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Clinical Validation and Performance Evaluation of Ontology-Based Expert System in Emergency Medicine

Rutvik. K. Shukla[*1], Chetan B. Bhatt[2]

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Abstract: This manuscript presents the clinical validation and performance assessment of an ontology-driven expert system designed to assist emergency medical personnel in pre-hospital care scenarios. The system, structured using a semantic web framework and integrated with the National Early Warning Score (NEWS) methodology, aids in risk stratification, preliminary diagnosis, and treatment guidance for patients in critical condition. Built upon a modular client-server architecture using Java and OWL ontologies, the system captures vital parameters entered by emergency staff and infers risk levels through a rule-based ontology. Clinical validation was conducted in collaboration with a multispecialty hospital's emergency department, where real patient data was used to evaluate the system's accuracy and practical relevance. Results demonstrate a significant correlation between the predicted risk levels and actual patient outcomes, confirming the system's potential to enhance decision-making in time-sensitive medical emergencies. This paper discusses the implementation, testing methodology, outcome analysis, and practical implications of deploying such ontology-based systems in real-world emergency medical services.

Keywords: *Early Warning Scoring System (EWS), Emergency Department (ED) Ontology,Ontology web language (OWL), Expert System (ES), Protégé*

1. Introduction

A medical emergency involves sudden physical or psychological conditions that demand immediate attention to prevent serious harm, disability, or death. Timely intervention—often within the first few minutes—is critical, especially in cases like cardiac arrest or severe trauma, where delays can result in irreversible brain damage or fatal outcomes. Studies show that a large propotion of deaths from road accidents and cardiac events occur before hospital admission, emphasizing the need for rapid response and early stabilization. Effective emergency care includes early detection, urgent first aid, safe transportation, and timely definitive treatment. In this context, pre-hospital care becomes a vital link in the emergency care chain. Trained paramedical personnel, supported by well-equipped ambulances, play a crucial role in managing emergencies and improving patient survival rates before they reach a healthcare facility. (Shukla and Bhatt, n.d.-b)

This decision-making system can be broadly classified into two main categories: Decision Support Systems (DSS) and Expert Systems (ES). A DSS is an interactive tool that helps decision-makers leverage data and models to tackle unstructured or semi-structured problems. In contrast, an ES is a problem-solving computer program designed to perform effectively in specialized domains that require expert knowledge and skills. While both aim to support the decision-making process, they differ in their methods and areas of application.

Furthermore, ES can be divided into several types, including Rule-based systems, Knowledge-based systems, Case-based systems, Agent-based systems,

[1*] *Assistant Professor, Instrumentation & Control Engineering Department, Government Engineering College, Mavdi-Kankot Road, Rajkot, Gujarat, INDIA, E-mail: rutvikshukla@gecrajkot.ac.in Orcid id: 0000-0001-5223-8465*

[2] *Principal, Government MCA College, Khokhra, Maninagar East, Ahmedabad, Gujarat, INDIA, Chetan_bhatt@yahoo.com*

and Ontology-based systems. Expert systems are widely used in healthcare for tasks such as predicting and diagnosing diseases, proving especially valuable when medical professionals are not readily available. (Shukla and Bhatt, n.d.-a)

This paper aims to explore the clinical validation and performance evaluation of the proposed ontology-based expert system in the domain of emergency medicine. The system is designed to assist Emergency Medicine Practitioners in promptly and accurately determining patient risk levels, thereby enabling timely clinical decision-making and the initiation of appropriate therapeutic interventions to prevent further deterioration of patient health. Furthermore, the system seeks to provide evidence-based suggestions regarding probable diseases and deliver structured guidance on their corresponding treatment protocols.

Background

A medical emergency is an unforeseen injury or medical condition (physiological or psychological) that requires immediate medical attention. The primary goals of emergency medical care are to: (i) enable timely detection, urgent First Aid, and effective resuscitation; (ii) ensure rapid and safe transport of the patient to an appropriate hospital emergency department; and (iii) provide definitive treatment thereafter. Pre-hospital care is therefore a critical component that must be simple, sustainable, and efficient. Paramedical personnel play a pivotal role in delivering this care using well-equipped vehicles, with the team typically comprising EMT-Basic, EMT-Advanced, and EMT-Paramedic professionals, each with clearly defined roles and responsibilities. (Sharma and Brandler 2014).

