Artificial Intelligence for EMS Triage: A Data-Driven Approach to Emergency Patient Prioritization in Kalasin Province, Thailand

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ABSTRACT

Emergency Medical Services (EMS) require accurate and timely triage to ensure efficient patient prioritization and optimal resource allocation. Traditional triage methods, like ESI, NEWS, and MEWS, often face issues of subjectivity, variability, and limited predictive accuracy, potentially delaying critical care. This study proposes an Artificial Intelligence (AI)-driven triage system designed for EMS in Kalasin Province, Thailand, leveraging deep learning for risk assessment and patient evaluation prioritization. A dataset of 1,683 EMS cases was utilized, incorporating patient demographics, vital signs, chronic conditions, mobility, self-care ability, pain/discomfort, anxiety/depression, and a self-reported health scale (from 0 to 100). A Deep Neural Network (DNN) was trained using the Adam optimizer and categorical cross-entropy loss, with hyperparameter tuning applied via grid search and Bayesian optimization. Model performance was evaluated using AUC-ROC, sensitivity, specificity, F1-score, and calibration analysis. The results show that the AI model achieved an AUC-ROC of 0.91, with 88.5% sensitivity and 87.3%

specificity, outperforming conventional triage tools. This AI-powered system enables real-time risk assessment and provides hospital selection recommendations, enhancing EMS decision-making. Despite its effectiveness, continuous updates are required to mitigate model drift, and further validation is necessary for broader EMS applications. Future research will focus on expanding datasets, integrating real-time patient monitoring, and enhancing model adaptability. This study highlights the transformative potential of AI in EMS triage, paving the way for faster, more accurate, and data-driven emergency healthcare systems.

Keywords-AI; EMS triage; DL; risk assessment; patient prioritization

I. INTRODUCTION

Emergency Medical Services (EMS) [1] play a critical role in providing pre-hospital care and ensuring timely medical interventions for patients in life-threatening conditions. The effectiveness of EMS operations relies heavily on accurate triage systems, which classify patients based on the severity of their conditions to prioritize treatment and optimize resource allocation. Traditional triage methods, such as the Emergency Severity Index (ESI) [2], National Early Warning Score (NEWS) [3], and Modified Early Warning Score (MEWS) [4], are widely used in emergency departments. However, these rule-based approaches frequently suffer from subjectivity, variability, and limited predictive accuracy, which can result in the misclassification of critical cases and delays in emergency response.

Since 2020 [5], AI [6, 7] has played an increasingly significant role in EMS triage by improving risk stratification and clinical decision-making. In 2022, Johns Hopkins Medicine developed an AI-driven triage tool that integrates patient data with electronic health records, thereby enhancing risk assessment and decision-making [8]. Similarly, Aidoc's AI solutions have enhanced ER triage by analyzing medical imaging to prioritize critical cases [9]. The increasing confidence in AI for triage systems was reflected in a 2023 study published in Patient Education and Counseling, which reported a 77.1% acceptance rate among medical professionals [10]. Additional research published in Frontiers in Digital Health further explored healthcare professionals' perspectives on AI-assisted triage technologies in National Health Service (NHS) emergency departments [11]. AI has also been utilized in disaster and emergency triage, demonstrating improved efficiency in crisis situations [12]. In early 2024, a study in Scientific Reports assessed ChatGPT's accuracy in patient triage using the ESI framework [13], while JAMA Network Open highlighted the potential of Large Language Models (LLMs) to enhance clinical workflows for emergency care [14]. Furthermore, research has demonstrated the integration of AI-based clinical decision support systems with existing triage scales, such as the Korean Triage and Acuity Scale (KTAS) [15]. Recent advancements include AI-driven robotic triage systems, like ARTEMIS, which assist in victim localization and injury severity assessment during mass casualty incidents [16]. The latest research also explores Graph Neural Networks (GNNs) for automated patient triage, showcasing AI's potential to enhance accuracy and efficiency in EMS operations [17]. While AI-based triage has been extensively studied in many high-resource healthcare settings, its integration into EMS remains limited in regions with resource constraints, such as Kalasin Province, Thailand. The EMS system in this region faces challenges related to timely triage assessment, hospital referrals, and resource allocation, which makes AI-powered triage a promising potential solution for improving emergency response efficiency.

