© MAY 2026 | IRE Journals | Volume 9 Issue 11 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV9I11-1717487

AI-Powered Intelligent Ambulance Dispatch and Hospital Coordination System

ANAND P S[1], GEORGE REJI[2], SRADHA K P[3], SUZEN SAJU KALLUNGAL[4], BASIL JOY[5], RICHU SHIBU[6]

[1, 2, 3]Student, Department of Computer Science and Engineering (Data Science), Mar Athanasius College of Engineering, Kothamangalam, India

[4, 5, 6]Professor, Department of Computer Science and Engineering (Data Science), Mar Athanasius College of Engineering, Kothamangalam, India

Abstract- Emergency medical response systems often face significant delays due to traffic congestion, inefficient ambulance allocation, and poor coordination between emergency services and hospitals. This project proposes an AI-powered intelligent ambulance dispatch coordination system designed to improve emergency response efficiency and reduce ambulance arrival time. The system integrates a citizen reporting application, ambulance driver interface, hospital dashboard, and a centralized control room for effective communication and decision-making. Emergencies can be reported by citizens or bystanders through location input, symptom description, image uploads, and a speech-to-text module that converts voice input into text for faster reporting. An AI-based triage system utilizing the XG Boost algorithm analyzes emergency data to determine the severity of the patient's condition and prioritize dispatch decisions. The platform also evaluates ambulance availability, hospital capacity, and real-time traffic conditions to select the most suitable hospital and ambulance. Route optimization using the A* algorithm identifies the fastest path primarily through main roads to ensure safe and rapid ambulance movement. Additionally, nearby traffic control rooms are automatically notified to clear traffic routes. The proposed system aims to enhance emergency coordination, reduce response time, and improve patient survival outcomes in critical situations.

Index Terms - Ambulance Dispatch System, Emergency Response, XG Boost, Route Optimization, A* Algorithm, Speech-to-Text, Traffic Management, Hospital Resource Allocation, Smart Healthcare, Intelligent Transportation Systems.

I. INTRODUCTION

Timely medical response during accidents and emergencies is essential for saving human lives. However, traditional ambulance dispatch systems often face challenges such as traffic congestion, delayed communication, inefficient ambulance allocation, and lack of coordination between hospitals and emergency responders. These issues frequently increase response time and may delay critical medical treatment for patients.

Recent advancements in artificial intelligence, machine learning, and intelligent transportation systems have enabled the development of smart emergency response frameworks. These systems can collect emergency information from mobile applications, voice inputs, or image uploads and process the data in real time to support faster decision-making. Technologies such as speech-to-text allow citizens or bystanders to report emergencies quickly even without manual typing.

Machine learning algorithms can further analyze the reported information to determine the severity of the patient's condition and prioritize emergency cases accordingly. In addition, intelligent ambulance allocation and route optimization algorithms help identify the nearest available ambulance and the fastest route to the accident location while considering road conditions and traffic flow.

Effective coordination with hospitals is also crucial in emergency situations. By monitoring hospital resources such as bed availability and medical services, the system can direct patients to the most suitable healthcare facility and avoid treatment delays.

Motivated by these advancements, this work proposes an AI-powered ambulance dispatch and hospital coordination system that integrates emergency reporting, patient prioritization, ambulance allocation, route optimization, and hospital resource monitoring within a unified framework. The proposed system aims to reduce response time, improve coordination among emergency services, and enhance the overall efficiency of medical emergency management.

II. NEED OF STUDY

The rapid growth of urban population and the increasing demand for emergency medical services have created serious challenges in ambulance dispatch and hospital coordination. In many emergency situations, delays occur due to lack of real-time communication between ambulances, hospitals, and control centres. Patients often face critical waiting time because ambulances may be dispatched without considering traffic conditions, ambulance availability, hospital bed occupancy, ICU availability, or specialist readiness. This results in overcrowding of certain hospitals, wastage of valuable emergency resources, and sometimes loss of life due to delayed treatment.

An AI-powered ambulance dispatch and hospital coordination system is therefore essential to ensure faster response time, efficient route planning, and proper allocation of patients to the most suitable hospital. The system can assist in predicting emergency severity, identifying the nearest available ambulance, and selecting hospitals based on real time factors such as bed availability, emergency facilities, and required medical departments. By integrating AI, cloud computing, GPS tracking, and real-time hospital database updates, the proposed system improves decision-making, reduces delays, and strengthens emergency healthcare management. Hence, this study is needed to develop a smart and automated solution that enhances emergency response efficiency and increases the chances of saving human lives.