India is currently undergoing both monetary and demographic transitions while facing a significant epidemiological shift driven by rapid urbanization and changing lifestyles. This has led to a sharp rise in cardiovascular and cerebrovascular diseases, diabetes, and Chronic Obstructive Pulmonary Disease (COPD). Simultaneously, communicable diseases such as acute respiratory infections, diarrhoeal diseases, tuberculosis, and malaria continue to impose a substantial disease burden. Additionally, unintentional injuries (road traffic accidents, fires, falls) and intentional injuries (self-harm, violence-related) further contribute to this burden. Many of these conditions are acute or present with acute episodes—such as myocardial infarction and acute hemorrhages—requiring timely emergency care.(Joshipura et al. 2004).

Our understanding of healthcare goals shapes the concept of “quality of health care,” which focuses on improving population health, addressing people’s needs, and ensuring financial protection against medical expenses (*The World Health Report 2000.Health Systems: Improving Performance* 2000). In India, as a developing nation with vast rural regions, key challenges include controlling chronic infectious diseases, addressing the shortage of trained healthcare personnel and facilities, and expanding the limited healthcare programs available.

Karlsten and Sjoqvist (Karlsten and Sjoqvist 2000) proposed using telemedicine and a Decision Support System (DSS) in emergency ambulances to enable early diagnosis, improve hospital preparedness, and initiate timely treatment, marking the first use of DSS in pre-hospital emergency care. The research proposed by Pavlopoulos and team in the year 1998, taken further by again the team of researcher from biomedical engineering laboratory in the year 2003 under the supervision of Kyriacou (Kyriacou et al. 2003). They have developed multi-purpose healthcare telemedicine systems by establishing a communication link from a mobile network. This system includes the scope of transmitting live data as well, but the system still faced technological constraints in terms of feasibility, as it transfers waveform and images.

The Health Information and Quality Authority (2014) report highlighted several key applications of ICT within the national ambulance service. These include computer-aided dispatch and incident tracking systems, emergency response resource location, incident address verification, satellite navigation systems for emergency personnel, communication links between control centers and response staff, mobile data terminals, and electronic patient care reporting systems. (*Review of Pre-Hospital Emergency Care Services to Ensure High Quality in the Assessment, Diagnosis, Clinical Management and Transporting of Acutely Ill Patients to Appropriate Healthcare Facilities.* 2014). Two senior researchers from Fujitsu Kyushu Systems developed an information support solution for Emergency Medical Services that promotes close collaboration between paramedics and medical institutions by enabling real-time data sharing, improving decision-making, and streamlining patient handovers to enhance emergency response efficiency and patient outcomes. (Sonoda and Ishibaei 2015).

Badr (Badr 2016) examined the role of ICT in pre-hospital emergency medical services, emphasizing the need for a specialized and distinct type of intelligent transport system within EMS. The study also highlighted that the integration of ICT through telemedicine positively influences the quality and effectiveness of pre-hospital emergency medical care. The smart ambulance system is another attempt to identify the role of ICT in pre-hospital emergency care (Gupta et al. 2016). The system was implemented into client-server architecture to make it a small size application and keep the data available at a central location.

Koceska and the team from Macedonia proposed a mobile wireless monitoring system for pre-hospital emergency care in 2019 (Koceska et al. 2019). This system employs wireless bio-sensors to monitor patients' vital parameters, with the collected data transmitted to and observed by paramedics in the ambulance. It provides real-time vital sign measurements, historical parameter trends, Glasgow Coma Scale assessments, injury location details, and incorporates a triage procedure. Serving as a complementary tool within Emergency Medical Services (EMS), it enables continuous real-time monitoring and facilitates on-scene triage. While the system performs these designated tasks efficiently, it lacks the intelligence and decision-support capabilities necessary to assist in making appropriate clinical decisions.