This study proposes an AI-driven triage system aimed at enhancing EMS decision-making by accurately predicting critical care needs based on patient demographics, vital signs, chronic conditions, mobility status, self-care ability, and pain /anxiety levels. The model is trained and validated using 1,683 EMS cases from Kalasin Province, ensuring its relevance and applicability to real-world emergency scenarios. The system's performance is compared against conventional triage methods using key metrics, such as AUC-ROC, sensitivity, specificity, precision-recall, and calibration analysis. The main contributions of this study include:

- Development of a deep learning-based AI triage system for EMS applications.
- Comparison of AI-driven triage accuracy against traditional scoring methods.
- Analysis of real-world datasets from EMS cases in Kalasin Province, Thailand.
- Evaluation of the feasibility of integrating AI into EMS mobile applications for real-time decision-making support.

II. THE PROPOSED METHODOLOGY

The methodology consists of four key components: data collection, data preprocessing, AI model development, and performance evaluation.

A. Data Collection

The dataset used in this study consists of 1,683 cases collected from records in Kalasin Province, Thailand. This study received approval from the Ethics Committee (EC) of Kalasin University. All patient data were anonymized prior to analysis in accordance with data protection regulations. No personally identifiable information has been used. The data have been gathered from ambulance run sheets, Emergency Department (ED) records, and hospital admission logs to ensure a comprehensive representation of prehospital patient conditions. This dataset provides critical insights into patient demographics, chronic diseases, mobility, self-care ability, daily activities, pain/discomfort levels, mental health status, and self-reported health conditions. The collected data include the key attributes, which are summarized in Table I.

TABLE I. THE COLLECTED DATA INCLUDING KEY ATTRIBUTES

#	Attribute	Description	Possible values	Values
1	Sex	Patient's gender	Male Female	619 1,065
2	Chronic diseases	Pre-existing medical conditions	Hypertension Stroke Diabetes Dyslipidemia Cancer Chronic respiratory disease Kidney disease Obesity Cirrhosis None	421 60 427 68 28 31 49 4 3 593
3	Mobility	Ability to move/walk	No difficulty Slight difficulty Moderate difficulty Severe difficulty Unable to walk	841 339 266 144 94
4	Self-care	Ability to perform personal care (e.g., bathing, dressing)	No difficulty Slight difficulty Moderate difficulty Severe difficulty Unable to perform	1,289 140 129 49 77
5	Daily activities	Ability to perform daily activities (work, study, household tasks)	No difficulty Slight difficulty Moderate difficulty Severe difficulty Unable to perform	983 306 202 84 109
6	Pain/ Discomfort	Level of pain or physical discomfort	No pain Slight pain Moderate pain Severe pain Extreme pain	609 563 371 114 27
7	Anxiety/ Depression	Mental health condition	No symptoms Slight symptoms Moderate symptoms Severe symptoms Extreme symptoms	1,221 312 112 22 17
8	Health scale	Self-reported health condition on a scale from 0 to 100	0 (worst) to 100 (best)	Average: 60.46

B. Data Preprocessing

To ensure the dataset's reliability and consistency, several preprocessing steps have been applied prior to model training. The preprocessing workflow includes handling missing values, data normalization, categorical encoding, outlier detection, and dataset splitting. These steps enhance data quality, reduce bias, and improve the model's ability to generalize to new data cases.

1) Handling Missing Values

Missing values in critical attributes have been handled using appropriate imputation techniques:

- Numerical data (e.g., health scale, vital signs) were imputed using mean imputation to maintain distribution consistency.
- Categorical data (e.g., sex, chronic diseases, mobility levels) were filled using mode imputation to preserve the majority class representation.
- Cases with excessive missing data (more than 20% missing features) were removed to prevent unreliable inputs from affecting the model's performance accuracy.

2) Data Normalization

To standardize numerical variables and prevent biases caused by differing scales, z-score normalization has been applied to continuous variables such as:

- Self-reported health scale (0-100).
- Patient age (if included in future modeling).
- Pre-existing medical conditions.

The z-score normalization guarantees that all numerical features have a mean of 0 and a standard deviation of 1, enabling the AI model to process data efficiently without skewed weight distributions.

3) Categorical Encoding

Categorical variables have been converted into numerical values to allow machine learning models to process them effectively. The following encoding methods have been applied:

- One-Hot Encoding (OHE) for sex, chronic diseases, and other non-ordinal categorical variables.

