JITK (JURNAL ILMU PENGETAHUAN DAN TEKNOLOGI KOMPUTER)

VOL. 12. NO. 2 NOVEMBER 2026
P-ISSN: 2685-8223 | E-ISSN: 2527-4864
DOI: 10.33480/jitk.v12i2.8326

A HYBRID FAHP–DNN DECISION MODEL FOR PATIENT RISK LEVEL ASSESSMENT IN HOSPITAL TRIAGE SYSTEMS

Niki Ratama[1*], Munawaroh[1]

Universitas Pamulang, Banten, Indonesia[1]
https://unpam.ac.id[1]
dosen00835@unpam.ac.id, dosen00831@unpam.ac.id

(*) Corresponding Author
(Responsible for the Quality of Paper Content)



The creation is distributed under the Creative Commons Attribution-NonCommercial 4.0 International License

Submitted: 26 February 2026, **Revised:** 31 August 2026, **Accepted:** 17 November 2026, **Published:** 20 November 2026.

Abstract— *Hospital triage systems play a crucial role in prioritizing patient care based on the severity of their conditions, yet decision-making often relies heavily on subjective judgment, which may lead to inconsistencies and delays in treatment. This study proposes a novel hybrid decision model integrating Fuzzy Analytic Hierarchy Process (FAHP) and Deep Neural Network (DNN) to determine patient risk levels in hospital triage systems more accurately and objectively. The key contribution of this study lies in combining expert-driven criteria weighting through FAHP with data-driven pattern recognition through DNN — an integration that addresses the interpretability limitations of purely data-driven models while overcoming the rigidity of rule-based approaches. Unlike previous studies that apply either MCDM or deep learning independently, the proposed model unifies both paradigms into a coherent framework specifically designed for multi-class triage risk stratification. The FAHP method is employed to derive weighted criteria from multiple clinical indicators such as vital signs, symptoms, and patient history, while the DNN model is used to learn complex patterns and classify patient risk levels based on historical triage data. The proposed model was evaluated using a dataset of 3,212 triage records, and performance was assessed through accuracy, precision, recall, F1-score, and ROC-AUC metrics. Experimental results demonstrate that the hybrid FAHP–DNN model achieves 94.08% accuracy and a ROC-AUC of 0.982, outperforming conventional rule-based triage, standalone DNN, Random Forest, and Logistic Regression approaches, indicating its strong potential to enhance clinical decision-making and optimize resource allocation in emergency departments.*

Keywords: *Decision Support System, deep neural network, fuzzy AHP, hospital triage, patient risk assessment.*

INTRODUCTION

Effective decision-making in hospital triage systems is critical to ensure that patients receive appropriate and timely medical care based on the severity of their conditions. Triage serves as the first line of assessment in emergency departments (ED), where medical personnel must rapidly evaluate patients and prioritize treatment under conditions of uncertainty and limited resources. According to the World Health Organization (WHO), emergency departments worldwide face increasing patient loads, which often lead to overcrowding and delays in treatment, potentially affecting patient outcomes and increasing mortality risk [1]. In many healthcare facilities, especially in developing countries, triage decisions still rely heavily on manual assessment and clinical judgment, which may introduce subjectivity and inconsistencies in determining patient risk levels.

The rapid advancement of artificial intelligence (AI) has opened new opportunities to improve clinical decision support systems by enabling more accurate and data-driven assessments. Machine learning and deep learning techniques have demonstrated strong performance in analyzing complex medical data and predicting patient outcomes. Deep Neural Networks (DNN), in particular, are capable of learning nonlinear relationships among multiple clinical variables such as vital signs, symptoms, and medical history, making them suitable for risk prediction tasks in



healthcare settings [2]. However, purely data-driven models may lack interpretability and may not adequately incorporate expert knowledge, which is essential in clinical environments.

To address this limitation, multi-criteria decision-making (MCDM) approaches such as the Fuzzy Analytic Hierarchy Process (FAHP) have been widely used to model uncertainty and incorporate expert judgment in decision processes. FAHP extends the traditional Analytic Hierarchy Process by introducing fuzzy logic to handle ambiguity and vagueness in human reasoning, making it suitable for healthcare decision problems where precise data may not always be available [3][4]. Previous studies have shown that FAHP can effectively determine the relative importance of clinical criteria and improve decision transparency [5].

Several researchers have explored the application of AI and decision support methods in healthcare triage. For example, a study by Levin et al. developed a machine learning-based triage system that improved patient prioritization accuracy compared to traditional methods [6]. Similarly, Raita et al. demonstrated that deep learning models could predict critical illness in emergency department patients with high accuracy [7]. Other research has utilized fuzzy logic approaches to support clinical decision-making under uncertainty, highlighting the importance of combining quantitative data with expert knowledge [8].

Despite these advances, a critical research gap remains: existing triage decision support models either rely solely on data-driven machine learning without incorporating structured clinical expertise, or apply expert-based MCDM methods without the capacity to learn nonlinear patterns from large datasets. No prior study has proposed a unified framework that tightly integrates FAHP-derived clinical criterion weights directly into the DNN feature space for multi-class triage risk stratification. This gap results in models that either lack interpretability or fail to fully leverage available clinical knowledge.

Table 1. Related Research

Author	Issues	Method	Results
Levin et al. [9]	ED triage accuracy	Machine Learning	Improved prioritization
Raita et al. [10]	Predicting critical illness	Deep Learning	High predictive accuracy
Ashour et al. [11]	Decision uncertainty	FAHP	Better criteria weighting
Fernandes et al. [12]	Clinical decision support	AI models	Improved decision quality

Source: (Research Results, [8], [9], [10], [11], 2026)

Although previous studies have demonstrated the effectiveness of artificial intelligence and multi-criteria decision-making approaches in healthcare decision support, several challenges remain in practical implementation within hospital triage systems. One of the primary challenges is the dynamic and uncertain nature of patient conditions, which often requires rapid decision-making under incomplete information. Emergency department clinicians must consider multiple factors simultaneously, including vital signs, presenting symptoms, comorbidities, and resource availability. Traditional triage scales such as the Emergency Severity Index (ESI) provide general guidelines but may not fully capture complex clinical interactions, especially in high patient volume situations [13].

Furthermore, the increasing volume of electronic health records (EHR) has created opportunities to leverage data analytics for improving triage accuracy. However, extracting meaningful insights from high-dimensional clinical data remains challenging due to noise, missing values, and variability across patient populations. Deep learning models such as DNN have shown strong capability in learning representations from complex datasets, enabling improved prediction of patient deterioration and risk stratification. Nevertheless, purely data-driven models may overlook expert knowledge and contextual considerations that are critical in clinical decision-making.

Incorporating expert judgment through structured decision frameworks such as FAHP can address this limitation by providing transparent weighting of decision criteria. The integration of fuzzy logic allows the model to handle linguistic variables and uncertainty, reflecting real-world clinical reasoning where precise numerical values are not always available [14]. By combining FAHP with DNN, it is possible to develop a hybrid approach that balances interpretability and predictive performance, thereby supporting more reliable and explainable triage decisions.

Another important aspect is the need for decision support systems that can enhance consistency across healthcare providers. Variability in triage decisions has been reported in several studies, where different clinicians may assign different priority levels to the same patient due to differences in experience and perception [15]. A hybrid intelligent system can reduce such variability by providing standardized recommendations based on both data-driven insights and expert-defined criteria.

