RESEARCH PAPER

An Intelligent Healthcare And Human Interface Technology Using AI

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ABSTRACT
The use of technology in healthcare, particularly in emergency medical services, has steadily progressed over the years. Artificial Intelligence (AI) has already demonstrated its value in areas such as disease prediction, outbreak forecasting, and medical image interpretation. These advancements have opened opportunities for integrating AI into ambulance and emergency response systems. At the same time, human-computer interaction has evolved significantly, supported by innovations in augmented reality, virtual reality, and natural language processing.Combining these modern technologies has led to the concept of an Intelligent Ambulance System that incorporates AI and advanced human-interface mechanisms. This system aims to improve the performance, precision, and responsiveness of emergency medical services by embedding intelligent algorithms and interactive technologies into ambulance operations.Conventional ambulance services largely depend on manual procedures for receiving emergency calls, assigning vehicles, and delivering patient care. Call operators typically dispatch ambulances based on limited information provided during distress calls. Once at the location, paramedics evaluate the patient with restricted access to prior medical records or comprehensive clinical data. Communication between field personnel and hospital teams may also be delayed or insufficient, potentially affecting timely diagnosis and treatment decisions.Given the urgent and life-critical nature of emergency healthcare, there is a strong need for more intelligent and data-driven systems.

KEYTERMS: Integration,Healthcare,Intelligent,Ambulance,Emergency,Facilitates,Conventional
How to cite this article: Devi MR, Shravani K, Sudheshna P, Srikanth P, Apsarunnisa, An Intelligent Healthcare And Human Interface Technology Using AI. Int J Drug Deliv Technol. 2026;16(4s): 782-787; DOI: 10.25258/ijddt.16.4s.90

1 INTRODUCTION

Efficient and well-coordinated Emergency Medical Services (EMS) play a critical role in improving survival and recovery during pre-hospital emergencies such as stroke and cardiac arrest. In such situations, both the speed of response and the appropriateness of the dispatched resources significantly influence patient outcomes. The conventional method of sending the nearest available ambulance to an incident has been found to be sub-optimal in many cases. When ambulance resources are limited, accurately determining the urgency level of each case becomes essential for effective dispatch decisions.

To improve prioritization, EMS organizations around the world have developed and adopted various pre-hospital triage systems to classify emergency calls based on severity. Broadly, these systems fall into two main categories. The first category includes protocol-driven models such as the Medical Priority Dispatch System, which originated in North America. This approach assigns priority levels using structured scripts and standardized questions asked by call handlers. The second category consists of Criteria-Based Dispatch systems, which rely on predefined clinical guidelines to assess patient symptoms and determine the appropriate response level. These systems are commonly used in several Nordic and European countries. Despite their widespread use, research indicates that the precision of current dispatch prioritization methods remains a concern, and there is limited evidence available to further refine pre-hospital triage accuracy.

In Singapore, national EMS operations are managed by the Singapore Civil Defence Force (SCDF). The organization handles more than 190,000 emergency calls annually through the national “995” hotline. With a fleet of only 84 ambulances serving a growing and aging population, efficient allocation of resources is increasingly important.

Currently, SCDF utilizes a rule-based dispatch framework comprising 30 internally developed protocols that resemble the Criteria-Based Dispatch approach. During an emergency call, dispatchers follow specific questioning guidelines based on the patient's primary complaint. Using the collected information, they assign a severity rating through the Patient Acuity Category Scale (PACS), which is Singapore's nationwide EMS triage classification system.

The PACS system categorizes cases into five levels: P1+, P1, P2, P3, and P4. The most critical cases—P1+ and P1—include life-threatening conditions such as cardiac arrest and severe head injuries. For P1+ incidents, a fire bike responder may be deployed to navigate traffic quickly and provide rapid initial assistance before the ambulance arrives. P2 cases involve serious emergencies where patients are typically unable to walk and may deteriorate without timely care. P3 cases refer to less severe emergencies where patients experience mild to moderate symptoms but are still ambulatory; early treatment can still improve outcomes. Finally, P4 cases involve non-urgent situations, such as chronic conditions or old injuries, that do not require immediate emergency intervention.

