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# INTELLIGENT EMERGENCY TRANSIT AND ADAPTIVE AI HUMAN INTERFACE FRAMEWORK

V.NANDINI[1],
G. RANGANADHA RAO[2]
M-Tech Student, Dept.of CSE, UNIVESAL COLLEGE OF ENGINEERING AND TECHNOLOGY,Andhra pradhesh, India 1
Associate Professor,Dept.of CSE,UNIVERSAL COLLEGE OF ENGINEERING AND TECHNOLOGY,Andhra pradhesh, India2
nandinivelivela4567@gmail.com , ranganath19@gmail.com

## ABSTRACT

The integration of technology in healthcare, including emergency services, has been an ongoing process. The application of artificial intelligence (AI) in healthcare, such as predictive analytics for disease outbreaks and medical image analysis, has paved the way for its implementation in ambulance services. Human-machine interfaces have also evolved, with advancements in augmented reality, virtual reality, and natural language processing. The convergence of these technologies led to the development of intelligent ambulance-AI and human interface technology, which refers the integration of AI and advanced human-machine interfaces in ambulance services. The primary goal is to enhance the efficiency, accuracy, and responsiveness of emergency medical services. Traditional ambulance systems typically rely on manual processes for call handling, dispatching, and patient care. Emergency calls are received by human operators, who then dispatch the nearest ambulance based on limited information. Paramedics assess the situation on-site, often with minimal data about the patient's medical history or condition. Communication between paramedics and hospitals might be limited, leading to delays in decision-making and treatment.In addition, the need for intelligent ambulance-AI and human interface technology arises from the critical nature of emergency medical services. Swift and accurate response during emergencies can significantly impact patient outcomes. Therefore, this research develops a system by implementing AI algorithms for predictive analytics, and decision support. By automating certain tasks and providing actionable insights, this technology significantly improves the efficiency and effectiveness of ambulance services, ensuring timely and optimal care for patients in critical situations. Further, this proposed system can automate processes, provide data-driven insights, and improve communication, ultimately saving

lives and reducing the burden on healthcare facilities.

**KEYTERMS:** Integration, Healthcare, Intelligent, Ambulance, Paramedics, Automating, Significantly.

## 1 INTRODUCTION

Efficient and effective Emergency Medical Services (EMS) are vital for good outcomes during pre- hospital emergencies such as stroke and cardiac arrest, where the response time and the type of response matters. The traditional approach that dispatches the closest available vehicle to an emergency has been shown to be far from optimal [4, 5]. With limited ambulance resources, the priority of a case is a crucial factor for dispatch decisions.

EMS systems worldwide have investigated and implemented various pre-hospital triage systems to determine the priority level of a pre-hospital emergency case. Most of these systems can be categorized into 2 groups. The Medical Priority Dispatch System and its variants assign priority levels to each case based on protocols with scripted questions put to the caller and originated in North America. On the other hand, Criteria-Based Dispatch systems involve guidelines to determine response levels based on patient signs and symptoms collected by the dispatcher and are used, for ex - ample, in Nordic and European countries. However, studies have shown that the accuracy of these priority dispatch systems remains an issue of concern and there is a paucity of research to guide pre-hospital triage systems.

In Singapore, the Singapore Civil Defence Force (SCDF) serves as the national EMS organization, and their ambulance crews respond to more than 190,000 calls (national emergency “995” hotline) every year. With only a fleet of 84 ambulances, the need for efficient resource utilization is pressing, especially as the population continues to grow and age. At present, the SCDF uses a rule-based system containing 30 in-house protocols similar to the Criteria-Based Dispatch system. For different chief complaints, the dispatcher at the call center will ask questions based on the respective protocol and assign a Patient Acuity Category Scale (PACS)for medical dispatch. The PACS is the emergency scale used nationwide in Singapore's EMS system that includes 5 levels (P1+, P1, P2, P3, and P4). P1+ and P1 are assigned to the most severe cases that are immediately life-threatening, such as cardiac arrest and head injury. P1+ cases will trigger a fire bike that beats the traffic on the road and will arrive faster than an ambulance. P2 cases are emergencies where the patients are usually unable to walk and are in some form of distress. If not attended early, then their medical status could deteriorate quickly. P3 cases are minor emergencies involving patients who have mild to moderate symptoms and are able to walk. Early intervention will still result in a better patient outcome in P3 cases. P4 cases are non-emergencies such as old injuries or chronic conditions that do not require immediate attention.

