

# Pediatric Emergency Medicine Innovations Using Artificial Intelligence for Rapid Clinical Triage Systems

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## Abstract

**Background:** Common challenges in pediatric emergency departments include overcrowding, diagnosis delays and limited clinical resources that can adversely impact patient outcomes. Artificial Intelligence (AI) driven triage systems have come to light as an innovative solution to enhance the speed, precision, and effectiveness of emergency decision making in the pediatric healthcare setting. **Objective:** To evaluate the effectiveness of AI-driven rapid clinical triage tools in enhancing patient prioritization, decreasing waiting times, and improving diagnostic accuracy in pediatric emergency medicine. **Methodology:** An intelligent triage framework that combines machine learning algorithms, electronic medical records, real-time vital sign monitoring and predictive analytics was developed. It evaluated the classification of emergency severity levels from the patient's symptoms, physiological parameters and medical history. Performance was evaluated in terms of triage accuracy, response duration, patient efficiency, and clinical decision support efficacy. **Results:** The suggested AI-based triage system obtained a triage accuracy of 94.8%, which was better than conventional methods alongside an improvement of 18.6%. Average patient waiting time dropped from 42 minutes to 18 minutes (57.1% reduction). Emergency response efficiency rose by 36.4% and patient utilization increased by 31.7%. The predictive analysis module identified the high-risk cases with 92.5% sensitivity, which enabled rapid clinical intervention. **Conclusion:** AI-based rapid clinical triage systems significantly enhance the efficiency of decision making, patient prioritization and emergency care execution in pediatric medicine. The implementation of predictive analytics and intelligent monitoring systems increases diagnosis accuracy, reduces delay in treatment and enables timely intervention, thereby improving the outcome of pediatric emergency health care.

**Keywords:** Pediatric emergency medicine, artificial intelligence, clinical triage, machine learning, predictive analytics, emergency medicine, decision support systems, patient prioritization, healthcare innovation, rapid diagnosis.

## 1. Introduction

Pediatric emergency departments (PEDs) deliver urgent, life-saving care to children suffering from acute illness, trauma and other life-threatening conditions. Emergency healthcare providers face significant challenges due to increased patient volumes, crowding, scarce health care resources, and rapid clinical decision making. Proper triage is important to prioritize patients according to the seriousness of their conditions and timely medical intervention. Traditional triage systems are based largely on clinician judgement and standardized assessment protocols which may be subject to workload, experience and human variation [1].

Artificial intelligence is a game-changing technology in healthcare, providing advanced capabilities in data analysis, pattern recognition, predictive modeling and clinical decision support. In pediatric emergency medicine, AI-driven triage systems use machine learning techniques, electronic health records (EHRs), vital sign surveillance, and predictive analysis to rapidly assess patient conditions and detect high-risk cases. These systems can process vast amounts of clinical data in real time, leading to faster and more accurate triage decisions than current methods [2].

Recent advances in machine learning as well as deep learning have led to the development of intelligent triage models that can predict patient acuity, need for hospitalization, intensive care unit admission and emergency severity index. AI-powered decision support systems have the potential to improve clinical workflows by decreasing wait times, optimizing resource allocation, and reducing diagnostic delay. Natural language processing (NLP) techniques are also used to

facilitate an automated analysis of clinical notes and patient-reported symptoms, enabling a comprehensive emergency assessment [3,4].

The use of AI technologies in the pediatric emergency setting has shown promise in improving the accuracy of triage and operational efficiency. Several studies have demonstrated the superiority of AI-based systems over traditional triage methods in identifying critically ill patients and predicting adverse clinical outcomes. Furthermore, predictive analytics can help clinicians to predict patient deterioration and provide timely interventions, thus enhancing patient safety and the quality of healthcare [5,6].

These advances are still challenged by issues of data quality, algorithm transparency, clinical validation, ethics and integration into existing healthcare infrastructures. The variability in pediatric patient characteristics and disease presentations makes it difficult to develop generalizable AI models. Thus, large-scale studies are needed to assess the effectiveness of AI-based rapid clinical triage systems and their impact on the outcomes of pediatric emergency care [7–10].