RELATED WORKS

Several studies have explored intelligent ambulance dispatch and routing systems to improve emergency medical service response times. Research on ambulance positioning and dispatch strategies highlights that geographic factors such as terrain, road networks, traffic congestion, and population density significantly influence response efficiency. Earlier works also evaluated differences in response times between urban and rural areas, emphasizing the challenges caused by long travel distances and limited accessibility in sparsely populated regions.

Recent developments focus on integrating technologies such as IoT, GPS, and machine learning to enhance ambulance monitoring and dispatch operations. Some systems use GPS and GSM technologies to track ambulance locations and provide real-time updates to hospitals and patients, while other approaches use IoT-based accident detection to automatically notify emergency services.

Optimization techniques such as the Vehicle Routing Problem (VRP) and Traveling Salesman Problem (TSP) have also been widely applied for ambulance route planning. However, many existing approaches rely on static optimization and fail to adapt to dynamic conditions such as real-time traffic congestion, roadblocks, or multiple emergencies. These limitations highlight the need for intelligent systems capable of real-time decision making, adaptive routing, and improved coordination between ambulances, hospitals, and traffic control systems.

PROPOSED SYSTEM ARCHITECTURE

The proposed AI-powered ambulance dispatch coordination system is designed as an intelligent framework that enables rapid emergency response through automated decision-making and real-time communication between citizens, ambulances, hospitals, and traffic control authorities. Emergency situations require quick information processing, efficient ambulance allocation, and reliable route planning to minimize response time and ensure timely medical assistance. To address these challenges, the system decomposes emergency response operations into several interconnected functional modules that operate collaboratively.

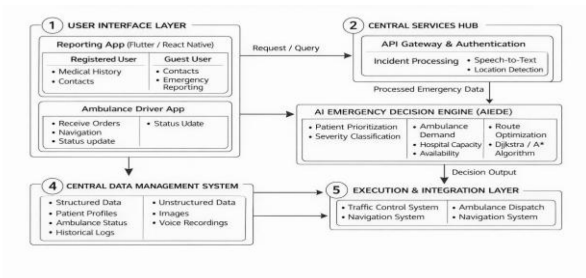
The architecture consists of three primary components:

- Emergency Reporting and Data Acquisition
- Intelligent Decision and Resource Allocation

© MAY 2026 | IRE Journals | Volume 9 Issue 11 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV9I11-1717487

- Routing, Traffic Coordination, and Hospital Integration

Each subsystem performs specialized processing while exchanging critical information through a centralized decision engine. This modular design improves scalability, supports real-time decision making, and enables efficient coordination between emergency responders and healthcare facilities.



A. Emergency Reporting and Data Acquisition

The emergency reporting subsystem allows both registered users and bystanders to report accidents or medical emergencies through a mobile application interface. Users can provide incident information by selecting predefined medical condition icons, entering symptoms, uploading images, or placing emergency calls. To simplify interaction during critical situations, the system incorporates a speech-to-text module that converts voice input into structured textual information. This allows individuals to quickly describe the emergency without requiring manual data entry. The system simultaneously captures location information through GPS to identify the exact incident location. The collected data including user inputs, images, voice descriptions, and geographic coordinates are transmitted to the central processing system for further analysis.

B. Intelligent Decision and Resource Allocation

The decision engine processes the collected emergency information to determine the severity of the situation and identify appropriate response resources. A machine learning based classification model is used to analyze symptoms, environmental conditions, and incident descriptions to perform patient prioritization and severity assessment. Based on this analysis, the system identifies the most suitable ambulance and healthcare facility.

Demand prediction techniques are applied to evaluate ambulance availability in nearby regions, ensuring that the nearest available driver is assigned to the emergency. Simultaneously, the hospital coordination module evaluates healthcare facility availability, including bed capacity and medical service readiness. This ensures that the selected hospital can provide the required treatment without delays upon patient arrival.