## 2 LITERATURE SURVEY

**Blomberg SN, Folke F, Ersbøll AK, Christensen HC, Torp-Pedersen C, Sayre MR, Counts CR, Lippert FK. Machine learning as a supportive tool to recognize cardiac arrest in emergency calls. Resuscitation. 2019;138:322–329.**

This study explores the use of machine learning algorithms to aid in recognizing cardiac arrest situations during emergency calls. The researchers investigate the potential of machine learning as a supportive tool for identifying cardiac arrest cases based on information provided during emergency calls.

**Blomberg SN, Christensen HC, Lippert F, Ersbøll AK, Torp-Petersen C, Sayre MR, Kudenchuk PJ, Folke F. Effect of machine learning on dispatcher recognition of out-of- hospital cardiac arrest during calls to emergency medical services: A randomized clinical trial. JAMA Netw Open. 2021;4(1):e2032320.**

This paper presents the results of a randomized clinical trial that examines the impact of machine learning on dispatcher recognition of out-of-hospital cardiac arrest cases. The study assesses how machine learning algorithms affect the ability of emergency medical service dispatchers to recognize cardiac arrest situations during calls, providing valuable insights into the effectiveness of these technologies in real-world scenarios.

**Tollinton L, Metcalf AM, Velupillai S. Enhancing predictions of patient conveyance using emergency call handler free text notes for unconscious and fainting incidents reported to the London Ambulance Service. Int J Med Inform. 2020;141:104179**

This research focuses on improving predictions related to patient conveyance by analyzing free text notes provided by emergency call handlers. Specifically, the study concentrates on incidents involving unconsciousness and fainting reported to the London Ambulance Service. By leveraging natural language processing techniques, the researchers enhance the accuracy of predictions, highlighting the importance of textual information in emergency medical services.

## 3 EXISTING SYSTEM

In the traditional emergency medical response system, ambulances rely on human assessment and communication with hospitals. However, challenges such as traffic congestion, lack of real-time monitoring, and limited medical resources often lead to delays in providing medical care. Additionally, patients may not receive appropriate treatment during transit due to the absence of real-time vital sign monitoring and communication with healthcare professionals.

## 4 PROPOSED SYSTEM

To implement this initiative, two applications have been designed:

**Hospital Application:** This application loads and preprocesses the dataset, trains all algorithms on the processed data, and initiates a cloud server to receive requests from ambulances.

**Ambulance Application:** In the absence of IoT sensors, this application uploads test data, representing the patient's vital signs, from a file. The application then transmits this data to the hospital server, where the patient's condition is predicted. The hospital server sends back the response to the ambulance, enabling timely and accurate medical interventions.

This advanced AI-based Ambulance system not only addresses the challenges posed by the burgeoning population but also significantly enhances the efficiency and effectiveness of emergency medical services, ultimately saving lives in critical situations. Finally, the AI-based Ambulance System represents a significant leap forward in the field of emergency medical services, offering a solution to the challenges posed by the increasing population and urbanization. By leveraging modern technologies, the proposed model ensures that every moment counts in saving lives during medical emergencies.

## 5 RELATED WORK

The advantages of intelligent ambulance-AI and human interface technology encompass improved efficiency, accuracy, patient care, and decision-making, ultimately leading to better outcomes for patients in emergency situations and creating a more responsive and effective emergency medical services system. The integration of intelligent ambulance-AI and human interface technology in emergency medical services offers several advantages, including:

**Enhanced Efficiency:** Automation of tasks and processes leads to quicker response times, streamlined operations, and efficient allocation of resources. AI algorithms can optimize ambulance routes, ensuring the fastest possible response to emergencies.

**Improved Accuracy:** AI-driven predictive analytics and decision support systems provide accurate insights based on vast amounts of data. This accuracy can aid paramedics in making informed decisions about patient care, leading to better treatment outcomes.

**Optimized Resource Utilization:** By analyzing data and predicting demand, the system can optimize the allocation of ambulances and medical staff. This ensures that resources are used efficiently, reducing idle time and improving overall service availability.

**Enhanced Patient Care:** Access to real-time data and historical patient information allows paramedics to provide personalized and targeted care. They can arrive at the scene better prepared, with insights into the patient's medical history and specific conditions, leading to more effective treatments.

**Faster Decision-Making:** AI algorithms can process information rapidly and provide instant recommendations. This speed is crucial in emergency situations, where swift decision- making can significantly impact patient outcomes.