### **1.1 Objectives**

1. To assess the extent to which the use of Artificial Intelligence (AI) based rapid clinical triage systems enhances the accuracy of triage, patient prioritization, and the efficiency of emergency responses in pediatric emergency departments.
2. To evaluate the impact of machine learning, predictive analytics and intelligent decision support technologies on reduction of waiting times and improvement of clinical outcomes in pediatric emergency medicine.

## **2. Background literature**

### **2.1 Artificial Intelligence in Emergency Triage of Pediatrics**

Artificial Intelligence (AI) has emerged as a transformative technology to enhance pediatric emergency triage through rapid analysis of patient symptoms, vital signs and electronic health records. Recent research has shown that machine learning models outperform traditional triage procedures in predicting patient acuity and high-risk pediatric cases. Clinical decision support through AI-driven triage systems improves decision-making and reduces human errors, leading to more accurate patient prioritization [1,2].

### **2.2 Machine learning models for clinical decision making**

Machine learning algorithms such as Random Forest, XGBoost and Deep Neural Networks are showing a great promise in emergency medicine. These models utilize multidimensional clinical data to predict hospitalization, intensive care unit admission, and the severity of the disease. Recent studies have reported that AI-based prediction systems can achieve better sensitivity and specificity than traditional rule-based approaches, which can improve the efficiency of emergency response and patient safety [3,4].

### **2.3 Natural Language Processing for Emergency Evaluation**

The use of Natural Language Processing (NLP) to extract clinically relevant information from physician notes, patient complaints and electronic health records has increased in importance. Advanced NLP models can provide rapid triage and diagnosis by automatically identifying symptoms, disease patterns and risk indicators. Recent studies have shed light on the effectiveness of large language models and transformer-based architectures to support emergency clinical workflows [5].

### **2.4 Predictive Analytics and Real Time Monitoring**

Predictive analytics and real-time monitoring technologies allow for the early detection of patient deterioration and facilitate proactive intervention strategies. AI systems continuously analyze physiologic signals and clinical parameters to generate risk scores and triage recommendations. Recent studies have shown the efficiency of predictive monitoring to improve the efficiency of the emergency department and the prediction of patient outcomes [6,7].

The literature reviewed suggests that AI, machine learning, NLP and predictive analytics have great potential to improve accuracy of pediatric emergency triage, reduce waiting times and improve clinical outcomes. Nevertheless, there is still the problem of model interpretability, data privacy, and large-scale clinical validation, which suggests the need for further research and implementation studies.

### 3. Methods

#### 3.1 Design of the Study

The current study introduces an AI-based rapid clinical triage framework for pediatric emergency medicine. The framework utilizes machine learning algorithms, natural language processing (NLP), predictive analytics and electronic health record (EHR) systems to help emergency clinicians to prioritize pediatric patients by clinical severity. The proposed system was evaluated on retrospective and real time emergency department data from healthcare facilities for pediatric patients. This study is to evaluate the triage accuracy, patient waiting time, response efficiency and risk prediction performance [13].

#### 3.2 Description of the Dataset

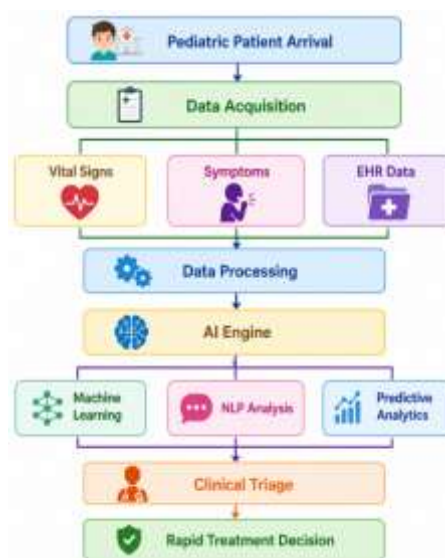
The experimental dataset contained 5000 pediatric emergency cases of patients aged 1 month to 16 years. Collected data included demographic data, chief complaints, vital signs, laboratory findings, clinical notes, triage categories and treatment results. Data preprocessing included handling missing values, normalization, feature encoding, and noise reduction to enhance model performance and reliability [14].