XG Boost Prediction Model

$$\hat{y}_i = \sum_{k=1}^{K} f_k(x_i), f_k \in F$$

where

- x_i= feature vector (symptoms, injury type, environment etc.)
- f_k= decision tree
- K= number of trees

Objective function

$$\mathrm{Obj} = \sum_{i=1}^{n} L(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k)$$

where

- L= loss function (log loss / squared loss)
- Ω= regularization term

Regularization Term

- $\Omega(f)=\gamma T+1/2\ \lambda\sum_{(j=1)}^{T} w_j^2$

where

- T= number of leaves
- w_j= leaf score
- γ,λ= penalty parameters

C. Routing, Traffic Coordination, and Hospital Integration

Efficient route planning is critical to minimizing ambulance travel time. The system applies route optimization algorithms to identify the fastest path from the ambulance location to the accident site and from the accident site to the selected hospital.

To ensure smoother travel, routing decisions prioritize major road networks and avoid narrow internal streets that may delay emergency vehicles. In addition to route optimization, the system communicates with nearby traffic control rooms to notify authorities about the approaching ambulance. These notifications enable traffic personnel to clear congested roads or adjust signal timings to facilitate faster ambulance movement. Once the route and hospital are finalized, dispatch instructions are transmitted to the ambulance driver along with navigation guidance. The integrated coordination between ambulance services, hospitals, and traffic management authorities ensures a faster and more reliable emergency response process.

A* Algorithm

A* Cost Function

$$f(n) = g(n) + h(n)$$

where

- $g(n)$= cost from start to node n
- $h(n)$= heuristic estimate from node nto destination

Common heuristic:

$$h(n)=\sqrt{(x_n-x_g)^2+(y_n-y_g)^2}$$

III. IMPLEMENTATION DETAILS

The proposed AI-powered ambulance dispatch coordination system is implemented as a modular multi-component framework integrating emergency reporting, speech processing, machine learning–based decision making, ambulance allocation, hospital coordination, and intelligent route optimization. The implementation follows the architectural design presented in Section III and consists of three primary subsystems: emergency data acquisition, intelligent decision processing, and routing and coordination services. The system operates continuously by processing real-time emergency requests generated through the user application, enabling rapid emergency response and efficient medical resource allocation.

A. Emergency Reporting and Data Acquisition Implementation

The emergency reporting subsystem enables both registered users and bystanders to report accidents or medical emergencies through a mobile application interface. Users can submit incident information using predefined medical icons, symptom descriptions, image uploads, or emergency voice calls. The application also captures geographic coordinates using the device GPS module, allowing accurate identification of the accident location. To simplify user interaction during critical situations, a speech-to-text module is integrated into the reporting interface. Voice input is captured through the mobile device microphone and processed using a speech recognition engine that converts spoken descriptions into textual data. The extracted information is combined with location coordinates and image evidence to form a structured emergency request. These inputs are transmitted to the central server using REST-based API communication for further processing.

B. Intelligent Decision and Patient Prioritization Implementation

The decision processing subsystem analyzes emergency data to determine the severity of the incident and assign response priority. Emergency attributes such as symptoms, incident description, reported medical indicators, and contextual information are converted into structured feature vectors. Patient severity classification is implemented using the Extreme Gradient Boosting (XG Boost) algorithm due to its high predictive accuracy and efficiency when handling structured healthcare datasets. The model is trained on simulated emergency datasets containing features such as symptom type, injury severity indicators, patient condition reports, and environmental factors.

The trained model predicts priority levels such as critical, moderate, or low urgency, enabling the system to allocate resources efficiently. In addition to severity classification, the system performs demand prediction by analyzing ambulance availability and historical emergency request distribution. This mechanism assists in identifying the nearest available

© MAY 2026 | IRE Journals | Volume 9 Issue 11 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV9I11-1717487

ambulance driver capable of responding to the incident.

C. Hospital Coordination Implementation

The hospital coordination module ensures that the selected healthcare facility has adequate resources to provide immediate treatment. The system maintains a database containing hospital information including location, available bed capacity, emergency services, and specialized medical facilities.

Upon receiving an emergency request, the system evaluates nearby hospitals based on distance, treatment capability, and bed availability. Hospitals that cannot accommodate new patients due to capacity limitations are excluded from selection. This coordination mechanism helps prevent delays caused by hospital overcrowding and ensures that patients are transported directly to suitable medical facilities.