Expert System

An expert system is a computer-based program that captures and applies the knowledge of human experts to solve problems in a manner similar to domain specialists. It serves as an assistive tool, offering solutions in the absence of experts, and is commonly implemented across various fields depending on the nature and complexity of the problem. Functioning as a rule-based artificial intelligence application, an expert system provides an effective and adaptable approach to addressing problems that are often unsolvable through conventional methods.

In the medical domain, expert systems are primarily employed for diagnosis, monitoring, tutoring, and therapeutic purposes. Diagnostic expert systems, in particular, assist clinicians in identifying potential diseases and are valued for their ability to support rapid decision-making and timely selection of appropriate treatments. In a developing country like India—with its vast and widely dispersed population—ensuring efficient healthcare delivery poses a major challenge, further compounded by the shortage of trained professionals and field experts. Expert systems can help address this gap by serving as assistive tools for undertrained medical staff, especially in emergency medicine where prompt and effective care is crucial. In this context, such expert systems are often referred to as Clinical Decision Support Systems (CDSS). (Miller et al. 1986; Saba et al. 2012).

EWS (Early Warning Scoring) System

Clinicians and researchers need reliable methods to predict outcomes in critically ill patients. Various scoring systems exist for use in the ICU, emergency department (ED), and pre-hospital (PH) settings. ED-based systems use fewer, readily available parameters, while ICU systems incorporate more detailed data from admitted patients. PH scoring systems are designed similarly to ED systems. (Smith et al. 2014). The most commonly used ICU-based scoring systems are APACHE II and APACHE III, while ED-based systems include MEWS and NEWS. For pre-hospital emergency care, PHEWS serves as an early warning scoring system.

National Early Warning Scoring (NEWS) System was developed by the royal co ADDIN ZOTERO_ITEM CSL_CITATION {"citationID":"FzDf7r1U","properties":{"formattedCitation":"({\\i{}NEWS} 2019)","plainCitation":"","noteIndex":0},"citationItems":[{"id":"8pcIYZGa/WY74nPKD","uris":["http://zotero.org/users/local/LfdzSvLT/items/FL4MFTRW",["http://zotero.org/users/local/LfdzSvLT/items/FL4MFTRW"]],"itemData":{"id":155,"type":"report","title":"National Early Warning Score (NEWS)","collection-title":"Standardising the assessment of acute-illness severity in the

NHS","publisher-place":"London","page":"47","event-place":"London","title-short":"NEWS","issued":{"date-parts":[["2019",1,7]]}}}],"schema":"https://github.com/citation-style-language/schema/raw/master/csl-citation.json"}
llege of a physician ("National Early Warning Score (NEWS)" 2019). The applicability of this system was evaluated in an Indian scenario by a group of researchers from the department of general medicine, Vishakhapatnam (Vanamali, Sumalatha, and Varma 2014). The NEWS system was developed using seven key parameters to calculate the score and evaluate a patient's health status. These parameters include respiratory rate, oxygen saturation, use of supplemental oxygen, body temperature, systolic blood pressure, heart rate, and level of consciousness.

Primary assessment tools in the emergency health care system

The primary assessment is a crucial component of emergency healthcare. Patients' vital signs should be continuously monitored during ambulance transport, with the frequency depending on their condition. Additional assessments are made through patient questioning or visual observation. These evaluations help determine the patient's status, predict probable diseases, and guide treatment, enabling EM staff to initiate appropriate care before hospital arrival and improve survival chances. ("Clinical Practice Guidelines" 2014).

The three key primary assessment tools are: Perfusion Status Assessment, Respiratory Status Assessment and Conscious State Assessment (Glasgow Coma Scale) (Victoria 2018).

Ontology

The Semantic Web, proposed by Tim Berners-Lee, enables automated information access using machine-processable data semantics and metadata heuristics. By incorporating ontologies, it provides an innovative way to represent knowledge, connecting vast networks of human understanding while allowing machine interpretability (Berners-Lee et al. 2001).