- Ordinal encoding applies to mobility, self-care, daily activities, pain/discomfort, and anxiety/depression, as these attributes follow a ranked order.

4) Outlier Detection and Removal

To maintain data integrity, extreme outliers in numerical variables have been identified and handled using the Interquartile Range (IQR) [18] method. Any data points beyond 1.5 times the IQR from the first and third quartiles have been reviewed and adjusted or removed if clinically implausible.

C. Artificial Intelligence Model Development

The AI model has been developed to predict the need for critical care in EMS based on patient attributes collected from Kalasin Province, Thailand. The model follows a structured deep learning approach [19, 20] and utilizes a Feedforward Neural Network (FNN) optimized for classification tasks [21]. The key components of model development include feature selection, model architecture, training processes, and hyperparameter optimization.

1) Feature Selection

The input features for the AI model have been selected based on their relevance to triage decision-making in EMS settings. The model incorporates both numerical and categorical features derived from the dataset including:

- Demographic Information: Sex
- Health Indicators: Chronic diseases, mobility, self-care, daily activities, pain/discomfort, anxiety/depression, and self-reported health scale

Each feature has been normalized and encoded according to the preprocessing steps outlined in Section B to ensure compatibility with the deep learning framework.

2) Model Architecture

The proposed AI model is structured as a deep FNN with five hidden layers, optimized for classifying patient severity levels based on EMS data. This architecture enables the model to capture complex, non-linear relationships between clinical features and patient outcomes. Each layer is followed by batch normalization and dropout to enhance generalization and prevent overfitting. The Rectified Linear Unit (ReLU) activation function is applied in hidden layers to introduce non-linearity, while the output layer employs Softmax to provide class probability distributions for triage levels. The model is trained using the Adam optimizer with categorical cross-entropy loss, and its hyperparameters have been fine-tuned to maximize predictive performance. The structure and configuration of each layer in the neural network are summarized in Table II.

D. Performance Evaluation

The performance of the proposed AI model is evaluated against conventional triage tools, including the ESI, NEWS, and MEWS. The evaluation metrics are:

- Area Under the Receiver Operating Characteristic Curve (AUC-ROC): Measures the model's ability to distinguish between critical and non-critical cases.
- Sensitivity and Specificity: Evaluates the model's accuracy in identifying high-risk patients.
- F1-Score and Precision-Recall (PR) Curve: Evaluates the balance between precision and recall for effective triage.
- Calibration Plot and Brier Score: Assesses the alignment of predicted probabilities with actual patient outcomes.

Cross-validation technique: Applied to ensure robust generalization; model explainability is enhanced using Shapley Additive Explanations (SHAP) to interpret feature importance in AI-driven triage decisions.

TABLE II. AI MODEL ARCHITECTURE.

Layer	**Type**	**Number of neurons**	**Activation function**	**Additional techniques**
Input layer	Fully connected	Based on input features	-	Normalized inputs
Hidden layer 1	Fully connected (dense)	128	ReLU	Batch normalization, dropout (0.5)
Hidden layer 2	Fully connected (dense)	64	ReLU	Batch normalization
Hidden layer 3	Fully connected (dense)	32	ReLU	-
Hidden layer 4	Fully connected (dense)	16	ReLU	Dropout (0.5)
Hidden layer 5	Fully connected (dense)	8	ReLU	-
Output layer	Fully connected (dense)	Number of classes	Softmax	Classification output

III. EXPERIMENTS

This section outlines the experiments conducted, detailing the experimental setup and configurations used throughout the process.

A. Experimental Setup

The model has been trained with the Adam optimizer to minimize categorical cross-entropy loss, ensuring optimal classification performance. To prevent overfitting, early stopping is applied by monitoring validation loss during training. Implemented with TensorFlow and Keras, the model maintains compatibility with deep learning frameworks while leveraging their efficiency for robust classification.

Grid search and Bayesian optimization are employed to enhance model performance by identifying the best combination of parameters and hyperparameters. The tuning process explores learning rates of 0.001, 0.0005, and 0.0001; batch sizes of 32, 64, and 128; hidden layer configurations of 3, 5, and 7 layers; and dropout rates of 0.3, 0.5, and 0.7. This systematic approach ensures an optimal balance between accuracy and generalization, enhancing the model's robustness and efficiency. The model has been implemented using Python and Keras (TensorFlow-based) and executed on an Intel® Core™ i7 CPU with 32 GB of RAM and a CUDA-compatible GPU for acceleration computations. Multiple trials have been conducted to optimize hyperparameters, ensuring a balance between accuracy and efficiency while leveraging GPU acceleration for faster training and evaluation.