D. Route Optimization and Navigation Implementation

Efficient ambulance routing is essential for minimizing response time. The system implements route optimization using the A* search algorithm applied to a digital road network graph. Each road segment is assigned a travel cost based on distance and estimated traffic conditions. To ensure smoother ambulance movement, routing decisions prioritize major road networks while avoiding narrow internal streets that may slow emergency vehicles. The algorithm calculates the optimal path between the ambulance location, accident site, and selected hospital. The resulting navigation route is transmitted to the ambulance driver through the mobile driver interface.

E. Traffic Control Notification Implementation

To further reduce travel delays, the system integrates a traffic coordination mechanism. Once the ambulance route is finalized, nearby traffic control rooms are automatically notified about the emergency dispatch. The notification includes route details and estimated arrival times, enabling traffic authorities to clear congested roads or adjust signal timings to facilitate faster ambulance movement.

F. System Integration and Runtime Flow

The integrated system operates through a continuous processing pipeline. When an emergency report is received, the system first processes the input data including location coordinates, voice descriptions, and incident images. The decision engine then performs patient prioritization and identifies the nearest available ambulance driver. Simultaneously, the hospital coordination module evaluates healthcare facility availability, and the route optimization module determines the fastest path between the ambulance, accident site, and hospital.

Traffic control notifications are issued automatically to assist in clearing the route.

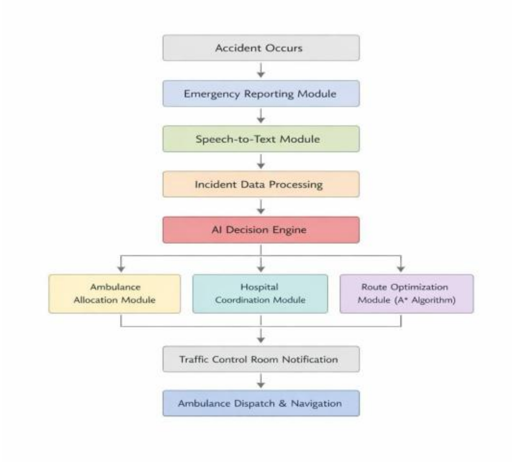
Finally, dispatch instructions and navigation guidance are transmitted to the ambulance driver. The integrated architecture enables seamless communication between users, emergency responders, hospitals, and traffic authorities, ensuring efficient emergency response.

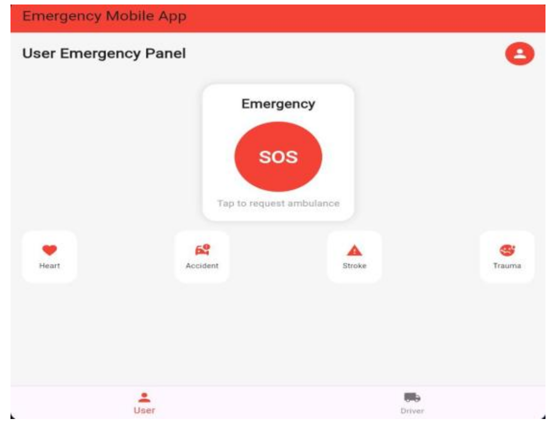
G. Performance Considerations

Performance optimization is achieved through lightweight machine learning models, efficient API communication, and modular processing pipelines.

The XG Boost model provides rapid prediction for emergency severity classification with minimal computational overhead. Route optimization using the A* algorithm efficiently computes shortest paths within the road network.

© MAY 2026 | IRE Journals | Volume 9 Issue 11 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV9I11-1717487





IV. EXPERIMENTAL RESULTS AND PERFORMANCE EVALUATION

This section presents the experimental evaluation of the proposed AI-powered ambulance dispatch coordination system in simulated urban emergency scenarios. The system was evaluated based on emergency reporting efficiency, patient prioritization accuracy, ambulance allocation performance, route optimization effectiveness, and hospital coordination capability.

A. Experimental Setup

Experiments were conducted using simulated emergency situations representing real-world urban medical incidents. The evaluation environment included the interaction between citizen reporting applications, ambulance driver interfaces, hospital dashboards, and a centralized emergency control system. The experimental setup included the following components:

• Citizen emergency reporting mobile application
• Ambulance driver navigation application
• Hospital coordination dashboard
• Central control room monitoring system

System configuration included:
• Standard laptop system used as the central server
• Python-based backend processing environment
• Speech-to-text API for voice emergency reporting
• Machine learning based triage model for patient prioritization

B. Emergency Reporting Performance

The emergency reporting subsystem allows both registered users and external bystanders to report accidents using multiple input methods. Supported reporting mechanisms include:

• GPS-based location reporting

• Voice description using speech-to-text conversion

• Image upload of accident scenes

• Symptom selection using predefined medical icons

The speech-to-text module successfully converted spoken emergency descriptions into structured textual information under normal network conditions. The system was able to quickly register incident reports and forward them to the dispatch decision engine.