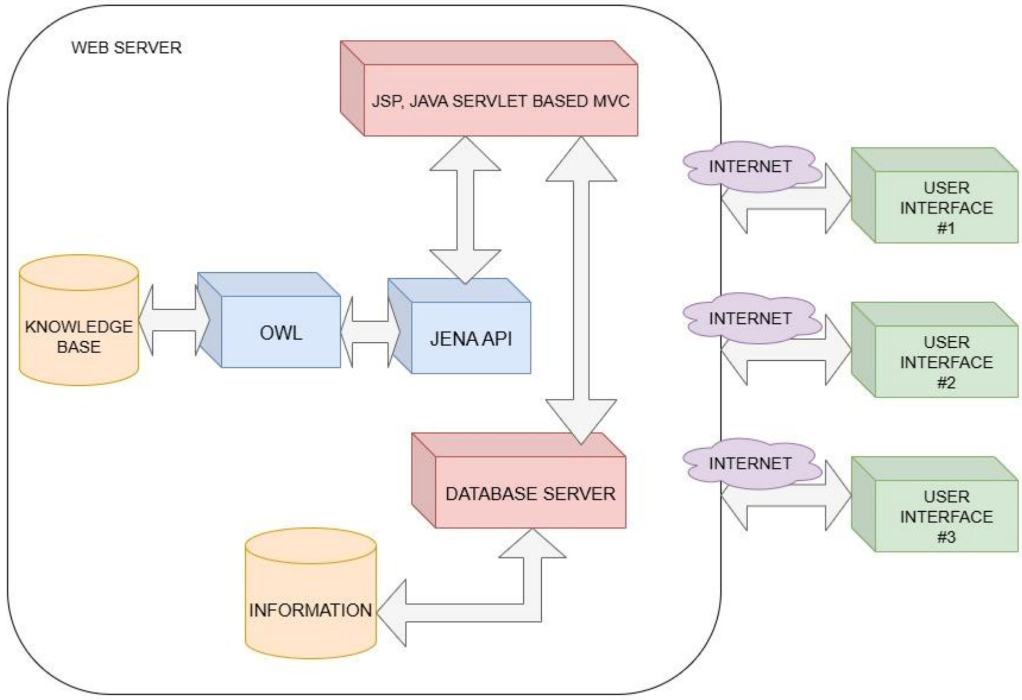
Ontologies organize the domain semantics by stating their components; thus, they contain the concepts which define the inner attributes of the stated concepts and the properties to describe their interrelationship. Ontologies are developed from the common vocabularies shared and agreed amongst the knowledge developers. These characteristics of the ontology make it suitable to utilize in various tasks of the diversified field of research (Maedche and Staab 2001). The ontology definition is given by Gruber (Gruber 1993) defined it as "a formal, explicit specification of a shared conceptualization". In this context, Gruber emphasized the formalization of concept specifications and their interrelationships, enabling the representation and sharing of knowledge among various agents. Guarino (Guarino 1998) has also given another definition of ontology: "a set of logical axioms designed to account for the intended meaning of a vocabulary". Where, Guarino focused on the role of logic theory as a way of representing an ontology (Corcho, Fernández-López, and Gómez-Pérez 2003; Gómez-Pérez and Corcho 2002; Liu and Zsu 2009). In ontology, knowledge can typically be described using five fundamental components: classes, instances, relations, functions, and axioms.

There are various formal languages available in computer science to create ontologies. These languages serve to encode knowledge within an ontology in the simplest, most formal, and human-understandable manner possible. The classification of ontology languages can be done in two parts: (Corcho and Gómez-Pérez 2000) Traditional ontology language and web-based semantic ontology language. XOL (Ontology Exchange Language, SHOE (Simple HTML Ontology Extension), RDF (Resource Description Framework) ("RDF/XML Syntax Specification (Revised)," n.d.), RDF Schema, DAML-OIL, OWL (Ontology Web Language) ("OWL Web Ontology Language Guide," n.d.) are some of the well-known examples of web-based semantic ontology languages.