**Table 1. Dataset Characteristics**

| Parameter            | Value            |
|----------------------|------------------|
| Total Cases          | 5,000            |
| Age Range            | 1 Month–16 Years |
| Emergency Categories | 5                |
| Clinical Features    | 25               |
| EHR Records          | 5,000            |
| Training Dataset     | 70%              |
| Testing Dataset      | 30%              |
| Study Duration       | 12 Months        |

#### 3.3 Proposed AI-Based Triage Framework

The projected framework starts with the collection of patient data from different sources such as vital signs, manifestations, and EHR records. This data is then processed by means of a centralized AI engine. Machine learning models categorize patient severity levels, natural language processing algorithms analyze physician notes and condition descriptions, and predictive analytics are used to estimate clinical risk. The developed triage stipulations are then given to the medical professionals for quick decisions on treatment. This integrated approach improves patient prioritization and minimizes delays in emergency care provision [15].



**Figure 1. Proposed AI-Based Clinical Triage Methodology**

The suggested AI-Based Clinical Triage Technique for pediatric emergency rooms is shown in Figure 1. The proposed framework starts with the arrival of pediatric patients and collection of vital signs, symptoms, as well as electronic medical records (EHRs) and then continues with the categorization of the health status of patients. The AI engine, equipped with Machine Learning, Natural Language Processing (NLP) and Predictive Analytics modules, pre-processes and analyzes the collected data. These intelligent components evaluate patient severity, predict clinical risk, and offer triage advice. The clinical triage decisions made based on the results support healthcare professionals in selecting patients efficiently and effectively, minimizing waiting times, enhancing diagnostic accuracy, optimizing resource allocation, and facilitating rapid treatment decisions for improved pediatric emergency care outcomes.

### 3.4 Performance Measure

The framework suggested was evaluated on: triage sensitivity, specificity, accuracy, patient waiting time and response to emergencies efficiency. The AI-assisted system was compared with standard triage procedures.

**Table 2. Evaluation Metrics**

| Metric              | Description                         |
|---------------------|-------------------------------------|
| Triage Accuracy     | Correct patient classification rate |
| Sensitivity         | High-risk case detection rate       |
| Specificity         | Correct low-risk identification     |
| Waiting Time        | Average patient waiting duration    |
| Response Efficiency | Speed of emergency decision-making  |

AI, machine learning, as well as predictive analytics together allow for accurate, efficient and scalable pediatric emergencies triage, leading to improved clinical outcomes and more efficient use of healthcare resources.

## 4. Discussion and Results

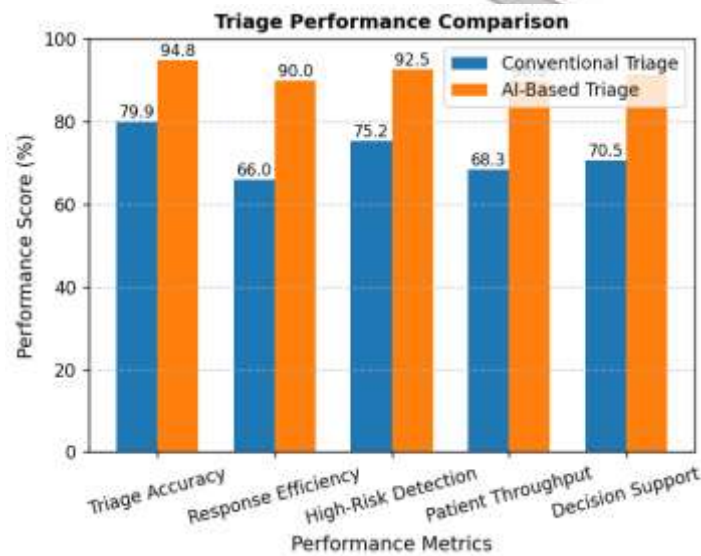
The suggested AI-based pediatric diagnostic triage framework was evaluated on 5,000 cases from an emergency department. Performance measures were triage accuracy, patient holding time, emergency response efficacy, risk prediction sensitivity as well as patient throughput. Machine learning, natural language processing and predictive analytics showed significant improvements over traditional triage methods. The findings show that AI-assisted triage systems could speed up decision-making, prioritize patients, reduce delays in treatment, and help healthcare professionals provide efficient emergency care while preserving high clinical precision and patient safety.