2 LITERATURE SURVEY

A study by Blomberg SN and colleagues (2019), published in Resuscitation, examined the application of machine learning techniques to assist in identifying cardiac arrest during emergency calls.

The researchers developed predictive models using information communicated by callers to emergency dispatch centers. Their findings suggest that machine learning algorithms can function as supportive decision-making tools, helping dispatchers recognize cardiac arrest cases more effectively and potentially reducing delays in life-saving interventions.

In a subsequent randomized clinical trial, Blomberg SN et al. (2021), published in JAMA Network Open, evaluated the real-world impact of integrating machine learning into emergency dispatch systems.

This study assessed whether AI-based decision support could enhance dispatcher recognition of out-of-hospital cardiac arrest during live emergency calls. The results demonstrated that the incorporation of machine learning significantly improved the identification rate of cardiac arrest cases compared to standard dispatch procedures. The trial provided strong clinical evidence supporting the practical value of AI-assisted emergency call triage.

Another important contribution was made by Tollinton L and colleagues (2020), whose work was published in the International Journal of Medical Informatics. This research focused on predicting whether patients involved in unconsciousness or fainting incidents would require transport to the hospital. The study utilized natural language processing (NLP) techniques to analyze free-text notes recorded by emergency call handlers at the London Ambulance Service. By incorporating textual data into predictive models, the researchers improved the accuracy of patient conveyance predictions. Their findings highlight the critical role of unstructured textual information in enhancing decision-making within emergency medical services.

3 EXISTING SYSTEM

In conventional emergency medical response systems, ambulance services primarily depend on manual evaluation by paramedics and basic communication with hospital staff. Although this approach has been widely practiced, it presents several operational challenges. Factors such as heavy traffic congestion, absence of intelligent route planning, and scarcity of medical resources frequently result in delayed response and treatment times.

Moreover, traditional ambulances often lack advanced real-time monitoring systems that continuously track patients' vital signs during transport. Without immediate data transmission to hospitals or direct consultation with medical specialists, paramedics may face difficulties in delivering optimal pre-hospital care. This limitation can delay critical clinical decisions and reduce the effectiveness of treatment provided en route to the hospital. Consequently, these constraints may negatively affect patient outcomes, especially in time-sensitive emergencies such as cardiac arrest, stroke, or severe trauma.

3.1 **DIS ADVANTAGES:**

3.1.1 Delayed Response Due to Traffic Congestion

Ambulances often face heavy traffic, especially in urban areas, which increases response and transport time. Without intelligent route optimization or traffic prediction systems, delays become unavoidable.

3.1.2 Limited Real-Time Patient Monitoring

Traditional ambulances may lack advanced systems for continuous real-time monitoring of vital signs such as ECG, oxygen saturation, blood pressure, and heart rate. This can reduce the ability to detect sudden deterioration during transit.

3.1.3 Manual Decision-Making Limitations

Dispatch decisions are largely based on human assessment, which can lead to errors or misjudgments, particularly in high-pressure situations. Inaccurate triage may result in either overuse or underuse of ambulance resources.

3.1.4 Inefficient Resource Utilization

Without data-driven allocation strategies, ambulances may be dispatched suboptimally, leaving certain regions underserved while others experience resource redundancy.

4 PROPOSED SYSTEM

To realize this proposed system, two separate applications have been developed: a Hospital Application and an Ambulance Application.

Hospital Application:

This module is responsible for loading and preprocessing the healthcare dataset, followed by training multiple machine learning algorithms using the processed data. Once the models are trained and validated, the hospital system activates a cloud-based server that continuously listens for incoming requests from ambulance units. The server processes patient data received from ambulances and generates predictions regarding the patient's medical condition.

Ambulance Application:

In situations where IoT-based medical sensors are not available, the ambulance module allows patient vital parameters to be uploaded manually from a file. These parameters simulate real-time vital signs such as heart rate, blood pressure, oxygen levels, and other clinical indicators. The application then securely transmits this data to the hospital server. Upon receiving the data, the trained AI model analyzes the information and predicts the patient's health status. The prediction results are immediately sent back to the ambulance team, enabling paramedics to take appropriate and timely medical actions during transit.