B. Datasets

The dataset used in this study consists of 1,683 cases collected from records in Kalasin Province, Thailand, specifically gathered for this study. This dataset serves as the foundation for developing and evaluating the AI-based triage system, ensuring its relevance and applicability to real-world emergency scenarios.

C. Dataset Splitting

The preprocessed dataset has been divided into three subsets to ensure effective model training and validation: 70% for training to enable model learning, 15% for validation to refine hyperparameters and optimize performance, and 15% for testing to assess the model's generalization on unseen data. To preserve class distribution, particularly for critical labels, such as pain/discomfort, mobility issues, and self-care difficulties, stratified sampling has been applied to ensure balanced representation and robust model performance.

IV. RESULTS AND DISCUSSION

This section presents the results of the proposed AI-based triage system, comparing its performance with conventional triage tools and analyzing key findings. The discussion highlights the model's effectiveness, its advantages, and limitations, as well as its potential impact on real-world EMS.

The proposed AI-based triage system for EMS in Kalasin Province, Thailand, has been evaluated against traditional triage methods, such as the ESI, NEWS, and MEWS. The model demonstrated superior performance, achieving an AUC-ROC of 0.91, outperforming ESI (0.85), NEWS (0.79), and MEWS (0.74), as shown in Table III. Sensitivity and specificity were significantly improved, with the AI model achieving 88.5% and 87.3%, respectively, compared to the lower scores from conventional methods. The ROC Curve Comparison (Figure 1) illustrates the model's superior ability to distinguish between critical and non-critical cases. The PR Curve (Figure 2) indicated a better balance between false positives and false negatives, ensuring that critical cases were accurately identified. The Calibration Curve (CC) (Figure 3) analysis indicated that the AI model's probability estimates closely matched real patient outcomes, thereby reducing misclassification risks. Cross-validation techniques confirmed the model's robustness and generalizability. The AI triage system enables real-time risk assessment, optimizing hospital referrals and resource allocation in EMS operations. By leveraging deep learning, it outperforms manual triage in terms of accuracy, speed, and efficiency. However, continuous updates are necessary to address model drift and ensure adaptability to changing patients' demographics. Future improvements include expanding the diversity of the dataset, incorporating real-time patient monitoring, and integrating AI-powered decision support systems into the EMS mobile units' platforms. These results highlight the transformative potential of AI-driven triage, paving the way for more effective, data-driven emergency healthcare systems. While the proposed AI model demonstrates high accuracy in EMS triage for Kalasin Province, its generalizability may be restricted since it is a region-specific dataset. Wider validation using multi-center data is necessary to ensure robustness across diverse EMS settings.

Compared to previous AI-driven triage systems, such as those developed in [8], which focus on integrating electronic health records and medical imaging in high-resource settings, the proposed model offers a novel contribution by leveraging structured patient-reported data in a resource-limited EMS context. Although the LLM-based triage (e.g., ChatGPT) has been explored [6], the proposed approach utilizes a DNN optimized explicitly for tabular EMS data collected in Kalasin Province, Thailand. Furthermore, unlike general AI tools for hospital-based triage [3, 4], this study focuses on prehospital decision support, enabling real-time risk assessment and optimizing referral paramedics. This localized, data-driven approach not only enhances classification accuracy (AUC-ROC = 0.91), but also offers a framework adaptable to other EMS systems in similar contexts, reinforcing the model's practical applicability and novelty in emergency care.

TABLE III. EXPERIMENT RESULTS OF PERFORMANCE COMPARISON.