Improved Communication: Advanced human-machine interfaces facilitate seamless communication between paramedics, emergency operators, and hospitals. Clear and instant communication ensures that vital information is relayed promptly, enabling more coordinated and effective care.

**Reduction in Errors:** Automation reduces the likelihood of human errors, ensuring that critical information is not overlooked. This leads to safer medical practices and minimizes the risk of mistakes in emergency situations.

Data-Driven Insights: The system generates valuable data that can be analyzed to identify patterns, trends, and areas for improvement. These insights can be used to enhance protocols, training programs, and overall emergency medical service strategies.

**Resource Conservation:** By optimizing routes and resources, the system contributes to the conservation of fuel and other valuable resources, making emergency medical services more environmentally friendly and sustainable.

**Cost Efficiency:** While initial implementation might require investment, the long-term benefits, including reduced hospitalization costs due to better initial care, streamlined operations, and optimized resource usage, can lead to significant cost savings for healthcare providers and organizations.

## 6 SYETEM ARCHITECTURE

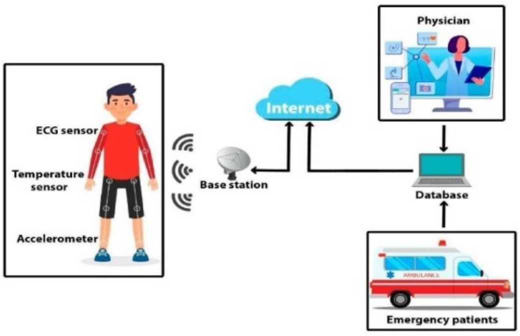
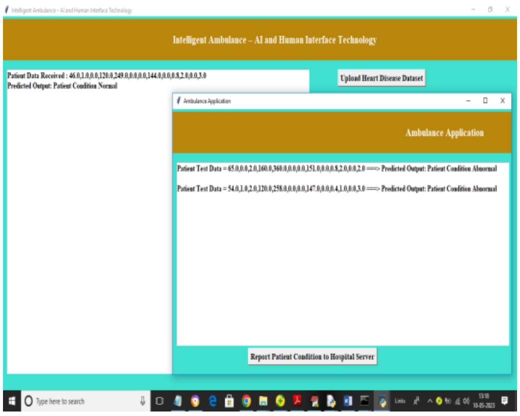
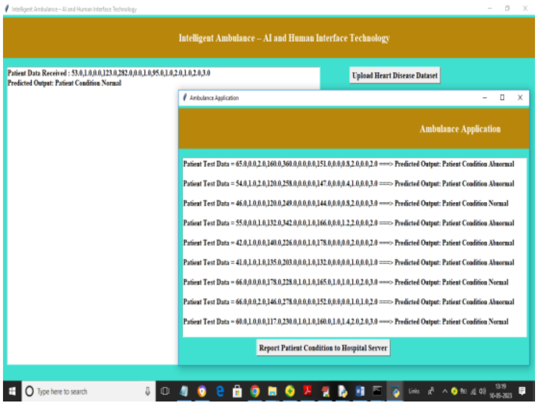



Fig : system architecture

## 7 RESULTS




In above screen ambulance sending test data and then server receiving patient data and then predicting condition as normal and abnormal and sending back response to ambulance




In above screen continuously ambulance will send patient data to server to get predicted condition and based on condition doctors will arrange medications

## 5. CONCLUSION

The Intelligence Ambulance project, integrating AI and human interaction technologies, has showcased the potential for significantly improving emergency medical services. The incorporation of artificial intelligence into ambulance systems, coupled with advanced human interaction technologies, has resulted in a more intelligent and responsive healthcare delivery system. The project has demonstrated successful outcomes in terms of faster response times, accurate patient assessment, and improved communication between healthcare providers and patients. The synergy between AI-driven decision support systems and human expertise has the potential to transform emergency medical care, enhancing both efficiency and patient outcomes.

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**FIRST AUTHORS:**

**V. NANDINI** Completed B.Tech in Computer Science And Engineering and pursuing her M.Tech in Computer Science And Engineering in Universal College Of Engineering And Technology.

**SECOND AUTHOR**:

**G. RANGANADHA RAO**,M.Tech and B.Tech received his degree's in computer science and engineering. He is currently working as a Associate Professor of CSE in Universal College Of Engineering And Technology.