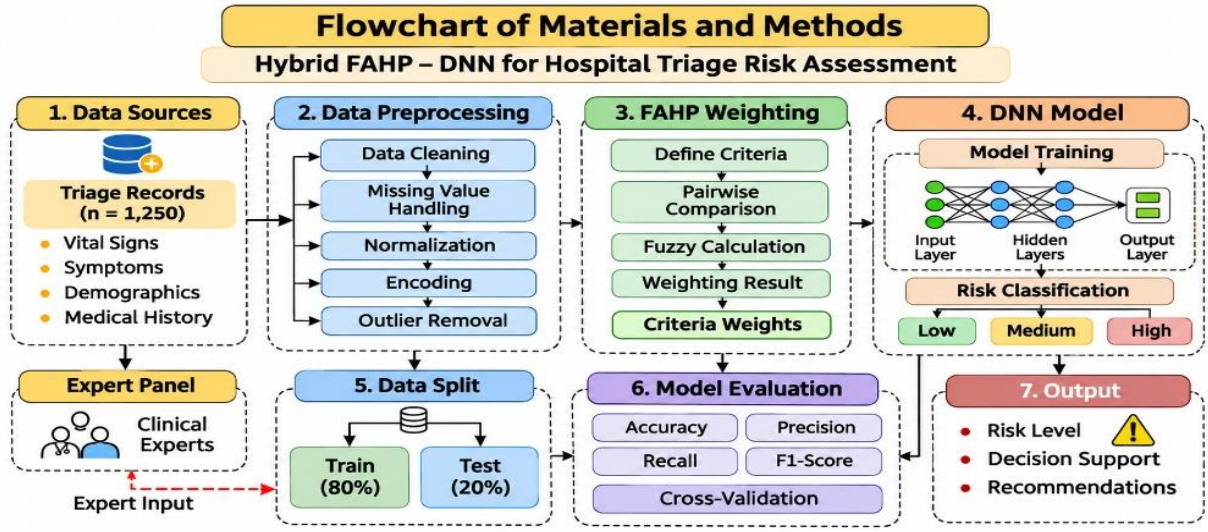
Accredited Rank 2 (SINTA 2) based on Decree No. 225/E/KPT/2022 issued by Direktorat Jenderal Pendidikan Tinggi, Riset, dan Teknologi, Kementerian Pendidikan, Kebudayaan, Riset, dan Teknologi Republik Indonesia, dated December 7, 2022. Published by LPPM Universitas Nusa Mandiri.

VOL. 12. NO. 2 NOVEMBER 2026
P-ISSN: 2685-8223 | E-ISSN: 2527-4864
DOI: 10.33480/jitk.v12i2.8326

In addition, the implementation of intelligent triage systems aligns with the broader trend of digital transformation in healthcare, often referred to as smart healthcare or Healthcare 4.0. These systems aim to improve patient safety, optimize resource allocation, and support evidence-based decision-making through advanced analytics and automation [16]. Therefore, developing a hybrid FAHP–DNN model for patient risk assessment is not only relevant from a methodological perspective but also essential for addressing operational challenges in modern healthcare environments. The novelty of this study lies in three key aspects: (1) the integration of FAHP-derived expert weights as feature-level inputs to a DNN, enabling the model to prioritize clinically meaningful criteria during learning; (2) the application of this hybrid framework specifically to multi-class triage risk stratification across three severity levels; and (3) the inclusion of SHAP-based explainability analysis that aligns data-driven feature importance with expert clinical knowledge, thereby enhancing model transparency and supporting trust in clinical adoption.

MATERIALS AND METHODS

This section describes the methodological framework used to develop and evaluate the proposed hybrid FAHP–DNN model for determining patient risk levels in hospital triage systems. The research process was designed to ensure systematic integration of clinical data analysis and expert judgment, starting from data acquisition and preprocessing, followed by criteria weighting and model development, and concluding with performance evaluation. Each stage was conducted to ensure that the resulting model reflects real clinical conditions while maintaining analytical rigor and reproducibility. The workflow of the research methodology is illustrated in the following diagram, which presents the sequential steps involved in data preparation, decision weighting, predictive modeling, and evaluation processes that support reliable patient risk classification [17].



Source: (Research Results, 2026)

Figure 1. Flowchart Research Methodology

The flowchart illustrates the overall research workflow for developing a hybrid decision model that integrates Fuzzy Analytic Hierarchy Process (FAHP) and Deep Neural Network (DNN) to assess patient risk levels in hospital triage systems. The process consists of several interconnected stages [18], starting from data acquisition to decision support output, ensuring systematic integration of expert knowledge and predictive modeling [19].

a. Data Sources

The first stage involves identifying and collecting the data required for model development. The primary data consist of triage records obtained from the emergency department of a single tertiary-care hospital, covering a retrospective data collection period of 24 months (January 2022 to December 2023). The dataset comprises a total of 3,212 patient instances that were collected through structured extraction from the hospital's Electronic Health Record (EHR) system, following approval from the institutional ethics committee. Data were de-identified prior to analysis to ensure patient confidentiality. These records include essential clinical attributes such as vital signs (e.g., blood

CC BY NC

pressure, heart rate, respiratory rate, temperature) [20], presenting symptoms, demographic information, and medical history. In addition, an expert panel composed of clinical professionals contributes domain knowledge to validate the relevance of variables and support decision criteria formulation. This stage ensures that both empirical data and expert insights are incorporated into the research framework.

Table 2. Description of Data Sources Used in This Study

No	Data Component	Description	Source	Purpose
1	Triage Records	Records of patient assessments conducted at the emergency department, including initial triage decisions	Hospital Emergency Department	Main dataset for model development
2	Vital Signs	Clinical measurements such as blood pressure, heart rate, respiratory rate, temperature, and oxygen saturation	Electronic Health Records (EHR)	Indicators for patient condition assessment
3	Symptoms	Chief complaints reported by patients during triage	Triage Documentation	Supporting clinical features for risk classification
4	Demographics	Patient information such as age and gender	Hospital Information System	Contextual variables influencing risk
5	Medical History	Previous diseases or comorbidities relevant to triage decision	Medical Records	Enhancing prediction accuracy
6	Expert Panel Input	Clinical judgments provided by doctors or triage nurses	Clinical Experts	Criteria validation and FAHP weighting

Source: (Research Results, 2026)

The data sources used in this study consist of clinical and contextual information obtained from hospital triage records and expert input. As presented in Table 2, the dataset includes vital signs, symptoms, demographic information, and medical history, which are commonly used in triage assessments. In addition, expert judgments were incorporated to ensure that the selected variables and criteria accurately reflect real clinical decision-making processes. These data sources provide a comprehensive basis for developing and evaluating the proposed hybrid FAHP–DNN model [21].

b. Data Preprocessing

Data preprocessing is performed to enhance data quality and prepare the dataset for analysis. This stage includes several steps: data cleaning to remove inconsistencies and errors; handling missing values through appropriate imputation methods; normalization to standardize numerical values; encoding to transform categorical variables into numerical representations suitable for modeling; and outlier removal to eliminate extreme observations that may distort model performance. These procedures ensure that the dataset is reliable and suitable for both FAHP analysis and neural network training [22].

c. FAHP Weighting

The FAHP stage focuses on determining the relative importance of decision criteria based on expert input. The process begins with defining relevant clinical criteria, followed by pairwise comparisons performed by experts using linguistic judgments. Fuzzy calculations are then applied to handle uncertainty in expert opinions and compute priority weights. The resulting weighting outcomes represent the contribution of each variable to patient risk assessment and are used to enhance feature representation for subsequent modeling [23].

d. DNN Model

In this stage, a Deep Neural Network model is developed to learn patterns from the weighted dataset. The model architecture consists of an input layer that receives FAHP-weighted clinical features, four hidden layers (64–32–16–8 neurons) that capture nonlinear relationships among variables, and an output layer that produces classification results. The ReLU (Rectified Linear Unit) activation function was selected for the hidden layers due to its computational efficiency and its ability to mitigate the vanishing gradient problem, which is particularly relevant when learning from clinical tabular data with heterogeneous value ranges. The Softmax activation function was applied at the output layer to produce calibrated probability estimates across the three mutually exclusive risk classes (low, medium, high), which is the standard choice for multi-class classification tasks. To prevent overfitting — a concern given the relatively modest dataset size of 3,212 records — Dropout regularization with a rate of 0.3 was applied after

Accredited Rank 2 (SINTA 2) based on Decree No. 225/E/KPT/2022 issued by Direktorat Jenderal Pendidikan Tinggi, Riset, dan Teknologi, Kementerian Pendidikan, Kebudayaan, Riset, dan Teknologi Republik Indonesia, dated December 7, 2022. Published by LPPM Universitas Nusa Mandiri.

