This is done in a manner where the design and development of the different subsystems, like emergency classification, first-aid advice, recommendation of the hospital to visit, and multi-agent orchestration, among others, is carried out independently.

A. Model Development and Integration

Emergency classification is achieved through the application of Large Language Models (LLMs) like Mistral and TinyLlama for text-based symptoms, and an injury classification system through a CNN-based model for image-based classification. Multimodal fusion enables an accuracy boost in classification. First-aid guidance support provides step- by-step directions through LLM-based reasoning compliant with medical protocols. Advisory LLMs support specialist suggestions. AutoGen and LangChain interact with all agents.

B. System Integration and Testing

Unit testing is done to validate a module, and then there is integration testing, which checks the communication that goes on between the UI, AI, backend, and the APIs. Performance test checking includes latency in the performance, which is a critical requirement in emergency care. Security features for protecting user data are also added.

C. Deployment Pipeline

MedikitAI employs a cloud-backed deployment architecture so that the scalability and availability of the service can be ensured. The deployment of backend services and AI models is made on cloud infrastructure capable of handling concurrent requests. CI/CD pipelines support continuous updates and model improvements, hence guaranteeing system reliability and long-term effectiveness.

VII. EXPECTED RESULTS

MedikitAI technology shall provide credible and real-time pre-hospital health care assistance by using multimodal AI processing and Multi-Agent systems. MedikitAI technology shall deliver approximately 85% accuracy in classifying an emergency condition by using LLM textual analysis and CNN- based image detection.

This system will ensure appropriate first aid responses are provided in a timely, concise, and clear fashion, according to standard medical protocols. These hospital and ambulance suggestions using the Global Positioning System will be helpful in lowering the latency associated with accessing proper care. There are likely to be low latencies with the performance of the modules.

VIII. CONCLUSION

MedikitAI is a smart and reliable AI-powered emergency healthcare assistant designed to bridge the critical gap between medical emergencies and professional healthcare services. By integrating Large Language Models, Computer Vision, and Multi-Agent AI architecture, the system provides real-time first-aid guidance, emergency classification, hospital recommendations, and specialist suggestions.

It achieves an accuracy of about 85% in emergency classification, allowing both text and image-based inputs to be used for improving diagnostic confidence and the reliability of the response. MedikitAI improves pre-hospital care by delivering timely and context-aware assistance, allowing users to make informed decisions during critical situations.

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