This AI-driven ambulance framework addresses the growing demand for efficient emergency care in rapidly expanding urban populations. By integrating predictive analytics, cloud communication, and automated decision support, the system enhances response speed, improves coordination between ambulances and hospitals, and optimizes medical interventions.

Overall, the proposed AI-based Ambulance System represents a major advancement in emergency medical services. By utilizing modern computational technologies, it ensures faster decision-making, better resource utilization, and improved patient outcomes—making every second count during life-threatening emergencies.

4.1 ADVANTAGES:

4.1.1 Faster Medical Decision-Making

The system uses trained machine learning models to quickly analyze patient vital signs and predict medical conditions, enabling paramedics to take immediate and informed action.

4.1.2 Improved Pre-Hospital Care

By receiving AI-generated predictions from the hospital server, ambulance staff can begin appropriate treatment during transit, improving patient survival chances.

4.1.3 Real-Time Communication

Continuous data exchange between the ambulance and hospital server ensures that healthcare professionals are prepared before the patient arrives.

4.1.4 Reduced Human Error

AI-based prediction minimizes dependency solely on manual assessment, reducing the risk of misjudgment during high-pressure emergency situations.

5 RELATED WORK

The integration of artificial intelligence and advanced human-machine interface technologies into ambulance services significantly enhances the performance of emergency medical systems. These innovations improve operational efficiency, clinical accuracy, communication, and overall patient outcomes, creating a more responsive and reliable emergency care framework.

5.1. Increased Operational Efficiency

Automation of routine tasks such as dispatch coordination, route planning, and data processing reduces response time and improves workflow management. AI-based route optimization helps ambulances avoid traffic congestion and reach emergency locations more quickly.

5.2. Greater Diagnostic Accuracy

AI-powered predictive analytics and decision-support tools analyze large volumes of medical data to generate reliable insights. This supports paramedics in making accurate clinical decisions, leading to improved diagnosis and treatment during pre-hospital care.

5.3. Better Resource Allocation

By evaluating historical data and forecasting emergency demand, the system enables optimal deployment of ambulances, medical personnel, and equipment. This minimizes resource wastage and ensures better coverage across service areas.

5.4. Improved Quality of Patient Care

Access to real-time patient information and medical history allows emergency responders to deliver personalized and condition-specific treatment. Being better informed before reaching the scene enhances preparedness and treatment effectiveness.

5.5. Rapid Clinical Decision Support

AI systems can process patient data instantly and provide immediate recommendations. In critical emergencies such as cardiac arrest or stroke, faster decision-making directly contributes to higher survival rates.

5.6 ALGORITHM INVOLVED

5.6.1 RANDOM FOREST ALGORITHM

Random Forest is a supervised machine learning algorithm used for classification and regression tasks. It was introduced by Leo Breiman in 2001 as an extension of decision tree models. The core idea is to build multiple decision trees and combine their predictions to improve accuracy and reduce over fitting.

Step-by-step process:

Select N random samples from the dataset.Build a decision tree for each sample.

At each node:

Select a random subset of features.Choose the best split among them.Repeat for many trees.

Aggregate results:

Classification → Majority Vote

Regression → Mean of predictions

If we denote:

- $T_1(x), T_2(x), \ldots, T_n(x)$ as individual tree predictions

Then:

- Classification Output:

$$\hat{y} = \mathrm{mode}(T_1(x), T_2(x), \ldots, T_n(x))$$

- Regression Output:

$$\hat{y} = \frac{1}{n}\sum_{i=1}^{n} T_i(x)$$

6 SYETEM ARCHITECTURE

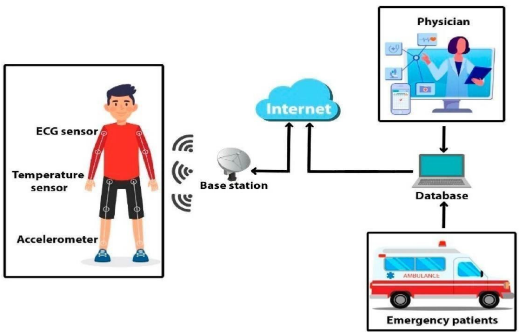

Fig1 : system architecture

7 RESULTS

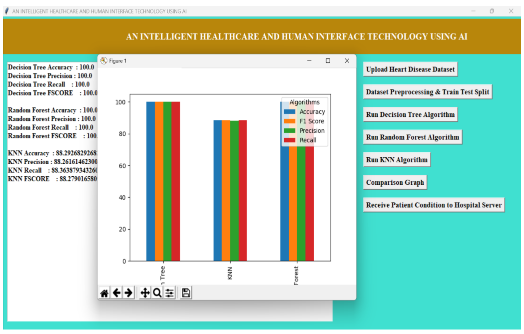

Fig 2:In the above system interface, the ambulance application first uploads the patient's test data, which represents vital health parameters. This data is then transmitted to the hospital server through the cloud connection. Upon receiving the patient information, the server processes the data using the trained AI model to analyze the patient's condition.After evaluation, the system classifies the condition as either normal or abnormal based on the prediction results. The server then immediately sends the prediction outcome back to the ambulance application. Based on this response, paramedics can take appropriate medical actions during transit and inform hospital staff for further preparation if the condition is identified as abnormal.

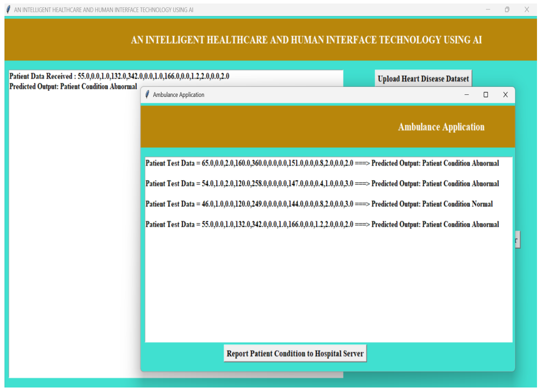

Fig3:In the proposed system, the ambulance application continuously transmits the patient's vital parameters to the hospital server. These parameters may include heart rate, blood pressure, oxygen saturation, temperature, and other relevant clinical indicators. The server processes this incoming data using trained AI models to predict the patient's medical condition in real time.Based on the predicted condition, doctors and hospital staff can immediately prepare the necessary medications, medical equipment, and treatment arrangements before the patient arrives. This proactive approach reduces delays in treatment, ensures better preparedness, and improves the chances of positive patient outcomes during critical emergencies.

5. CONCLUSION

The Intelligent Ambulance project, which combines artificial intelligence with advanced human interaction technologies, highlights the trans-formative impact of digital innovation in emergency medical services. By embedding AI capabilities into ambulance operations and enhancing human-machine communication, the system establishes a smarter and more adaptive emergency healthcare framework.The implementation of this approach has demonstrated notable improvements, including reduced response times, more precise patient condition analysis, and stronger coordination between paramedics and hospital teams. AI-powered decision support tools assist medical personnel in evaluating patient data quickly and accurately, while human expertise ensures appropriate clinical judgment in critical situations.The effective collaboration between intelligent algorithms and healthcare professionals strengthens emergency response efficiency and elevates the quality of patient care. Overall, the project illustrates how integrating AI with human-centered technologies can significantly advance pre-hospital emergency services, ultimately leading to better clinical outcomes and improved survival rates.

8 REFERENCES

[1] Advani R, Naess H, Kurz MW. The golden hour of acute ischemic stroke. Scand J Trauma Resusc Emerg Med. 2017;25(1):54.

[2] Heestermans T, van 't Hof AWJ, ten Berg JM, van Werkum JW, Boersma E, Mosterd A, et al. The golden hour of prehospital reperfusion with triple antiplatelet therapy: A subanalysis from the On-TIME 2 trial. Am Heart J. 2010;160(6):1079–1084.