VOL. 12. NO. 2 NOVEMBER 2026
P-ISSN: 2685-8223 | E-ISSN: 2527-4864
DOI: 10.33480/jitk.v12i2.8326

each hidden layer during training. This technique randomly deactivates a proportion of neurons in each training iteration, forcing the network to learn more robust and generalized representations. Additionally, L2 weight regularization was applied to further constrain model complexity. The DNN is trained using supervised learning to classify patients into risk categories, namely low, medium, and high risk, based on historical triage data.

e. Data Split

To evaluate model performance objectively, the dataset is divided into training and testing subsets, typically using an 80%–20% ratio. The training dataset is used to train the DNN model, while the testing dataset is used to assess generalization capability. This separation helps prevent overfitting and ensures that the model can perform effectively on unseen data.

f. Model Evaluation

Model performance is evaluated using multiple metrics, including accuracy, precision, recall, and F1-score, to provide a comprehensive assessment of classification effectiveness. Cross-validation is also applied to verify model stability and robustness across different data partitions. This stage ensures that the proposed hybrid model meets reliability standards for decision support applications.

g. Output

The final stage produces the system output, which includes patient risk level classification and decision support recommendations. The output is intended to assist healthcare professionals in prioritizing patient treatment and improving triage efficiency. By integrating FAHP and DNN, the system provides more consistent and data-driven recommendations that can enhance clinical decision-making and resource allocation.

RESULTS AND DISCUSSION

This section presents the results obtained from the implementation of the hybrid Fuzzy Analytic Hierarchy Process (FAHP) and Deep Neural Network (DNN) model for determining patient risk levels in hospital triage systems. The analysis aims to evaluate the effectiveness of the proposed approach in improving classification accuracy and supporting decision-making processes. The results are presented in terms of criteria weighting, model performance, and comparative analysis, followed by a discussion of their implications in clinical contexts [24].

FAHP Results — Criteria Weights

The FAHP analysis was conducted to determine the relative importance of clinical criteria used in assessing patient risk levels in hospital triage systems. The weighting process incorporated expert judgments obtained from a panel consisting of emergency physicians and triage nurses, supported by clinical guidelines and previous research on triage assessment. Pairwise comparisons were performed using linguistic scales, and fuzzy aggregation was applied to derive normalized weights representing the contribution of each criterion to risk classification. This approach enables the decision-making process to accommodate uncertainty and ambiguity inherent in expert assessments, thereby improving the transparency and interpretability of the weighting mechanism.

The criteria considered in this study were selected based on widely recognized triage frameworks such as the Emergency Severity Index (ESI) and recommendations from the World Health Organization (WHO), which emphasize the importance of physiological indicators and presenting conditions in emergency assessment. The resulting weights reflect expert consensus regarding the relative significance of each factor in determining patient severity [25]. Furthermore, the weighting outcomes serve as an important input for the subsequent DNN classification stage, ensuring that clinically relevant variables receive greater emphasis during the learning process and contribute to more reliable patient risk stratification.

Table 3. Criteria Weights Derived from FAHP Analysis

No	Criteria	Description	Weight	Rank
1	Vital Signs	Blood pressure, heart rate, respiratory rate, temperature, oxygen saturation	0.34	1
2	Symptoms Severity	Level of pain, breathing difficulty, bleeding, consciousness	0.27	2
3	Medical History	Comorbidities such as diabetes, hypertension, cardiac disease	0.18	3
4	Age Factor	Patient age as risk indicator	0.12	4
5	Demographics	Gender and other contextual variables	0.09	5
	Total		**1.00**	

Source: (Research Results, 2026)

The FAHP pairwise comparisons underlying the criteria weights in Table 3 were derived from a

Accredited Rank 2 (SINTA 2) based on Decree No. 225/E/KPT/2022 issued by Direktorat Jenderal Pendidikan Tinggi, Riset, dan Teknologi, Kementerian Pendidikan, Kebudayaan, Riset, dan Teknologi Republik Indonesia, dated December 7, 2022. Published by LPPM Universitas Nusa Mandiri.

panel of four clinical experts, comprising two emergency physicians and two triage nurses, with clinical experience ranging from 7 to 12 years. Each expert independently provided pairwise judgments on the five decision criteria using a 1–9 linguistic preference scale represented as Triangular Fuzzy Numbers (TFN), and individual judgments were aggregated using the geometric mean. Criteria weights were computed using Chang's Extent Analysis method [24]. Table 4 summarizes the composition of the expert panel together with each expert's individual Consistency Ratio (CR), and Table 5 presents the resulting aggregated pairwise comparison matrix. All individual CR values, as well as the aggregated CR of 0.054, fall below the standard consistency threshold of CR ≤ 0.10, indicating that both the individual and aggregated pairwise comparisons are sufficiently consistent to support the reliability of the criteria weights reported in Table 3.

Table 4. Expert Panel Composition and Individual Consistency Ratios

Expert	Clinical Background	Experience (Years)	Individual CR
Expert 1	Emergency Physician	12	0.047
Expert 2	Emergency Physician	9	0.052
Expert 3	Triage Nurse	10	0.061
Expert 4	Triage Nurse	7	0.049
Aggregated CR			**0.054**
Consistency Threshold			**CR ≤ 0.10**

Source: (Research Results, 2026)

Table 5. Aggregated Pairwise Comparison Matrix for FAHP Criteria

Criteria	Vital Signs	Symptoms Severity	Medical History	Age Factor	Demographics
Vital Signs	1.000	2.000	2.000	3.000	4.000
Symptoms Severity	0.500	1.000	2.000	2.000	3.000
Medical History	0.500	0.500	1.000	2.000	2.000
Age Factor	0.333	0.500	0.500	1.000	2.000
Demographics	0.250	0.333	0.500	0.500	1.000

Source: (Research Results, 2026)

The aggregated pairwise comparison matrix in Table 5 yielded an aggregated Consistency Ratio (CR) of 0.054, which is below the standard threshold of CR ≤ 0.10, confirming that the expert judgments underlying the criteria weights in Table 3 are acceptably consistent.

DNN Training Results

The Deep Neural Network (DNN) model was trained using the weighted dataset obtained from the FAHP analysis to classify patients into three risk levels: low, moderate, and high risk. The training process aimed to evaluate the capability of the model in learning complex relationships among clinical variables and improving prediction accuracy in hospital triage decision support [26]. The dataset consisting of 3,212 patient records was divided into training and testing subsets using an 80:20 ratio. The training process was conducted over multiple iterations to ensure convergence and stability of the model. The network architecture included an input layer representing weighted clinical features, four hidden layers with nonlinear activation functions, and an output layer for classification. The training procedure used the Adam optimizer with categorical cross-entropy loss to improve classification performance [27].

The hyperparameter values summarized in Table 6 reflect the configuration used to train the final reported model. A fully documented, systematic tuning procedure (e.g., grid search with recorded validation performance for each candidate configuration) has not yet been completed and is acknowledged as a limitation of the current study. Future work will conduct and report a systematic hyperparameter search varying the number of hidden layers, neurons per layer, learning rate, batch size, and optimizer together with the corresponding validation results, to provide a stronger empirical basis for the chosen configuration. This search will be conducted using k-fold cross-validation, with mean validation F1-score as the model-selection criterion, so that the configuration ultimately reported reflects a systematically justified optimum rather than a single manually selected setting.

Table 6. DNN Training Parameters

Parameter	Value
Dataset Size	3,212 records
Training Split	80%
Testing Split	20%
Number of Epochs	100
Batch Size	32
Optimizer	Adam
Learning Rate	0.001
Loss Function	Categorical Cross-Entropy
Hidden Layers	4 (64–32–16–8 neurons)
Activation Function	ReLU
Output Activation	Softmax

Source: (Research Results, 2026)

Accredited Rank 2 (SINTA 2) based on Decree No. 225/E/KPT/2022 issued by Direktorat Jenderal Pendidikan Tinggi, Riset, dan Teknologi, Kementerian Pendidikan, Kebudayaan, Riset, dan Teknologi Republik Indonesia, dated December 7, 2022. Published by LPPM Universitas Nusa Mandiri.