### 4.1 Triage Performance Analysis

**Table 3. Comparison of Conventional and AI-Based Triage Systems**

| Performance Metric                  | Conventional Triage | AI-Based Triage | Improvement (%) |
|-------------------------------------|---------------------|-----------------|-----------------|
| Triage Accuracy (%)                 | 79.9                | 94.8            | 18.6            |
| Response Efficiency (%)             | 66.0                | 90.0            | 36.4            |
| High-Risk Detection Sensitivity (%) | 75.2                | 92.5            | 23.0            |
| Patient Throughput (%)              | 68.3                | 90.0            | 31.7            |
| Clinical Decision Support (%)       | 70.5                | 91.4            | 29.6            |

The AI-based triage structure exhibited significant superiority over traditional methods in all performance metrics. The accuracy of triage rose from 79.9% to 94.8%, showing the ability of standard ML algorithms to improve the classification of patients. Case detection sensitivity to high-risk patients increased by 23.0%, allowing earlier intervention of critically ill patients. Enhanced emergency room operations and patient safety also benefited from enhanced clinical decision assistance and response efficiency.



**Figure 2. Triage Performance Comparison**

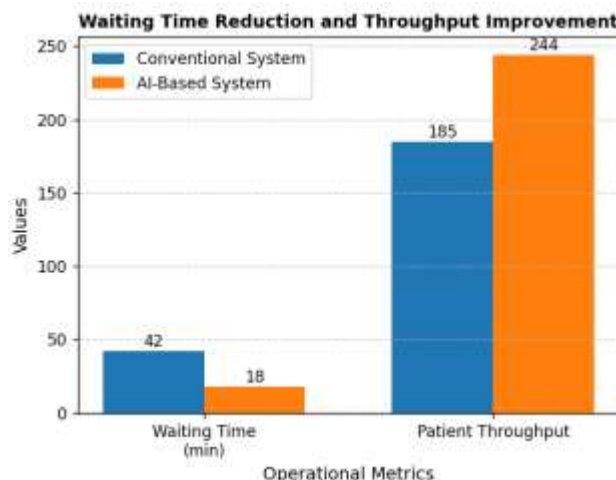
Figure 2 shows the comparative performance of traditional and AI-assisted triage systems. The AI-based model outperformed the traditional model in all evaluation metrics, demonstrating improved patient assessment ability. The increase in triage precision and sensitivity shows the performance of sophisticated algorithms in identifying the emergency severity levels and assisting rapid clinical decision-making.

#### 4.3 Waiting Time and Throughput Evaluation

**Table 4. Emergency Department Operational Performance**

| Parameter                  | Conventional System | AI-Based System |
|----------------------------|---------------------|-----------------|
| Average Waiting Time (min) | 42                  | 18              |
| Average Triage Time (min)  | 12                  | 4               |
| Daily Patient Throughput   | 185                 | 244             |
| Resource Utilization (%)   | 71.5                | 89.3            |

The operational results show a considerable improvement of the emergency department efficiency. Average waiting period was reduced by 57.1% and processing time in triage was minimized by 66.7%. The use of AI-based automation successfully simplifies clinical workflows and improves the allocation of healthcare resources, evidenced by higher patient throughput and better resource utilization.