C. Patient Prioritization Accuracy

Patient prioritization was performed using an XG Boost-based machine learning model. The model analyzed symptoms, incident descriptions, and emergency indicators submitted during the reporting stage. The system classified emergencies into different priority categories:

•Critical

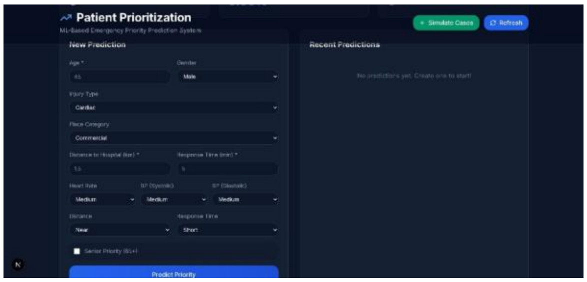
•High priority

•Moderate

•Low priority

© MAY 2026 | IRE Journals | Volume 9 Issue 11 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV9I11-1717487

Experimental evaluation showed that the prioritization model effectively distinguished severe medical emergencies from lower-priority cases, ensuring that life-threatening situations received immediate response.



D. Ambulance Allocation Performance

The ambulance dispatch module evaluated available ambulance units and selected the most suitable driver based on several parameters:

- Distance to the accident location
- Current availability of ambulance units
- Estimated response time
- Predicted emergency demand in nearby regions

Demand prediction mechanisms helped identify the nearest available ambulance capable of responding quickly to the incident, thereby reducing response delays.

E. Route Optimization Efficiency

Efficient ambulance routing is essential for minimizing emergency response time. The system implemented route optimization algorithms to determine the fastest path from the ambulance location to the accident site and subsequently to the selected hospital.

Since ambulances primarily travel through major road networks, the routing algorithm prioritized main roads while avoiding narrow internal streets. Route computation considered the following factors:

- Road network structure
- Traffic conditions
- Distance to nearby hospitals
- Estimated travel time

Experimental results showed that the routing mechanism successfully identified efficient travel paths that minimized ambulance travel time.

F. Traffic Control Coordination

To further improve emergency response efficiency, the system automatically notified nearby traffic control rooms after ambulance dispatch. The notification included:

- Ambulance route details
- Accident location
- Estimated travel path

Traffic authorities could use this information to assist in clearing congested roads or adjusting traffic signals, enabling faster ambulance movement.

G. Hospital Coordination and Resource Availability

The hospital coordination module evaluated nearby healthcare facilities to determine their ability to receive emergency patients.

- Bed availability
- Emergency department capacity
- Medical service capabilities
- Distance from accident location

Hospitals with insufficient capacity were excluded from selection. This ensured that patients were transported directly to hospitals capable of providing immediate treatment.

H. Overall System Performance

The integrated system demonstrated effective coordination between emergency reporting, ambulance dispatching, hospital selection, and route optimization. The system achieved the following outcomes:

- Rapid emergency reporting using voice and mobile input
- Accurate patient prioritization using machine learning
- Efficient ambulance allocation and dispatch
- Optimized ambulance routing through main road networks

© MAY 2026 | IRE Journals | Volume 9 Issue 11 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV9I11-1717487

- Real-time coordination with traffic control rooms
- Improved hospital selection based on resource availability

The modular system architecture enabled independent evaluation of each subsystem while maintaining seamless communication between emergency responders, hospitals, and traffic authorities.

V. DISCUSSION

The proposed AI-powered ambulance dispatch coordination system demonstrates how intelligent technologies can significantly improve emergency medical response through automated decision support and efficient resource coordination. By integrating citizen-based emergency reporting, speech-to-text processing, machine learning–based patient prioritization, ambulance allocation, route optimization, and hospital coordination, the system provides a comprehensive framework for rapid emergency response.

Compared to traditional ambulance dispatch systems that rely heavily on manual communication and human decision making, the proposed system introduces automated analysis and data-driven prioritization. The integration of machine learning algorithms enables accurate classification of patient severity, ensuring that critical emergencies receive immediate attention.