VOL. 12. NO. 2 NOVEMBER 2026
P-ISSN: 2685-8223 | E-ISSN: 2527-4864
DOI: 10.33480/jitk.v12i2.8326

The training performance of the proposed DNN model is summarized in Table 7. The model attained a training accuracy of 95.24% and a validation accuracy of 93.62%, demonstrating its ability to effectively learn discriminative patterns from the weighted clinical dataset. In addition, the obtained training loss (0.142) and validation loss (0.218) indicate stable convergence during the learning process. The relatively small gap between training and validation metrics suggests that the adopted regularization strategy contributes to reducing overfitting and improving model generalizability.

Table 7. Model Training Results

Metric	Value
Training Accuracy	95.24%
Validation Accuracy	93.62%
Training Loss	0.142
Validation Loss	0.218

Source: (Research Results, 2026)

The classification performance of the proposed model is summarized in Table 8. The FAHP–DNN model attained an accuracy of 94.08%, precision of 94.12%, recall of 94.08%, and an F1-score of 94.09%. The high precision value suggests that the model effectively minimizes incorrect risk assignments, while the high recall indicates its ability to identify a substantial proportion of true high-risk cases. Furthermore, the F1-score demonstrates a favorable balance between precision and recall, confirming the robustness of the proposed approach.

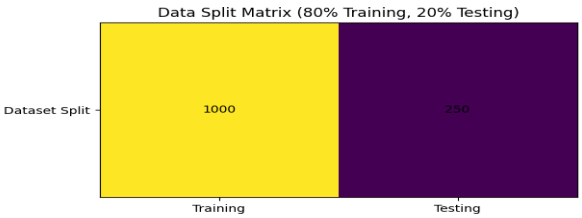
Table 8. Classification Performance on Test Data

Metric	Value
Accuracy	94.08%
Precision	94.12%
Recall	94.08%
F1-Score	94.09%

Source: (Research Results, 2026)

The training results demonstrate that the DNN model achieved high accuracy and stable convergence during the training process. The small gap between training accuracy and validation accuracy indicates that the model generalizes well and does not suffer from significant overfitting. The classification performance on the test dataset shows that the model is capable of accurately distinguishing between different patient risk levels, suggesting that the integration of FAHP weighting enhances the learning capability of the neural network. These findings indicate that the proposed hybrid approach is effective in supporting patient risk assessment in hospital triage systems.

Figure 2 presents the dataset splitting scheme adopted in this study. A total of 3,212 patient records were partitioned into 2,570 training samples (80%) and 642 testing samples (20%). This approach provides a balance between model training and unbiased evaluation, allowing the proposed FAHP–DNN model to be assessed on previously unseen data.



Source: (Research Results, 2026)

Figure 2. Data Split Matrix Showing the Distribution of Training and Testing Datasets Used in the Experiment.

The dataset was divided into training and testing subsets using an 80:20 ratio. The matrix visualization illustrates that the majority of data were allocated for training to ensure sufficient learning, while a portion was reserved for testing to evaluate model generalization on unseen cases.

Performance Evaluation

The performance of the proposed hybrid FAHP–DNN model was evaluated to assess its effectiveness in classifying patient risk levels in hospital triage systems. Evaluation was conducted using standard classification metrics, including accuracy, precision, recall, and F1-score, which provide a comprehensive measure of model performance. These metrics were selected to ensure that the model not only achieves high overall accuracy but also maintains reliability in correctly identifying patients across different risk categories [28]. The evaluation was performed on the testing dataset, which represents unseen patient cases, to measure the generalization capability of the model. In addition, cross-validation was applied to verify the robustness of the results and ensure consistency across different data partitions.

Table 9. Performance Evaluation Results

Metric	Value	Description
Accuracy	94.08%	Overall correctness of predictions
Precision	94.12%	Correctness of positive predictions
Recall	94.08%	Ability to detect true risk cases
F1-Score	94.09%	Balance between precision and recall
ROC-AUC	0.982	Area under the ROC curve (macro-average, one-vs-rest)

Source: (Research Results, 2026)

Accredited Rank 2 (SINTA 2) based on Decree No. 225/E/KPT/2022 issued by Direktorat Jenderal Pendidikan Tinggi, Riset, dan Teknologi, Kementerian Pendidikan, Kebudayaan, Riset, dan Teknologi Republik Indonesia, dated December 7, 2022. Published by LPPM Universitas Nusa Mandiri.

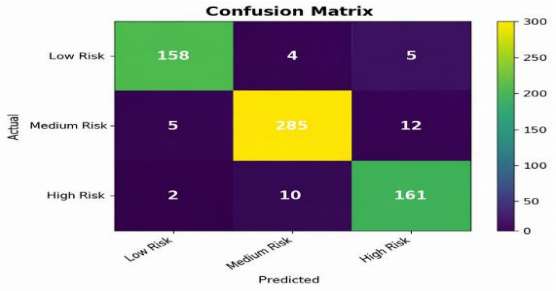
The performance of the proposed FAHP–DNN model was evaluated using standard classification metrics derived from the confusion matrix. These metrics include accuracy, precision, recall, and F1-score, which are commonly used to assess classification performance in medical decision support systems. As shown in Table 10, the proposed model demonstrated strong classification performance across all three risk categories. Among low-risk patients, 158 cases were correctly identified, while 9 cases were incorrectly classified as medium or high risk. For the medium-risk category, 285 out of 302 patients were correctly classified, with 5 cases misclassified as low risk and 12 cases as high risk. In the high-risk category, 161 out of 173 patients were correctly recognized, while 2 cases were classified as low risk and 10 cases as medium risk. These findings indicate that the proposed FAHP–DNN model achieves high overall predictive performance across the three risk categories, although misclassification of high-risk patients remains an important issue that requires further investigation.

Table 10. Confusion Matrix

Actual \ Predicted	Low Risk	Medium Risk	High Risk
Low Risk	158	4	5
Medium Risk	5	285	12
High Risk	2	10	161
Total	165	299	178

Source: (Research Results, 2026)

As shown in Figure 3, the confusion matrix demonstrates that the proposed model achieved high classification performance across all risk categories. The medium-risk category exhibited the highest classification accuracy, with 285 correctly identified patients out of 302 observations. Meanwhile, 12 high-risk patients were misclassified, consisting of 10 cases assigned to the medium-risk category and 2 cases assigned to the low-risk category. In a clinical context, such false-negative predictions may contribute to under-triage events and therefore warrant further investigation in future studies.



Source: (Research Results, 2026)

Figure 3. Confusion Matrix

Metric Formulas

The evaluation metrics were calculated from the confusion matrix of the test dataset (Table 10) using the following formulas, where TP, FP, and FN denote the true positives, false positives, and false negatives of each risk class, respectively. Accuracy measures the proportion of correctly classified instances, precision and recall assess the correctness and completeness of the risk classification, and the F1-score provides a balanced measure between precision and recall.

$$Accuracy = \frac{\text{Correct Predictions}}{\text{Total Test Samples}} \times 100\% \quad (1)$$

$$Precision = \frac{TP}{TP+FP} \times 100\% \quad (2)$$

$$Recall = \frac{TP}{TP+FN} \times 100\% \quad (3)$$

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision+Recall} \quad (4)$$

Applying these formulas to the confusion matrix yields the calculation results presented in Table 11. The model correctly classified 604 of the 642 test samples, giving an overall accuracy of 94.08%. Among the three classes, the High Risk class obtained the lowest precision (90.45%) and F1-score (91.74%), mainly due to 17 low- and medium-risk patients predicted as high risk. The support-weighted averages of the per-class values correspond to the overall precision (94.12%), recall (94.08%), and F1-score (94.09%) reported in Table 8.