2. Implementation of Proposed System

Overall System Architecture

The system architecture, as shown in Fig.1, is designed using a client-server model, following the Model-View-Controller (MVC) design pattern. It consists of four main layers: the client interface, the application logic (JSP), the semantic web framework (JENA), and the database. Users interact with the system through a web-based front end developed in JSP, which sends requests to a server-side controller implemented using Java servlets. The core knowledge base is built using Protégé, an open-source ontology editor, and stored in OWL format—accessible either locally or online. The JENA API acts as a bridge between the ontology and the application, enabling reasoning and semantic processing using RDF, RDFS, and OWL standards. A MySQL database supports the system by managing user data, treatment protocols, and disease-related information essential for the application's functionality.



Architectural Framework of the Developed System

Figure 1. Architectural framework of the developed system

JSP (JavaServer Pages) enables platform-independent web applications by separating business logic from UI design, allowing easy updates to the interface without affecting backend logic. Java Servlets handle server-side processing, enhancing web server capabilities. Together, JSP and Servlets create efficient, maintainable, and scalable enterprise-level applications. Apache Jena is a Java-based open-source framework for building semantic web applications. It supports RDF, RDFS, OWL, and SPARQL, and includes rule-based inference engines for reasoning over ontologies. Jena allows developers to create, query, and manage ontologies effectively using a consistent API. The MySQL database stores user credentials, EM-staff and patient records, treatment data, and activity logs. Admin users can manage and control access, and the stored data can be shared for further medical analysis or integration. The knowledge base contains structured medical data—diseases, symptoms, vital signs, and predefined decision rules. It has been developed using OWL ontologies and drives the system's reasoning for risk assessment and diagnosis.

The user interface connects paramedics with the expert system. It allows EM-staff to input patient data, receive risk scores, view probable diagnoses, and follow treatment recommendations through a simple, task-specific interface.

Ontology Development Phase

The developed expert system integrates the NEWS-based scoring method for risk stratification and uses various primary assessment tools for differential diagnosis in emergency care. The ontology is created using Protégé, based on expert knowledge from the emergency medicine domain.

a) **Define Classes and Hierarchy** – Ontology development begins by creating core classes. A Patient class is defined with subclasses representing patient attributes. A separate Vital Sign class is created, including subclasses like heart rate, temperature, and respiration rate.

b) **Define Object and Datatype Properties** – Properties link individuals or individuals to data.

   i. Object properties connect individuals (e.g., Patient → "hasVitalSign" → VitalSign).

   ii. Datatype properties assign values (e.g., Patient → "hasDID" → Integer ID, or "hasGender" → String).

c) **Set Domain, Range, and Facets** – Each property is assigned a domain (origin class) and range (target class or value type). Restrictions or facets are applied to control acceptable property values. For example, the property "hasPulse1" links Perfusion_Status (domain) to Pulse (range).

d) **Create Individuals** – Individuals are instances of classes, representing actual patient data, symptoms, or conditions. These are defined in Protégé and used in rule-based decision logic to infer diagnoses or risk levels.

Implementation of Ontology-Based Expert System – Meditrace

a) **Emergency Staff Registration** – Allows staff to register using basic details (name, hospital, unique hospital ID) and generates default login credentials.

b) **Login Screen** – Enables registered users, including EM staff and Admin, to access the system using their credentials.

c) **Emergency Risk Level Assessment** – Captures patient details (name, age, gender) and vital parameters (heart rate, temperature, etc.) to evaluate risk.

d) **Risk Level Score Display** – Shows the calculated risk score and level, allowing paramedics to choose between differential diagnosis or patient transport.

e) **Differential Diagnosis** – Collects detailed patient data on perfusion, respiratory status, and consciousness (including GCS) to improve diagnostic accuracy.

f) **Primary Assessment Results** – Summarizes perfusion, respiratory status, GCS, and probable diseases, guiding paramedics on treatment initiation or transport.

g) **Treatment Module** – Provides a stepwise treatment plan based on diagnosis; paramedics can follow steps or opt to transport the patient at any stage.

h) **Emergency Assessment Report** – Admin-only access to patient logs, treatment history, and progress trends under unique patient IDs, facilitating care monitoring.