The route optimization mechanism improves ambulance travel efficiency by identifying the fastest routes through major road networks while avoiding congested or narrow roads. Additionally, the integration of traffic control notifications enhances coordination between emergency services and urban traffic management systems, further reducing response delays.

However, system performance may depend on the availability of reliable network connectivity, accurate hospital resource updates, and real-time traffic information. Despite these challenges, the proposed framework demonstrates the potential of AI-driven emergency management systems to improve response efficiency and patient survival outcomes.

LIMITATIONS

Despite the promising capabilities of the proposed system, several limitations were identified during system design and evaluation:

- Emergency reporting accuracy depends on the quality of information provided by users or bystanders.
- Speech-to-text processing may experience delays or recognition errors under poor network conditions or noisy environments.
- Real-time traffic information may not always be available or completely accurate.
- Hospital resource availability requires continuous updates from healthcare facilities to ensure accurate coordination.
- Route optimization performance may be affected in extremely congested urban environments.

VI. CONCLUSION

This paper presented an AI-powered intelligent ambulance dispatch and hospital coordination system aimed at enhancing the overall efficiency, accuracy, and responsiveness of emergency medical services through real-time automation and intelligent decision-making. The proposed framework integrates multiple advanced technologies such as citizen based emergency reporting through a mobile platform, GPS enabled incident location tracking, speech-to-text processing for rapid emergency description extraction, and machine learning based patient severity classification for prioritizing critical cases. In addition, the system incorporates ambulance demand prediction to ensure effective utilization of available emergency vehicles and to support quick assignment of the nearest ambulance based on availability and proximity.

Furthermore, the system employs intelligent route optimization techniques to determine the fastest and most reliable path from the ambulance location to the incident site and then to the selected hospital. By prioritizing major road networks and dynamically avoiding congested routes, the dispatch process significantly reduces travel delays. To strengthen real-time response efficiency, the architecture also includes a traffic control coordination module that communicates with nearby traffic authorities, enabling signal adjustments and congestion clearance for smoother ambulance movement. Simultaneously, the hospital resource management module continuously monitors hospital capacity, bed availability, and emergency service readiness, ensuring that patients are transported only to hospitals capable of providing immediate treatment without overcrowding delays.

Experimental evaluation and performance analysis indicate that the proposed system improves emergency response coordination, reduces dispatch and travel time, and enhances the reliability of patient transfer decisions compared to conventional ambulance dispatch methods. The modular and scalable design of the framework supports seamless integration into existing smart city infrastructures, making it suitable for deployment in large urban regions with high emergency case volumes. Overall, the proposed system demonstrates the strong potential of artificial intelligence, intelligent transportation systems, and cloud-based coordination platforms in modernizing emergency healthcare operations, optimizing resource allocation, and ultimately improving patient survival outcomes during critical situations.

VII. FUTURE WORK

Although the proposed AI-powered ambulance dispatch and hospital coordination system demonstrates efficient emergency response management, there remain several promising directions for future enhancement and research expansion. Future work can primarily focus on improving the system's real-time intelligence, scalability, and integration with advanced smart city technologies to ensure more accurate and faster emergency decision-making in complex urban environments.One major improvement involves the integration of real-time traffic monitoring infrastructures such as CCTV-based traffic surveillance, smart traffic signals, and live vehicle density sensors. By combining these data sources with intelligent traffic forecasting models, the system can perform highly dynamic route optimization rather than relying only on static road network assumptions. In addition, incorporating advanced deep learning approaches such as LSTM, GRU, or transformer-based models for traffic prediction can further improve route planning accuracy, especially during peak hours, roadblocks, or unexpected congestion conditions.

Another important direction is enhancing ambulance allocation and demand prediction by using large-scale historical emergency datasets and spatial-temporal analytics. Future systems can implement advanced predictive models that learn emergency patterns based on time, location, seasonal variations, and population density. This would allow proactive ambulance positioning strategies, ensuring that emergency vehicles are already stationed in high-risk zones before incidents occur. Such improvements would be particularly valuable in metropolitan cities where emergency requests occur frequently and resource optimization is crucial.