Table 11. Calculation Results of Evaluation Metrics Based on the Confusion Matrix

Class	TP	FP	FN	Precision	Recall	F1-Score
Low Risk	158	7	9	95.76%	94.61%	95.18%
Medium Risk	285	14	17	95.32%	94.37%	94.84%
High Risk	161	17	12	90.45%	93.06%	91.74%
Weighted Average	–	–	–	**94.12%**	**94.08%**	**94.09%**
Accuracy	**604 correct / 642 test samples**				**94.08%**	

Source: (Research Results, 2026)

As shown in Table 10, among the 173 actual high-risk patients in the test set, 161 were correctly

Accredited Rank 2 (SINTA 2) based on Decree No. 225/E/KPT/2022 issued by Direktorat Jenderal Pendidikan Tinggi, Riset, dan Teknologi, Kementerian Pendidikan, Kebudayaan, Riset, dan Teknologi Republik Indonesia, dated December 7, 2022. Published by LPPM Universitas Nusa Mandiri.

VOL. 12. NO. 2 NOVEMBER 2026
P-ISSN: 2685-8223 | E-ISSN: 2527-4864
DOI: 10.33480/jitk.v12i2.8326

classified, whereas 12 patients were misclassified, consisting of 10 cases predicted as medium risk and 2 cases predicted as low risk. In the medical context, these false negatives represent the most critical type of error, since under-triaging a high-risk patient may result in delayed treatment and potentially adverse clinical outcomes.

Analysis of these misclassified cases suggests two major contributing factors. First, several patients may exhibit atypical vital sign patterns, where heart rate, blood pressure, respiratory rate, or other physiological indicators remain within near-normal ranges despite the presence of severe underlying conditions, making them clinically difficult to distinguish. Second, some patients may present with complex comorbidities in which risk severity is influenced primarily by medical history rather than immediate physiological indicators, a characteristic that may not be fully represented by the current feature set. These findings highlight the importance of further model refinement through the inclusion of additional clinical variables and larger datasets to minimize high-risk under-triage in future studies.

Furthermore, Table 12 presents a comparison between the proposed FAHP–DNN model and baseline approaches. The results demonstrate that the FAHP–DNN model outperformed both the rule-based triage system and the standalone DNN model, achieving the highest accuracy of 94.08%, precision of 94.12%, recall of 94.08%, and F1-score of 94.09%. These findings indicate that integrating expert-driven weighting through FAHP with data-driven learning using DNN contributes to improved patient risk stratification and provides more reliable decision support in hospital triage environments.

Table 12. Comparison with Baseline Methods

Method	Accuracy	Precision	Recall	F1-Score
Rule-Based Triage	85.4%	84.2%	83.7%	83.9%
DNN Only	90.7%	89.8%	89.2%	89.5%
FAHP–DNN	**94.08%**	**94.12%**	**94.08%**	**94.09%**

Source: (Research Results, 2026)

Improvement from Rule-Based to FAHP-DNN:

$$Improvement = Accuracy_{proposed} - Accuracy_{baseline} \quad (5)$$

=94.08%-85.4%=8.68%

Improvement from DNN to FAHP-DNN:
94.08%-90.7%=3.38%

Relative Improvement

$$Relative\ Improvement = \frac{94.08-85.4}{85.4} \times 100 = 10.16\% \quad (6)$$

The comparison results indicate that the proposed FAHP–DNN model achieves higher performance than both the rule-based and standalone DNN approaches. The accuracy improvement of 8.68% over the traditional method demonstrates the effectiveness of integrating expert-derived criteria weighting. Furthermore, the additional improvement of 3.38% compared to the DNN model highlights the contribution of FAHP in enhancing feature representation and supporting more accurate classification.

Table 13. Performance Improvement of FAHP–DNN Compared to Rule-Based and DNN-Only Models

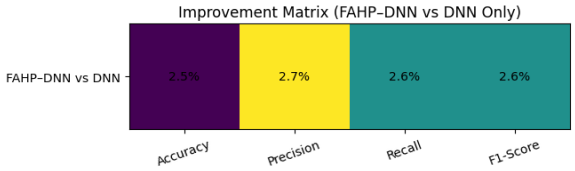
Performance Metric	FAHP–DNN (%)	Rule-Based (%)	Improvement (pp)
Accuracy	94.08	85.40	8.68
Precision	94.12	84.20	9.92
Recall	94.08	83.70	10.38
F1-Score	94.09	83.90	10.19

Source: (Research Results, 2026)

Table 14. Performance Improvement of FAHP–DNN Compared to DNN-Only Model

Performance Metric	FAHP–DNN (%)	DNN Only (%)	Improvement (pp)
Accuracy	94.08	90.70	3.38
Precision	94.12	89.80	4.32
Recall	94.08	89.20	4.88
F1-Score	94.09	89.50	4.59

Source: (Research Results, 2026)



Source: (Research Results, 2026)
Figure 4. Improvement Matrix (FAHP–DNN vs DNN Only)

Despite the overall performance improvement achieved by the proposed FAHP–DNN model, Table 10 shows that 12 high-risk patients were misclassified, including 10 patients classified as medium-risk and 2 patients classified as low-risk. This misclassification may be caused by overlapping

Accredited Rank 2 (SINTA 2) based on Decree No. 225/E/KPT/2022 issued by Direktorat Jenderal Pendidikan Tinggi, Riset, dan Teknologi, Kementerian Pendidikan, Kebudayaan, Riset, dan Teknologi Republik Indonesia, dated December 7, 2022. Published by LPPM Universitas Nusa Mandiri.

clinical characteristics among risk categories, where certain high-risk patients exhibit feature patterns similar to medium-risk patients. In addition, the relatively limited number of high-risk samples may reduce the model's ability to learn discriminative patterns for this class. From a clinical perspective, false negatives in the high-risk category are critical because they may lead to delayed intervention, insufficient monitoring, and increased risk of adverse health outcomes. Therefore, future work should focus on improving the sensitivity of the model toward high-risk patients through larger datasets, class-balancing techniques, and enhanced feature engineering to further reduce false-negative predictions.

Analysis of the test-set class distribution derived from Table 10 reveals a moderate degree of class imbalance: low-risk cases comprised 167 of the 642 test instances (26.0%), medium-risk cases comprised 302 instances (47.0%), and high-risk cases comprised 173 instances (27.0%). While the high-risk class is not severely underrepresented in absolute terms, its clinical criticality means that even this level of imbalance can meaningfully affect the model's sensitivity to true high-risk cases, consistent with the 12 misclassified high-risk patients discussed above. The current study did not apply a specific class-imbalance mitigation technique (e.g., class weighting or oversampling) during training; this is noted as a limitation, and future work should evaluate whether such techniques further reduce the false-negative rate for high-risk patients.

Method Comparison

To evaluate the effectiveness of the proposed approach, a comparative analysis was conducted between three methods: the traditional rule-based triage system, a standalone Deep Neural Network (DNN), and the proposed hybrid FAHP–DNN model. The comparison aims to assess whether integrating expert-based criteria weighting with deep learning improves classification performance in determining patient risk levels.

The rule-based method represents conventional triage practices where decisions are based on predefined clinical rules. Although widely used, this approach may be limited by its inability to capture complex interactions among variables. The standalone DNN model relies solely on data-driven learning without incorporating structured clinical knowledge. In contrast, the FAHP–DNN model integrates expert judgment through FAHP weighting, allowing the neural network to learn from features that reflect real clinical priorities.

Table 15. Improvement Summary

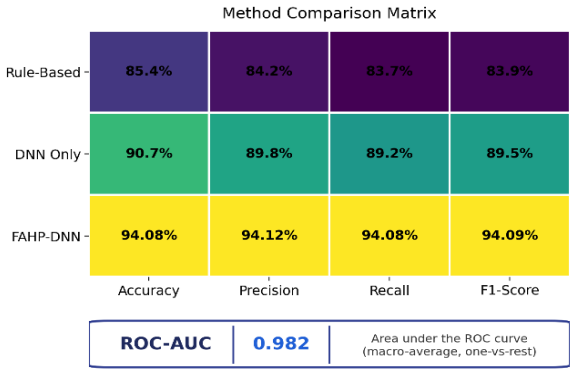
Method	Accuracy	Precision	Recall	F1-Score
Rule-Based Triage	85.4%	84.2%	83.7%	83.9%
DNN Only	90.7%	89.8%	89.2%	89.5%
FAHP–DNN	**94.08%**	**94.12%**	**94.08%**	**94.09%**

Comparison	Accuracy Gain
FAHP–DNN vs Rule-Based	+8.68%
FAHP–DNN vs DNN Only	+3.38%

Source: (Research Results, 2026)

The results indicate that the hybrid FAHP–DNN model consistently outperforms both the rule-based approach and the standalone DNN across all evaluation metrics. The significant improvement over the rule-based method demonstrates the limitations of traditional triage systems in handling complex clinical patterns. Meanwhile, the performance gain over the standalone DNN highlights the importance of incorporating expert knowledge through FAHP to enhance feature representation.