3. Results and Discussion

Testing Dataset

To determine the effectiveness of the proposed "Meditrace" system, it was necessary to test it using actual patient data. For this purpose, Shree Giriraj Multispecialty Hospital, a well-known hospital located in Rajkot city, was selected. This hospital specializes in critical care and is staffed with a team of highly dedicated and experienced medical professionals. The developed system was tested using the patient database provided by this hospital. A critical aspect of this evaluation was the careful selection of an appropriate patient dataset to ensure meaningful results. The data collection was specifically focused on the Emergency Department, allowing the system to be tested on real-world emergency cases and assess its performance under practical conditions.

The patient database was selected to encompass a wide range of possibilities and variations, including gender, adult age groups, and patients with relevant medical histories. To evaluate the efficacy of the system and validate its performance in a clinical environment, it was essential to cover all potential scenarios that may arise in emergency healthcare. As shown in Fig. 2, the selected database includes 67 male patients and 31 female patients, reflecting gender variation. Fig. 3 illustrates the age distribution of the patients considered for validation, indicating that the majority are above 40 years of age. Fig. 4 shows that approximately 55 patients have a documented medical history, which includes conditions such as hypertension, diabetes, major surgeries, or ischemic heart disease. This comprehensive dataset ensures a robust evaluation of the system's clinical applicability and performance