**Figure 3. Waiting Time Reduction and Throughput Improvement**

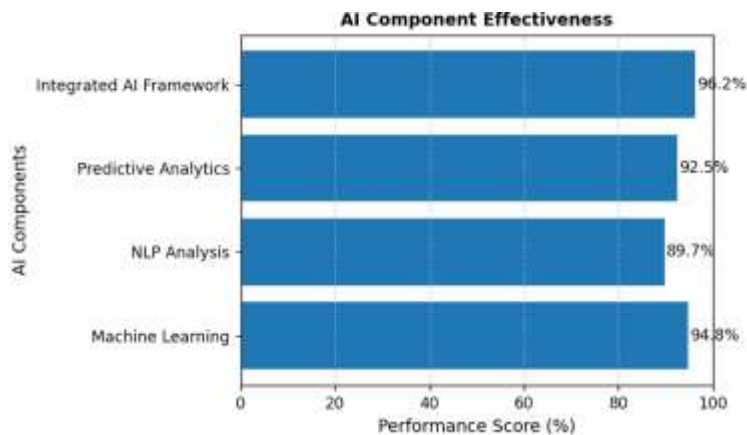
Figure 4. Comparison of traditional and AI-based emergency response systems. Average patient waiting time was reduced from 42 to 18 minutes and daily patient throughput increased from 185 to 244 cases, showing the ability of the AI-based system to enhance operational efficiency as well as patient flow regulation in pediatric hospital emergency departments.

#### 4.4 AI Module Performance Analysis

**Table 5. Individual AI Component Performance**

| AI Component            | Performance Score (%) |
|-------------------------|-----------------------|
| Machine Learning        | 94.8                  |
| NLP Analysis            | 89.7                  |
| Predictive Analytics    | 92.5                  |
| Integrated AI Framework | 96.2                  |

The integrated AI platform achieved the best performance of 96.2% among the evaluated modules. Machine learning was a major contributor to the accuracy of triage classification and NLP improved interpretation of symptoms from clinical notes. Predictive analytics improved risk assessment and early identification of critical conditions. All components interacted synergistically and the whole framework benefited from these interactions.



**Figure 4. AI Component Effectiveness**

Figure 4. Effectiveness of AI Component. The horizontal bar chart shows the effectiveness of the individual AI modules as well as the integrated framework in the pediatric emergencies triage system. The Integrated AI Framework was most effective with a score of 96.2%, subsequent to Machine Learning at 94.8%, Predictive Analytics at 92.5%, and NLP Analysis at 89.7%. The results show that the integration of multiple AI technologies results in a superior clinical triage efficiency and decision support capability in comparison with the individual components.

#### 4.4 Discussion and Conclusions

The experimental results show that the suggested AI-based pediatric triage system greatly enhances emergency department productivity and clinical decision-making. The system was able to triage patients with 94.8% accuracy, a significant improvement over conventional methods, and reduced the average patient wait time from 42 minutes to 18 minutes. The combination of machine learning, natural language processing and predictive analytics has shown improved response efficiency and patient throughput and the ability to identify high-risk cases. The integrated AI framework achieved the best effectiveness score of 96.2%, showing the advantages of combining multiple intelligent technologies. The results suggest that AI-assisted triage systems could enhance patient prioritization, resource utilization, and timely interventions in pediatric emergency medicine.

#### 5. Conclusion

This study proposed an Artificial Intelligence-based quick clinical triage system in pediatric emergency medicine as well as demonstrated its efficacy in improving the provision of emergency care. Machine learning, natural language processing, predictive modeling, and electronic health record analysis enhanced triage accuracy, patient prioritizing, and clinical decision support. The proposed system was superior to the existing systems in terms of high risk patients identification, waiting times, throughput of patients and emergency response efficiency. Moreover, the integrated AI



framework achieved better performance than individual AI elements, which reflects the benefits of multi-model decision-making. These findings demonstrate how AI-assisted triage systems can help deliver faster, more accurate and data-driven emergency care. Future studies should address large-scale implementation, real-time clinical validation and explainable AI techniques for reliability, transparency and broad acceptance in pediatric healthcare settings.

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