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AI-BASED HOSPİTAL TRİAGE SYSTEMS OPTİMİZED WİTH PARTİCLE SWARM OPTİMİZATİON AND MİGRATİNG BİRDS OPTİMİZATİON

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Abstract: Hospital emergency departments must rapidly evaluate patients and allocate limited medical resources efficiently. Traditional triage procedures rely heavily on human decision-making and may suffer from inconsistency and workload-induced errors. Artificial Intelligence (AI)-based triage systems have recently been proposed to support clinical decisions by automatically evaluating patient symptoms, physiological measurements, and historical data. However, the performance of such systems strongly depends on the parameter selection of the triage decision model. This study proposes a metaheuristic optimization framework for improving AI-based triage systems using Particle Swarm Optimization (PSO) and Migrating Birds Optimization (MBO). Mathematical models of the AI triage process are developed, and a hospital patient-flow simulation involving 1000 patients is implemented in Python without using machine learning libraries such as sklearn or TensorFlow. The simulation evaluates three systems: (1) a standard AI triage model, (2) PSO-optimized AI triage, and (3) MBO-optimized AI triage. Experimental results show that metaheuristic optimization improves classification accuracy and hospital flow efficiency. The MBO-optimized triage system achieves the highest performance, particularly in identifying critical patients.

Keywords: Artificial Intelligence in Healthcare, Hospital Triage Systems, Particle Swar Optimization, Migrating Birds Optimization, Medical Decision Systems, Hospital Workflow Simulation

I INTRODUCTION

Emergency departments are among the most complex and resource-constrained environments in modern healthcare systems. One of the most critical tasks performed in emergency departments is triage, which determines the priority of treatment for incoming patients based on the severity of their medical conditions [1].

Traditional triage methods such as the Emergency Severity Index (ESI) classify patients into different urgency levels based on clinical evaluation [2]. Although these systems are widely used, human-based triage decisions may suffer from inconsistencies due to workload pressure, fatigue, and subjective judgment [3].

Recent developments in artificial intelligence have enabled the creation of AI-based clinical decision support systems capable of predicting patient outcomes and prioritizing treatment [4]. Machine learning algorithms can analyze physiological signals, patient history, and symptom descriptions to estimate medical risk levels [5].

Several studies have demonstrated that AI-assisted triage systems can reduce waiting times, improve diagnostic accuracy, and optimize resource allocation in hospitals [6].

However, the effectiveness of these systems strongly depends on the optimization of model parameters such as feature weights and classification thresholds. Metaheuristic optimization algorithms provide powerful tools for solving such parameter optimization problems [7]. Among the most widely used algorithms are:

- Particle Swarm Optimization (PSO) [8]
- Genetic Algorithms (GA) [9]
- Ant Colony Optimization (ACO) [10]

In recent years, Migrating Birds Optimization (MBO) has emerged as a promising bio-inspired algorithm based on the cooperative flight behavior of bird flocks [11].

This paper investigates how PSO and MBO algorithms can optimize AI-based triage systems and improve hospital workflow performance.

2 ARCHITECTURE OF THE AI HOSPITAL TRIAGE SYSTEM

The proposed AI triage system consists of several interconnected components designed to process patient information and generate optimized triage decisions in a systematic manner. These components include:

1. Patient data acquisition
2. Feature processing
3. AI risk prediction model
4. Metaheuristic parameter optimization
5. Triage decision generation
6. Hospital resource allocation

Each component plays a critical role in transforming raw patient information into actionable clinical decisions. In particular, the integration of metaheuristic optimization enhances the adaptability of the AI model by dynamically tuning its parameters.

To better understand the interaction among these components, the overall system architecture is illustrated in **Figure 1.** This figure provides a high-level view of the data flow and class distribution within the simulated hospital environment.

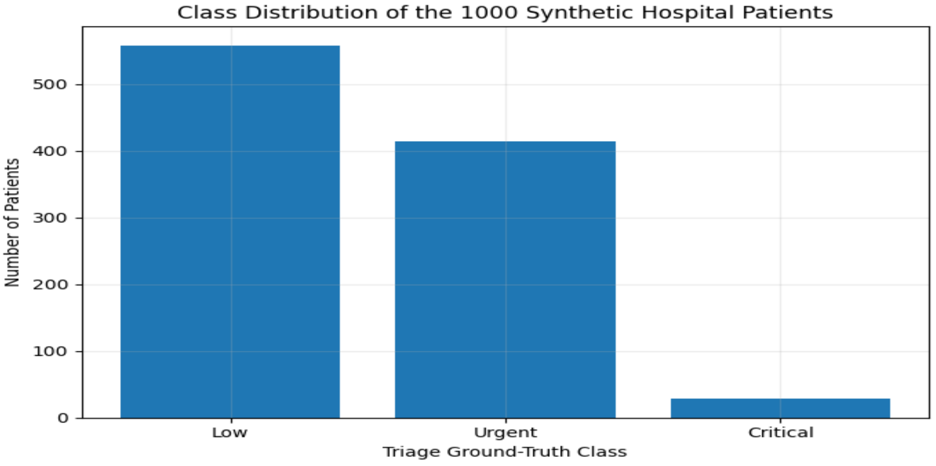


Figure 1.Class Distribution of the 1000 Synthetic Hospital Patients

To provide a clear overview of the proposed methodology, the conceptual workflow is illustrated in Figure 2. The flowchart summarizes the sequential structure of the algorithm and highlights the interaction between its main components.