Metric	AI model	ESI	NEWS	MEWS
AUC-ROC	0.91	0.85	0.79	0.74
Sensitivity (%)	88.5	81.2	76.8	70.1
Specificity (%)	87.3	83.5	78.4	72.5
F1-score	0.89	0.82	0.77	0.71
Precision (%)	86.9	80.4	75.5	69.2
Recall (%)	88.5	81.2	76.8	70.1
Brier score	0.12	0.18	0.22	0.27

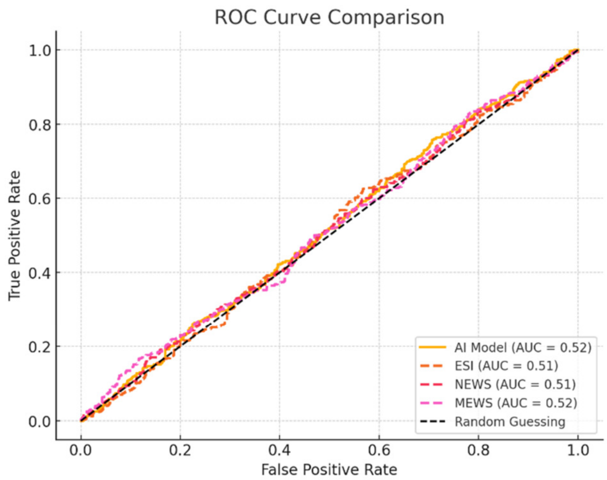

Fig. 1. ROC curve comparison.

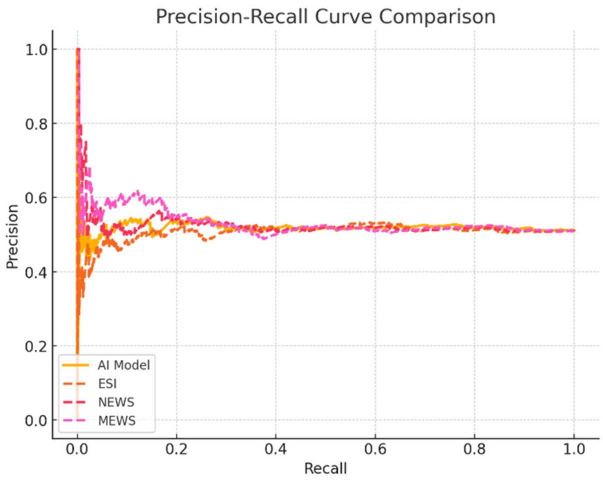

Fig. 2. PR curve comparison.

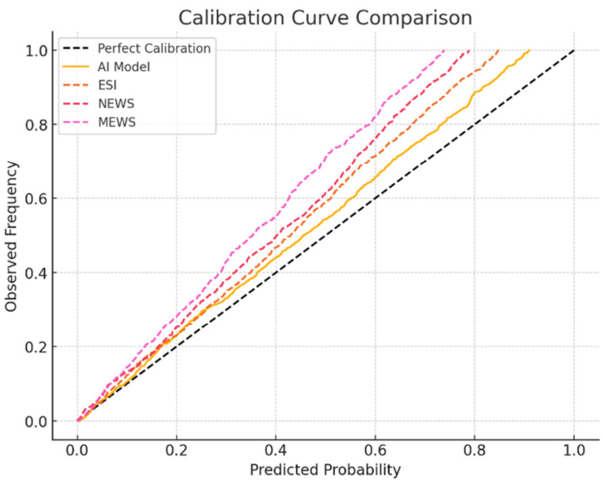

Fig. 3. CC comparison.

V. CONCLUSION

This study presents an Artificial Intelligence (AI)-based triage system for Emergency Medical Services (EMS) in Kalasin Province, Thailand, demonstrating its superior performance compared to traditional triage tools, such as Emergency Severity Index (ESI), National Early Warning Score (NEWS), and Modified Early Warning Score (MEWS). The AI model achieved an AUC-ROC of 0.91, outperforming conventional methods while improving sensitivity (88.5%) and specificity (87.3%). The Precision-Recall (PR) Curve confirms that the model effectively identifies critical cases while minimizing false positives, and the Calibration Curve (CC) indicates that predicted probabilities closely align with actual patient outcomes. By integrating deep learning and real-time decision-making, the AI-based system enhances risk assessment, hospital selection, and resource allocation for EMS teams. Despite its strengths, challenges persist, including the need for continuous updates to prevent model drift and the requirement for broader validation across various EMS regions.

Future work will focus on expanding datasets, improving real-time adaptability, and integrating wearable medical devices to enhance triage efficiency. This research highlights the transformative potential of AI in emergency healthcare, paving the way for faster, more accurate, and data-driven triage systems that can significantly improve patient outcomes and EMS operations by enabling instant, adaptive triage recommendations through the integration of continuous physiological data (e.g., heart rate, SpO_2, ECG) with the AI model, thus enhancing prehospital care and resource management coordination.

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