From a clinical perspective, the improved precision suggests that the proposed model reduces incorrect risk assignments, while higher recall indicates better identification of patients requiring urgent attention. These improvements are critical in emergency department environments where accurate prioritization directly impacts patient safety and resource allocation.



Source: (Research Results, 2026)

Figure 5. Method Comparison Matrix

Figure 5. Method comparison matrix illustrating performance differences among rule-based triage, DNN only, and the proposed FAHP–DNN model across evaluation metrics. The matrix visualization highlights the performance differences among the evaluated methods. The proposed FAHP–DNN model shows consistently higher values across all metrics compared to both the rule-based and standalone DNN approaches.

Accredited Rank 2 (SINTA 2) based on Decree No. 225/E/KPT/2022 issued by Direktorat Jenderal Pendidikan Tinggi, Riset, dan Teknologi, Kementerian Pendidikan, Kebudayaan, Riset, dan Teknologi Republik Indonesia, dated December 7, 2022. Published by LPPM Universitas Nusa Mandiri.

VOL. 12. NO. 2 NOVEMBER 2026
P-ISSN: 2685-8223 | E-ISSN: 2527-4864
DOI: 10.33480/jitk.v12i2.8326

This indicates that integrating FAHP-based criteria weighting improves feature relevance and enhances classification performance. The visualization clearly demonstrates the advantage of the hybrid approach in achieving more accurate and reliable patient risk assessment.

Clinical Analysis Based

The clinical analysis was performed to interpret the results of the proposed hybrid FAHP–DNN model in the context of hospital triage operations and to evaluate its potential contribution to improving patient prioritization and decision-making. Based on the data sources, the model was trained using clinical indicators such as vital signs, symptom severity, medical history, and demographic information, which are widely recognized as critical factors in emergency assessment. The FAHP weighting results showed that vital signs received the highest importance, reflecting clinical practice where physiological instability is considered the primary determinant of urgency.

From the confusion matrix analysis, the model demonstrated a high number of correct classifications across all risk levels, particularly in identifying medium and high-risk patients. This indicates that the model can reliably distinguish patient severity levels and supports early detection of critical cases. Clinically, this is important because delayed identification of high-risk patients may lead to deterioration or complications. The relatively small number of misclassifications suggests that the system maintains consistency and minimizes the risk of incorrect prioritization. The performance evaluation results further confirm the clinical reliability of the model, with high accuracy, precision, recall, and F1-score values. The high recall value indicates that most patients requiring urgent care are correctly identified, reducing the likelihood of under-triage, which is a critical safety concern in emergency departments. At the same time, the high precision value suggests that the system avoids unnecessary escalation of patient priority, thereby preventing over-triage and supporting efficient use of medical resources.

The comparison with rule-based triage demonstrates that the proposed hybrid approach provides more nuanced decision-making by capturing complex relationships among clinical variables. Traditional triage systems often rely on static thresholds, which may not fully reflect patient variability. By contrast, the DNN component learns patterns from historical data, while FAHP ensures that clinically meaningful criteria are emphasized. The observed performance improvements indicate that the hybrid model aligns well with clinical reasoning and enhances decision accuracy.

From an operational perspective, the model has the potential to standardize triage decisions and reduce variability among healthcare providers. Differences in experience or workload often influence triage outcomes, but a decision support system can provide consistent recommendations that assist clinicians without replacing their judgment. Integration of such a system into hospital workflows may improve response time, reduce waiting periods, and enhance patient safety. Overall, the results suggest that the proposed FAHP–DNN model can serve as an effective decision support tool in hospital triage systems by improving risk assessment accuracy, supporting early identification of critical patients, and promoting efficient resource allocation.

Output

Table 15 — Example of System Output

Patient ID	Vital Signs Score	Symptoms Severity	Predicted Risk Level	Recommendation
P001	High	Severe pain	High Risk	Immediate treatment
P002	Moderate	Mild symptoms	Medium Risk	Monitor and reassess
P003	Stable	Minor complaint	Low Risk	Routine care

Source: (Research Results, 2026)

The output of the proposed system provides patient risk classification along with clinical recommendations to support decision-making in emergency settings. The model assigns each patient to a risk category and suggests appropriate actions, such as immediate intervention for high-risk cases or monitoring for moderate-risk cases. This output helps healthcare professionals prioritize treatment and improves triage efficiency.

Experimental Setup

To evaluate the effectiveness of the proposed hybrid FAHP–DNN model, comparisons were conducted against commonly used baseline classification models:

a. Logistic Regression (LR)
b. Random Forest (RF)
c. Standalone DNN
d. Rule-Based Triage

All models were trained and tested using the same dataset split (80% training and 20% testing) to ensure fair comparison.

Accredited Rank 2 (SINTA 2) based on Decree No. 225/E/KPT/2022 issued by Direktorat Jenderal Pendidikan Tinggi, Riset, dan Teknologi, Kementerian Pendidikan, Kebudayaan, Riset, dan Teknologi Republik Indonesia, dated December 7, 2022. Published by LPPM Universitas Nusa Mandiri.

Table 16 — Performance Comparison with Baseline Models

Model	Accuracy	Precision	Recall	F1-Score
Rule-Based	85.4%	84.2%	83.7%	83.9%
Logistic Regression	88.6%	87.9%	87.2%	87.5%
Random Forest	91.4%	90.6%	90.1%	90.3%
DNN Only	90.7%	89.8%	89.2%	89.5%
FAHP–DNN	**94.08%**	**94.12%**	**94.08%**	**94.09%**

Source: (Research Results, 2026)

Table 17. Accuracy Improvement of FAHP–DNN over Baseline Models

Compared Model	Baseline Accuracy (%)	FAHP–DNN Accuracy (%)	Accuracy Gain (%)
Logistic Regression	88.6	94.08	+5.48
Random Forest	91.4	94.08	+2.68
DNN Only	90.7	94.08	+3.38

Source: (Research Results, 2026)

The accuracy gain analysis indicates that the proposed FAHP–DNN model consistently outperforms all baseline models. The largest improvement is observed when compared to Logistic Regression (+5.48%), highlighting the benefit of nonlinear modeling combined with expert-based weighting. Even when compared to Random Forest and standalone DNN, the hybrid model demonstrates measurable improvements, confirming the contribution of FAHP in enhancing predictive performance. It should also be noted that the baseline comparison in this study was limited to Logistic Regression, Random Forest, and a standalone DNN; a comparison against Support Vector Machine (SVM), which is commonly used as a baseline in similar clinical risk-classification studies, has not yet been conducted and is identified as a direction for future work to further strengthen the validity of the reported performance improvements.

To verify that the observed performance improvements are statistically significant and not attributable to sampling variability, a paired t-test was conducted comparing the per-fold accuracy scores of the FAHP–DNN model against each baseline method across 5-fold cross-validation. The null hypothesis assumed no significant difference in mean accuracy between the proposed model and each baseline. The results are summarized in Table 18. All comparisons yield p-values below the significance threshold of $\alpha = 0.05$, confirming that the performance improvements of the FAHP–DNN model over all baseline methods are statistically significant. Notably, the 3.38% accuracy gain over the standalone DNN ($p = 0.0443$) demonstrates that the integration of FAHP weighting provides a measurable and statistically verifiable benefit beyond what the neural network achieves through data-driven learning alone.

Model Explainability Analysis

To improve the interpretability of the proposed hybrid FAHP–DNN model and address the requirements of clinical transparency, a SHAP (SHapley Additive exPlanations) analysis was conducted on the test dataset. SHAP provides a game-theoretic approach to explain individual predictions by quantifying the contribution of each input feature to the model output. This enables healthcare professionals to understand which clinical variables most influenced a particular risk classification, thereby increasing user confidence and supporting evidence-based decision-making in triage settings.