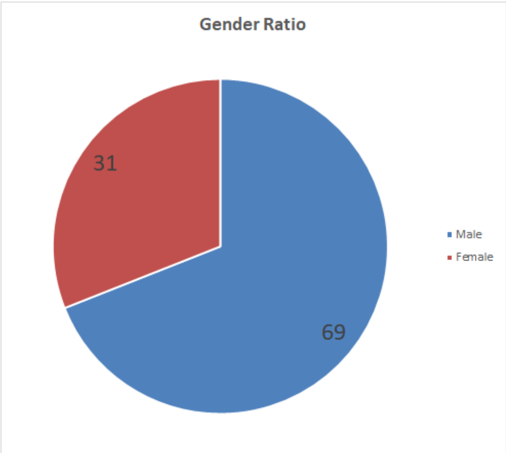


Figure 2. Patient database with Gender variation

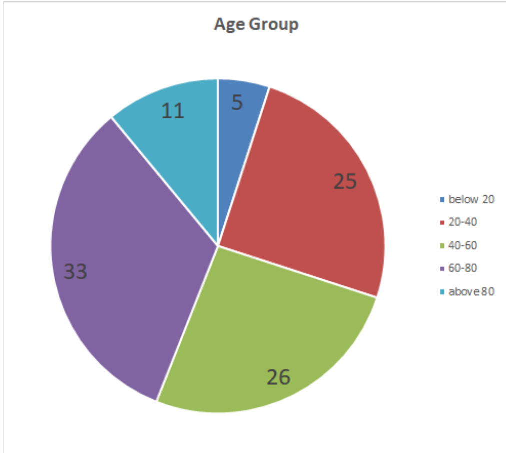


Figure 3. Patient database with Age variation

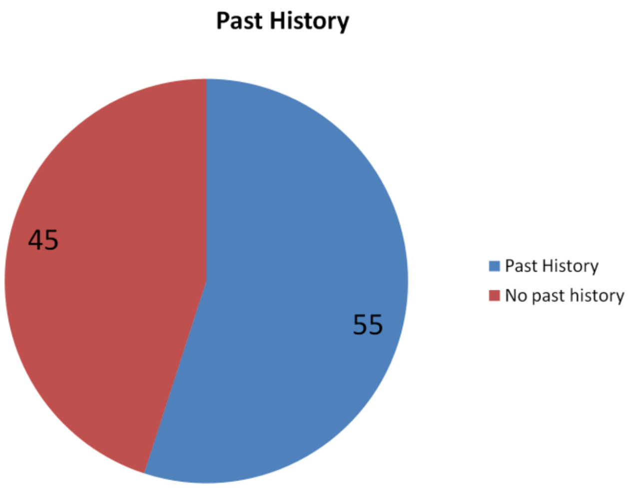


Figure 4. Patient database with variation in Past history

Validation Results

As illustrated in Figure 5, the patient dataset collected from the hospital was processed through the Meditrace system, and the resulting assessments were stored for analysis. The evaluation of these results revealed that approximately 24 patients were classified as high-risk, 14 as medium-risk, and the remaining 62 patients fell within the low-risk category. Among the high-risk group, most cases required immediate intervention by paramedic staff, and a majority of these patients unfortunately did not survive their in-hospital treatment. Notably, the NEWS scores of these patients were greater than 10, indicating that a higher NEWS score is strongly associated with increased mortality risk and can serve as a critical predictor of life-threatening conditions.

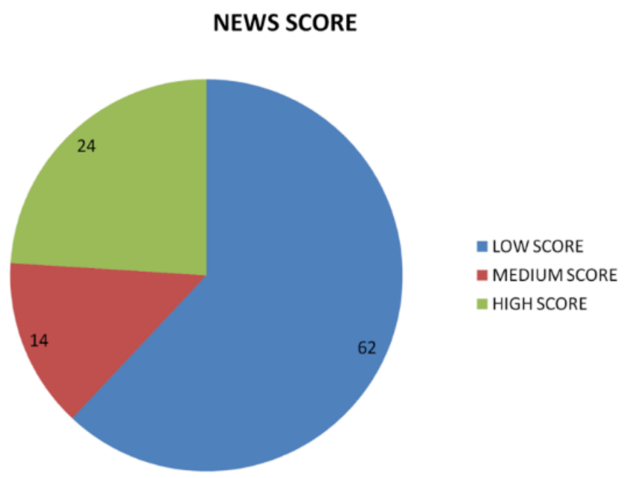


Figure 5. Patients NEWS score and its range variation

Fig. 6 presents the percentage distribution of patients with cardiac emergencies, showing that approximately 27% had NEWS scores above 7, another 27% fell into the medium-risk category, and the remaining 45% were classified as low-risk. This diverse scoring distribution, encompassing various disease profiles, provided valuable data for validating the Meditrace system. Similarly, Fig. 7 illustrates the percentage of patients with respiratory emergencies, where those scoring above 7 constituted a larger portion of the population, while medium- and low-risk patients collectively accounted for about 30% of the total cases. Using this broad and representative dataset, the Meditrace system was thoroughly tested and validated, and its risk-level stratification based on the calculated total score proved to be highly effective and accurate for time-critical cases.