Furthermore, the system can be strengthened by integrating IoT-based automatic emergency detection mechanisms. Vehicle crash detection sensors, smart helmet systems, wearable health monitoring devices (such as smartwatches measuring heart rate and oxygen saturation), and mobile accelerometer-based fall detection can be utilized to automatically identify accidents or medical emergencies. This would eliminate dependency on manual emergency reporting and significantly reduce the delay in generating emergency alerts. Additionally, integrating real-time patient vital signs monitoring during ambulance transport can help hospitals prepare critical care resources in advance, improving treatment readiness upon patient arrival.

Future work may also explore the use of advanced hospital coordination mechanisms by incorporating AI-driven hospital workload prediction and resource scheduling. Rather than selecting hospitals only based on bed availability, future systems can consider parameters such as doctor availability, ICU equipment readiness, emergency department crowd level, operation theatre availability, and expected waiting time. Implementing intelligent hospital ranking techniques such as TOPSIS, AHP (Analytic

Hierarchy Process), or reinforcement learning-based decision frameworks can further improve the accuracy of hospital selection and reduce overcrowding in major hospitals.

From a deployment perspective, implementing the system using scalable cloud-based infrastructure such as AWS, Microsoft Azure, or Google Cloud can enhance its capability to handle high volumes of emergency requests simultaneously. In addition, the use of mobile edge computing can reduce latency by processing emergency classification and routing decisions closer to the incident location rather than relying only on centralized servers. This would improve system performance in time-critical situations where milliseconds matter. Blockchain-based security solutions may also be considered in future work to ensure secure sharing of sensitive medical data between ambulances, hospitals, and control authorities while maintaining privacy and trust.

Finally, real-world implementation and large-scale field testing remain a critical future scope. Conducting pilot deployments in collaboration with ambulance providers, hospital management systems, and traffic control authorities would provide practical insights into real-time performance, system reliability, and user acceptance. Such trials can also help evaluate challenges such as network failures, inaccurate emergency inputs, sensor errors, and real-world traffic unpredictability. Overall, future research can expand this system into a fully smart-city integrated emergency healthcare framework that combines AI, IoT, cloud computing, and intelligent transportation systems to achieve faster response times and improved patient survival outcomes.

ACKNOWLEDGMENT

The authors would like to express their sincere gratitude to their academic institution for providing the necessary infrastructure, research environment, and technical resources required for the successful development of this project. The support and facilities provided by the institution played an important role in enabling the implementation and evaluation of the proposed ambulance dispatch coordination system. The authors also extend their appreciation to the project supervisors and faculty mentors for their continuous guidance, valuable suggestions, and encouragement throughout the course of this research work. Their expertise and constructive feedback greatly contributed to improving the system design and overall research quality. In addition, the authors acknowledge the contributions of the open-source research community whose tools and frameworks greatly facilitated the development of this project. Libraries and technologies related to machine learning, data processing, and software development played an essential role in implementing the system components.

Finally, the authors express their heartfelt thanks to their families and friends for their constant support, motivation, and encouragement throughout the research process.

REFERENCES

[1] Nazari, M., Oroojlooy, A., Lawrence, S., & Martin, T., “Reinforcement learning for solving the vehicle routing problem,” Advances in Neural Information Processing Systems, 2018.

[2] Alqahtani, M., & Mengqi, H., “Dynamic energy scheduling and routing of multiple electric vehicles using deep reinforcement learning,” Energy, 2022.

[3] Kulyukin, V., Mukherjee, S., & Prakhar, A., “Deep learning versus standard machine learning in classifying beehive audio samples,” Applied Sciences, 2018.

[4] Roy, S. & Rahman, M. S. Emergency vehicle detection on heavy traffic road from CCTV footage using deep convolutional neural network. In Proc. International Conference on Electrical, Computer and Communication Engineering (ECCE), pp. 1–6 (IEEE, 2019)

[5] Lim, C. S., Mamat, R. & Braunl, T. Impact of ambulance dispatch policies on performance of emergency medical services. IEEE Transactions on Intelligent Transportation Systems, 12(2), 624–632 (2011).

[6] Ramachandran, S. & Prabakaran, D. A novel deep reinforcement learning (DRL) method for

detecting evasion attack in IoT environment. In Proc. International Conference on Integrated Circuits and Communication Systems (ICICACS), pp. 1–6 (2024).

[7] Jagtenberg, C. J., van den Berg, P. L. & van der Mei, R. D. Benchmarking online dispatch algorithms for emergency medical services. European Journal of Operational Research, 258(2), 715–725 (2017).