[3] Al-Dury N, Ravn-Fischer A, Hollenberg J, Israelsson J, Nordberg P, Strömsöe A, et al. Identifying predictors of survival in out-of-hospital cardiac arrest using machine learning. Scand J Trauma Resusc Emerg Med. 2020;28(1):60.

[4] Carter GM, Chaiken JM, Ignall E. Response areas for two emergency units. Oper Res. 1972;20(3):571–594.

[5] Jagtenberg CJ, Bhulai S, van der Mei RD. Dynamic ambulance dispatching: Is the closest-idle policy always optimal? Health Care Manag Sci. 2017;20(4):517–531.

[6] Haghani A, Tian Q, Hu H. Simulation model for real-time emergency vehicle dispatching and routing. Transp Res Rec. 2004;1882(1):176–183.

[7] Bandara D, Mayorga ME, McLay LA. Priority dispatching strategies for EMS systems. J Oper Res Soc. 2014;65(4):572–587.

[8] Jagtenberg CJ, van den Berg PL, van der Mei RD. Benchmarking online dispatch algorithms for EMS. Eur J Oper Res. 2017;258(2):715–725.

[9] Leeies M, Ffrench C, Strome T, Weldon E, Bullard M, Grierson R. Prehospital application of the Canadian Triage and Acuity Scale by EMS. CJEM. 2017;19(1):26–31.

[10] Criteria Based Dispatch—Emergency Medical Dispatch Guidelines. Published July 2010.

[11] Andersen MS, Johnsen SP, Sørensen JN, Jepsen SB, Hansen JB, Christensen EF.

[12] Andersen MS, Johnsen SP, Sørensen JN, Jepsen SB, Hansen JB, Christensen EF. Implementing a nationwide criteria-based emergency medical dispatch system: A register-based follow-up study. Scand J Trauma Resusc Emerg Med. 2013;21:53.

[13] Dami F, Golay C, Pasquier M, Fuchs V, Carron PN, Hugli O. Prehospital triage accuracy in a criteria-based dispatch centre. BMC Emerg Med. 2015;15:32.

[14] Bohm K, Kurland L. The accuracy of medical dispatch—A systematic review. Scand J Trauma Resusc Emerg Med. 2018;26:94.

[15] Lidal IB, Holte HH, Vist GE. Triage systems for pre-hospital EMS—A systematic review. Scand J Trauma Resusc Emerg Med. 2013;21:28.

[16] Fong RY, Glen WSS, Mohamed Jamil AK, Tam WWS, Kowitlawakul Y. Comparison of the Emergency Severity Index versus the Patient Acuity Category Scale. Int Emerg Nurs. 2018;41:13–18.

[17] Blomberg SN, Folke F, Ersbøll AK, Christensen HC, Torp-Pedersen C, Sayre MR, et al. Machine learning as a supportive tool to recognize cardiac arrest in emergency calls. Resuscitation. 2019;138:322–329.

[18] Blomberg SN, Christensen HC, Lippert F, Ersbøll AK, Torp-Petersen C, Sayre MR, et al. Effect of machine learning on dispatcher recognition of out-of-hospital cardiac arrest: A randomized clinical trial. JAMA Netw Open. 2021;4(1):e2032320.

[19] Tollinton L, Metcalf AM, Velupillai S. Enhancing predictions of patient conveyance using emergency call handler free-text notes. Int J Med Inform. 2020;141:104179.

[20] Snoek J, Larochelle H, Adams RP. Practical Bayesian optimization of machine learning algorithms. arXiv. 2012. doi:10.48550/arXiv.1206.2944.

[21] Quinlan JR. Induction of decision trees. Mach Learn. 1986;1(1):81–106.

[22] Chen T, Guestrin C. XGBoost: A scalable tree boosting system. In: Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining; 2016; San Francisco, CA.

[23] Breiman L. Random forests. Mach Learn. 2001;45(1):5–32.

[24] Prieto JT, Scott K, McEwen D, Podewils LJ, al-Tayyib A, Robinson J, et al. Detection of opioid misuse from paramedic documentation using machine learning. J Med Internet Res. 2020;22(1):e15645.

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