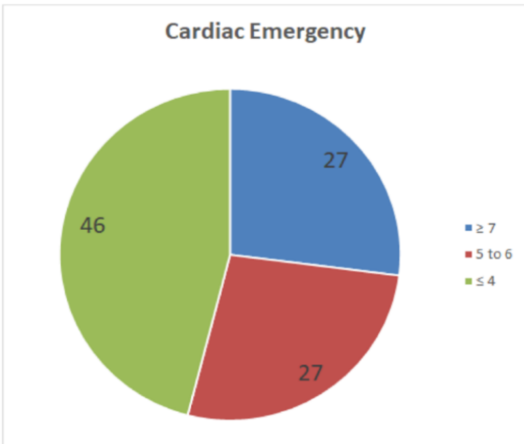


Figure 6. Patient database with cardiac emergency variation

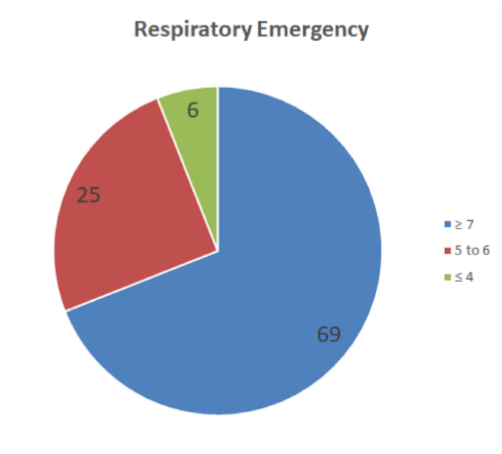


Figure 7. Patient database with respiratory emergency

As shown in Figure 8, validation of the system using the patient database demonstrated a disease prediction success rate of approximately 75%, indicating that the developed system can forecast probable diseases with this level of accuracy. This highlights the system's effectiveness and potential utility in emergency healthcare for assisting paramedics. Figure 9 presents the success rates for individual diseases within the validation dataset. For certain conditions, the system achieved 100% accuracy, demonstrating precise disease prediction capability, while for other diseases, the accuracy ranged between 20% and 80%.

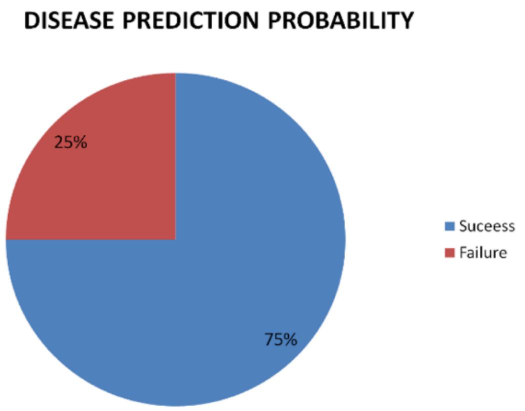


Figure 8. Disease prediction probability

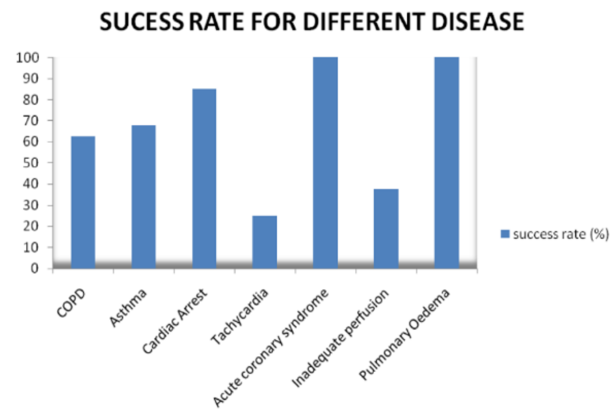


Figure 9. The success rate for different diseases

4. Conclusion

This study reports the clinical validation and performance evaluation of Meditrace, a semantic web-based expert system developed to support paramedic staff in emergency healthcare settings, particularly where immediate access to expert medical professionals is limited. The system performs three critical tasks—risk stratification, differential diagnosis, and treatment recommendation—using an ontology-driven architecture that ensures scalability and modular knowledge representation.

Clinical validation demonstrated that Meditrace's risk stratification module, built on the established National Early Warning Score (NEWS) framework, reliably classified patients into low-, medium-, and high-risk groups. Higher NEWS scores strongly correlated with poorer outcomes, confirming the system's reliability in early recognition of clinical deterioration within the Indian emergency care context. The differential diagnosis module, evaluated on a diverse patient database, achieved an overall prediction accuracy of about 75% and near-perfect accuracy for certain conditions, underscoring its potential to reduce diagnostic uncertainty in time-critical situations.

Additionally, the system provides treatment guidance aligned with recognized emergency medicine protocols, enabling standardized interventions and supporting paramedic training. The underlying semantic web-based ontology framework allows for dynamic knowledge base updates without altering the system's core structure, enhancing maintainability and adaptability.

In summary, the validation results substantiate Meditrace as an effective decision-support tool for emergency care, capable of augmenting paramedic performance and improving patient outcomes. Future work will focus on expanding the knowledge base, integrating real-time physiological data, and conducting large-scale multicentric trials to further strengthen its robustness and clinical acceptance.

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Conflict of Interest

The authors have declared that there are no conflicts of interest regarding the publication of this work.

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