[8] Nanwani, D., Kshirsagar, P., Kawalkar, B. & Pritish, D. Ambulance tracking and patient health monitoring using GPS and GSM. International Journal of Emerging Technology and Engineering Research, 5(3), 174–180 (2017).

[9] Karmokar, P., Bairagi, S., Mondal, A., Nur, F. N., Moon, N. N., Karim, A. & Yeo, K. C. A novel IoT based accident detection and rescue system. In Proc. International Conference on Smart Systems and Inventive Technology (ICSSIT), pp. 322–327 (IEEE, 2020).

[10] Theeuwes, N., van Houtum, G. J. & Zhang, Y. Improving ambulance dispatching with machine learning and simulation. In Machine Learning and Knowledge Discovery in Databases (ECML PKDD 2021), pp. 302–318 (Springer, 2021).

[11] Hajiali, M., Teimoury, E., Rabiee, M. & Delen, D. An interactive decision support system for real-time ambulance relocation with priority guidelines. Decision Support Systems, 155, 113712 (2022).

[12] Jagtenberg, C. J., Bhulai, S. & van der Mei, R. D. Optimal ambulance dispatching. Markov Decision Processes in Practice, pp. 269–291 (2017).

[13] Abdessalem, H. B., Chaouachi, M., Boukadida, M. & Frasson, C. Toward real-time system adaptation using excitement detection from eye tracking. In Intelligent Tutoring Systems Conference (ITS), pp. 214–223 (Springer, 2019).

[14] McNeff, J. G. The global positioning system. IEEE Transactions on Microwave Theory and Techniques, 50(3), 645–652 (2002).

[15] Fleischman, R. J., Lundquist, M., Jui, J., Newgard, C. D. & Warden, C. Predicting ambulance time of arrival to the emergency department using global positioning system and Google Maps. Prehospital Emergency Care, 17(4), 458–465 (2013).

[16] Park, E., Kim, J. H., Nam, H. S. & Chang, H. J. Requirement analysis and implementation of smart emergency medical services. IEEE Access, 6, 42022–42029 (2018).

[17] Chang, L.-C., Chiang, H.-K. & Chiang, W.-Y. SmartGIS: A SVGbased tool for visualizing and monitoring of SARS movement. In ITRE 2005 International Conference on Information Technology: Research and Education, pp. 282–286 (IEEE, 2005).

[18] Kherraki, A. & Rajae, O. E. Deep convolutional neural networks architecture for an efficient emergency vehicle classification in real-time traffic monitoring. IAES International Journal of Artificial Intelligence, 11(1), 110 (2022).

[19] Belanger, V., Ruiz, A. & Soriano, P. Recent optimization models and trends in location, relocation, and dispatching of emergency medical vehicles. European Journal of Operational Research, 272(1), 1–23 (2019).

[20] Dabiri, S., Markovic, N., Heaslip, K. & Reddy, C. K. A deep convolutional neural network based approach for vehicle classification using large-scale GPS trajectory data. Transportation Research Part C: Emerging Technologies, 116, 102644 (2020). **[21]** Belanger, V., Lanzarone, E., Nicoletta, V., Ruiz, A. & Soriano, P. A recursive simulation-optimization framework for the ambulance location and dispatching problem. European Journal of Operational Research, 286(2), 713–725 (2020).

[22] Schmid, V. Solving the dynamic ambulance relocation and dispatching problem using approximate dynamic programming. European Journal of Operational Research, 219(3), 611–621 (2012).

[23] Desai, D. D. et al. Optimal ambulance positioning for road accidents with deep embedded clustering. IEEE Access, 11, 59917–59934 (2023).

[24] Turnip, A., Rizgyawan, M. I., Kusumandari, D. E. & Hermida, I. D. P. Application of support vector machine classifier on developed wireless ECG system. International Journal of Pharma

Medicine and Biological Sciences, 5(3), 189–192 (2016).

[25] Li, M., Vanberkel, P. & Zhong, X. Predicting ambulance offload delay using a hybrid decision tree model. Socio-Economic Planning Sciences, 80, 101146 (2022)

[26] Ala, A. & Simic, V. Incorporating machine learning and optimization techniques for assigning patients to operating rooms by considering fairness policies. Engineering Applications of Artificial Intelligence, 136, 108980 (2024)