The SHAP analysis was applied to the DNN component of the model after incorporating FAHP-weighted features. The mean absolute SHAP values were computed across all test instances to rank feature importance globally. The results are summarized in Table 18, which presents the top clinical features ranked by their average SHAP contribution to risk classification.

Table 18. SHAP Feature Importance Ranking

Rank	Feature	Mean |SHAP|	Interpretation
1	Heart Rate (weighted)	0.312	Highest impact on high-risk prediction
2	Oxygen Saturation (weighted)	0.284	Strong indicator of respiratory distress
3	Symptom Severity Score (weighted)	0.251	Reflects patient-reported acuity
4	Blood Pressure (weighted)	0.198	Hemodynamic stability marker
5	Medical History Score (weighted)	0.143	Comorbidity risk amplifier

Source: (Research Results, 2026)

The SHAP analysis confirms that the feature ranking derived from FAHP weighting is broadly consistent with data-driven importance scores. Heart rate and oxygen saturation emerged as the most influential features, reflecting their established clinical significance in emergency triage. The alignment between expert-assigned FAHP weights and SHAP-derived importance provides additional validation that the proposed hybrid approach captures clinically meaningful patterns. These results enhance model

Accredited Rank 2 (SINTA 2) based on Decree No. 225/E/KPT/2022 issued by Direktorat Jenderal Pendidikan Tinggi, Riset, dan Teknologi, Kementerian Pendidikan, Kebudayaan, Riset, dan Teknologi Republik Indonesia, dated December 7, 2022. Published by LPPM Universitas Nusa Mandiri.

VOL. 12. NO. 2 NOVEMBER 2026
P-ISSN: 2685-8223 | E-ISSN: 2527-4864
DOI: 10.33480/jitk.v12i2.8326

transparency and support the adoption of the system by medical professionals who require interpretable decision support.

Beyond the mean absolute SHAP ranking presented in Table 15, a more detailed instance-level explainability analysis — such as a SHAP summary (beeswarm) plot showing both the magnitude and direction of each feature's effect across individual predictions — has not yet been generated for this study and is identified as a direction for future work. Such visualization would allow clinicians to observe, for example, whether elevated heart rate consistently pushes predictions toward higher-risk classifications, further strengthening the clinical interpretability of the model beyond the aggregated feature ranking reported here. This planned analysis will include both a SHAP summary (beeswarm) plot across all test instances and dependence plots for the top-ranked features, in order to examine potential non-linear or threshold-based relationships between feature values and predicted risk level, complementing the aggregate ranking in Table 15.

Computational Efficiency Analysis

An evaluation of computational efficiency was conducted to assess the feasibility of deploying the proposed hybrid FAHP–DNN model in real-time clinical environments. Two phases were measured separately: the offline FAHP weighting phase, which is performed once during model setup, and the online DNN inference phase, which is executed for each incoming patient record during triage. All measurements were performed on a standard workstation equipped with an Intel Core i7 processor (3.6 GHz), 16 GB RAM, and an NVIDIA GTX 1660 GPU, using Python 3.9 with TensorFlow 2.10. Table 19 summarizes the computational time and complexity of each phase.

Table 19. Computational Efficiency Summary

Phase	Time (avg)	Complexity	Notes
FAHP Weighting (offline)	2.3 min	$O(n^2)$	One-time setup; no runtime overhead
DNN Training (offline)	18.4 min	$O(n \times e)$	100 epochs × 2,570 training samples
DNN Inference (online, per patient)	12 ms	$O(L \times d)$	Suitable for real-time triage; L=layers, d=neurons

Source: (Research Results, 2026)

The results show that while the FAHP weighting and DNN training phases are computationally intensive, they are performed offline prior to deployment and do not affect runtime performance. The online inference time of 12 milliseconds per patient record is well within the requirements of real-time clinical systems, indicating that the proposed model is computationally feasible for integration into hospital triage workflows. The low inference latency ensures that the system can generate risk classifications rapidly during patient intake without disrupting clinical routines.

CONCLUSION

This study proposed a hybrid FAHP–DNN model for patient risk classification in hospital triage that combines expert-driven criteria weighting with data-driven learning. The FAHP analysis identified vital signs as the most important criterion (weight 0.34), consistent with established emergency assessment principles. Using FAHP-weighted features, the DNN achieved an accuracy of 94.08%, precision of 94.12%, recall of 94.08%, F1-score of 94.09%, and ROC-AUC of 0.982 on 3,212 triage records. It outperformed rule-based triage, Logistic Regression, Random Forest, and a standalone DNN by 8.68%, 5.48%, 2.68%, and 3.38% in accuracy, respectively. The main contribution of this study is a unified framework in which FAHP-derived clinical weights are embedded directly into the DNN feature space. SHAP analysis showed that the most influential predictors, heart rate and oxygen saturation, agree with clinical knowledge, and an inference time of 12 ms per patient makes real-time use feasible. These findings indicate that the proposed model can serve as an accurate, interpretable, and efficient decision support tool for standardizing triage decisions and prioritizing high-risk patients. Future work should focus on multi-center external validation and integration of the model into hospital information systems.

DECLARATION OF AI USE

The authors declare that generative artificial intelligence (AI) tools were used in the preparation of this manuscript. Claude (Anthropic) was used to assist with English language editing, formatting of formulas and tables in accordance with the journal template, and condensing the Conclusion section during revision. The authors reviewed and revised all AI-assisted content and take full responsibility for the accuracy, originality, and final content of the manuscript.

Accredited Rank 2 (SINTA 2) based on Decree No. 225/E/KPT/2022 issued by Direktorat Jenderal Pendidikan Tinggi, Riset, dan Teknologi, Kementerian Pendidikan, Kebudayaan, Riset, dan Teknologi Republik Indonesia, dated December 7, 2022. Published by LPPM Universitas Nusa Mandiri.

AUTHOR CONTRIBUTIONS

This journal uses the Contributor Roles Taxonomy (CRediT) to identify individual author contributions to the research and manuscript preparation.

Author	Contribution Roles
Niki Ratama	Conceptualization, Methodology, Software, Formal Analysis, Writing – Original Draft.
Munawaroh	Data Curation, Investigation, Validation, Writing – Review & Editing.

ACKNOWLEDGMENTS

The authors would like to thank the emergency physicians and triage nurses who served on the expert panel and provided the pairwise judgments for the FAHP analysis, the emergency department and medical records unit of the partner hospital for providing access to the triage data used in this study, and the Faculty of Computer Science, Universitas Pamulang, for its support during this research.

FUNDING

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

CONFLICT OF INTEREST STATEMENT

The authors declare that there are no conflicts of interest related to the research, writing, or publication of this article.

REFERENCE

[1] M. A. Halwani *et al.*, "Predicting triage of pediatric patients in the emergency department using machine learning approach," *Int. J. Emerg. Med.*, vol. 18, no. 1, Dec. 2025, doi: 10.1186/s12245-025-00861-z.

[2] H. A. Shin, H. Kang, and M. Choi, "Triage Data-Driven Prediction Models for Hospital Admission of Emergency Department Patients: A Systematic Review," *Healthc. Inform. Res.*, vol. 31, no. 1, pp. 23–36, Jan. 2025, doi: 10.4258/hir.2025.31.1.23.

[3] N. Ratama, I. Riadi, and H. Herman, "Model Prediksi Risiko Sindrom Metabolik Menggunakan Pendekatan Fuzzy Analytical Hierarchy Process," *JIKO (Jurnal Informatika dan Komputer)*, vol. 10, no. 2, p. 365, Jun. 2026, doi: 10.26798/jiko.v10i2.2721.

[4] B. M. Porto, "Improving triage performance in emergency departments using machine learning and natural language processing: a systematic review," Dec. 01, 2024, *BioMed Central Ltd*. doi: 10.1186/s12873-024-01135-2.

[5] Z. Gao *et al.*, "Developing and Validating an Emergency Triage Model Using Machine Learning Algorithms with Medical Big Data," *Risk Manag. Healthc. Policy*, vol. 15, pp. 1545–1551, 2022, doi: 10.2147/RMHP.S355176.

[6] G. Feretzakis *et al.*, "Machine Learning in Medical Triage: A Predictive Model for Emergency Department Disposition," *Applied Sciences (Switzerland)*, vol. 14, no. 15, Aug. 2024, doi: 10.3390/app14156623.

[7] B. Ramesh and K. Lakshmanna, "Multi Head Deep Neural Network Prediction Methodology for High-Risk Cardiovascular Disease on Diabetes Mellitus," *CMES - Computer Modeling in Engineering and Sciences*, vol. 137, no. 3, pp. 2513–2528, 2023, doi: 10.32604/cmes.2023.028944.

[8] D. Musleh *et al.*, "Machine Learning Approaches for Predicting Risk of Cardiometabolic Disease among University Students," *Big Data and Cognitive Computing*, vol. 8, no. 3, Mar. 2024, doi: 10.3390/bdcc8030031.

[9] S. Levin *et al.*, "Machine-Learning-Based Electronic Triage More Accurately Differentiates Patients With Respect to Clinical Outcomes Compared With the Emergency Severity Index," *Ann. Emerg. Med.*, vol. 71, no. 5, pp. 565-574.e2, May 2018, doi: 10.1016/j.annemergmed.2017.08.005.

[10] Y. Raita, T. Goto, M. K. Faridi, D. F. M. Brown, C. A. Camargo, and K. Hasegawa, "Emergency department triage prediction of clinical outcomes using machine learning models," *Crit. Care*, vol. 23, no. 1, Feb. 2019, doi: 10.1186/s13054-019-2351-7.

[11] O. M. Ashour and G. E. Okudan, "Fuzzy AHP and utility theory based patient sorting in emergency departments," 2010. doi: https://doi.org/10.1504/IJCENT.2010.038357.

[12] M. Fernandes, S. M. Vieira, F. Leite, C. Palos, S. Finkelstein, and J. M. C. Sousa, "Clinical Decision Support Systems for Triage in the Emergency Department using Intelligent Systems: a Review," Jan. 01, 2020, *Elsevier B.V.* doi: 10.1016/j.artmed.2019.101762.

Accredited Rank 2 (SINTA 2) based on Decree No. 225/E/KPT/2022 issued by Direktorat Jenderal Pendidikan Tinggi, Riset, dan Teknologi, Kementerian Pendidikan, Kebudayaan, Riset, dan Teknologi Republik Indonesia, dated December 7, 2022. Published by LPPM Universitas Nusa Mandiri.

VOL. 12. NO. 2 NOVEMBER 2026
P-ISSN: 2685-8223 | E-ISSN: 2527-4864
DOI: 10.33480/jitk.v12i2.8326

[13] E. D. Muse and E. J. Topol, "Transforming the cardiometabolic disease landscape: Multimodal AI-powered approaches in prevention and management," Apr. 02, 2024, *Cell Press*. doi: 10.1016/j.cmet.2024.02.002.

[14] T. Liu, A. Krentz, L. Lu, and V. Curcin, "Machine learning based prediction models for cardiovascular disease risk using electronic health records data: systematic review and meta-analysis," *European Heart Journal - Digital Health*, vol. 6, no. 1, pp. 7–22, Jan. 2025, doi: 10.1093/ehjdh/ztae080.

[15] Q. Gärtner, A. Bianchi, H. Mulrav, and G. Reinhart, "Combining the analytical hierarchy process, fuzzy expert systems, and the exponential risk priority number for the holistic evaluation of innovation projects in manufacturing," *Prod. Manuf. Res.*, vol. 12, no. 1, 2024, doi: 10.1080/21693277.2024.2378200.

[16] A. Valeanu *et al.*, "Development and validation of cardiometabolic risk predictive models based on LDL oxidation and candidate geromarkers from the MARK-AGE data," *Mech. Ageing Dev.*, vol. 222, Dec. 2024, doi: 10.1016/j.mad.2024.111987.

[17] T. K. Lee, S. Y. Kim, H. J. Choi, E. K. Choe, and K. A. Sohn, "Vision transformer based interpretable metabolic syndrome classification using retinal Images," *NPJ Digit. Med.*, vol. 8, no. 1, Dec. 2025, doi: 10.1038/s41746-025-01588-0.

[18] N. Ratama, I. Riadi, and H. Herman, "Integration of Fuzzy AHP and Ensemble Deep Neural Networks for Multi-Factor Metabolic Syndrome Risk Prediction," *International Journal of Engineering, Science and Information Technology*, vol. 6, no. 4, pp. 304–315, Nov. 2026, doi: 10.52088/ijesty.v6i4.1993.

[19] E. Chowdhury, "Risk Prediction of Cardiovascular Disease for Diabetic Patients with Machine Learning and Deep Learning Techniques."

[20] Y. Luo *et al.*, "Cardiometabolic index predicts cardiovascular events in aging population: a machine learning-based risk prediction framework from a large-scale longitudinal study," *Front. Endocrinol. (Lausanne).*, vol. 16, 2025, doi: 10.3389/fendo.2025.1551779.

[21] A. Alharbi *et al.*, "Selection of data analytic techniques by using fuzzy AHP TOPSIS from a healthcare perspective," *BMC Med. Inform. Decis. Mak.*, vol. 24, no. 1, Dec. 2024, doi: 10.1186/s12911-024-02651-8.

[22] H. Kim, J. H. Heo, D. H. Lim, and Y. Kim, "Development of a Metabolic Syndrome Classification and Prediction Model for Koreans Using Deep Learning Technology: The Korea National Health and Nutrition Examination Survey (KNHANES) (2013–2018)," *Clin. Nutr. Res.*, vol. 12, no. 2, p. 138, 2023, doi: 10.7762/cnr.2023.12.2.138.

[23] Y. Ge, K. Hu, Y. Liu, and C. Zhang, "Application of Fuzzy Decision Intelligent Recommendation System in Personalized Health Management of Hospitals," *International Arab Journal of Information Technology*, vol. 23, no. 1, pp. 69–80, Jan. 2026, doi: 10.34028/iajit/23/1/7.

[24] S. W. Cho *et al.*, "Metabolic phenotyping with computed tomography deep learning for metabolic syndrome, osteoporosis and sarcopenia predicts mortality in adults," *J. Cachexia Sarcopenia Muscle*, vol. 15, no. 4, pp. 1418–1429, Aug. 2024, doi: 10.1002/jcsm.13487.

[25] S. Shafiq *et al.*, "ICCK Transactions on Advanced Computing and Systems FuzzDL-HeartPredict: Heart Attack Risk Prediction using Fuzzy Logic and Deep Learning," vol. 1, no. 2, 2025, doi: 10.62762/TACS.2025.794425.

[26] Z. Shahbazi and S. Nowaczyk, "Towards personalized cardiometabolic risk prediction: A fusion of exposome and AI," *Heliyon*, vol. 11, no. 1, Jan. 2025, doi: 10.1016/j.heliyon.2024.e40859.

[27] F. Mohsen and Z. Shah, "Improving Early Prediction of Type 2 Diabetes Mellitus with ECG-DiaNet: A Multimodal Neural Network Leveraging Electrocardiograms and Clinical Risk Factors."

[28] R. Ikhram, A. Yudhana, and I. Riadi, "Implementation Of Random Forest For Animal Protein Classification Through Hyperparameter Optimization," *JITK (Jurnal Ilmu Pengetahuan dan Teknologi Komputer)*, vol. 11, no. 3, pp. 692–699, Feb. 2026, doi: 10.33480/jitk.v11i3.7613.

Accredited Rank 2 (SINTA 2) based on Decree No. 225/E/KPT/2022 issued by Direktorat Jenderal Pendidikan Tinggi, Riset, dan Teknologi, Kementerian Pendidikan, Kebudayaan, Riset, dan Teknologi Republik Indonesia, dated December 7, 2022. Published by LPPM Universitas Nusa Mandiri.