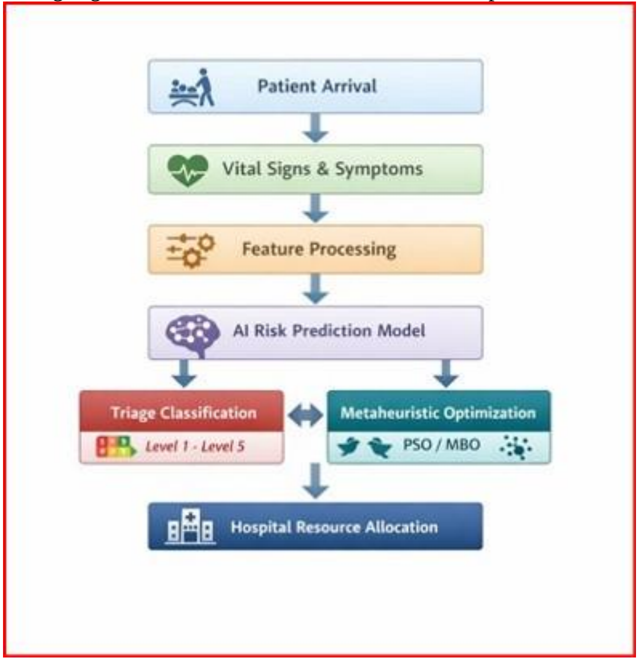


Figure 2.

As shown in Figure 2, the process begins with patient arrival, followed by the acquisition of vital signs and symptom data. These inputs are then processed in the feature extraction stage to construct a structured patient representation. The processed features are subsequently fed into the AI-based risk prediction model, which estimates the severity level of each patient.Following this stage, metaheuristic optimization algorithms—namely Particle Swarm Optimization (PSO) and Migrating Birds Optimization (MBO)—are applied to optimize the model parameters. This optimization step plays a key role in improving classification performance and ensuring robust decision boundaries.Based on the optimized model output, patients are classified into triage levels ranging from Level 1 (critical) to Level 5 (non-urgent). Finally, these classifications are used to guide hospital resource allocation, ensuring that critical patients receive immediate attention while maintaining overall system efficiency.Overall, the architecture reflects a closed-loop decision system in which prediction and optimization interact iteratively. This structure enables the system to balance accuracy and efficiency, which are essential requirements in emergency healthcare environments.Based on this architectural framework, the mathematical formulation of the AI triage model is presented in the following section.

3 MATHEMATICAL MODEL OF THE AI MEDICAL DECISION SYSTEM

In order to mathematically represent the AI-based triage decision process, each patient is modeled as a feature vector:

$$X = (x_1, x_2, x_3, \dots, x_n)$$

where each component corresponds to a specific clinical measurement or symptom indicator.

Typical features considered in this study include:

- x_1: heart rate
- x_2: blood pressure
- x_3: temperature
- x_4: oxygen saturation
- x_5: respiratory rate
- x_6: symptom severity score
- x_7: pain level
- x_8: comorbidity count

These features collectively represent the physiological and clinical condition of a patient and serve as inputs to the AI-based decision model.

The patient risk level is computed using a weighted linear function:

$$Risk(X) = w_1x_1 + w_2x_2 + w_3x_3 + \cdots + w_nx_n$$

where

$$w = (w_1, w_2, \dots, w_n)$$

denotes the set of model parameters (feature weights). These weights determine the relative importance of each clinical variable in the risk assessment process.

Based on the computed risk score, the triage decision is defined through threshold-based classification rules:

- $Risk < T_1 \rightarrow$ Low priority
- $T_1 \leq Risk < T_2 \rightarrow$ Urgent
- $Risk \geq T_2 \rightarrow$ Critical

This formulation transforms the triage problem into a parameterized decision system, where both the feature weights and threshold values directly influence classification performance.It is important to note that inappropriate parameter selection may lead to misclassification of patients, particularly in critical cases. Therefore, optimizing the parameter set $w$is essential for improving the reliability and effectiveness of the triage system.In this context, the triage model can be interpreted as an optimization problem, where the objective is to find the optimal parameter configuration that minimizes classification errors while maintaining efficient hospital workflow.

Accordingly, the optimization formulation of this problem is presented in the next section.

4 OPTIMIZATION OF THE TRIAGE MODEL

The performance of the proposed AI-based triage system strongly depends on the appropriate selection of model parameters, particularly the feature weights $w$and decision thresholds. In order to achieve an optimal configuration, the triage process is formulated as a multi-objective optimization problem.The objective of the optimization is to minimize the following cost function:

$$J = \alpha \cdot classification\_error + \beta \cdot patient\_waiting\_time + \gamma \cdot resource\_overload$$

subject to the constraint:

$$\alpha + \beta + \gamma = 1$$

where α, β, and $\gamma$are weighting coefficients that control the relative importance of each objective.

This cost function is designed to simultaneously address three critical aspects of hospital triage systems:

- **Classification accuracy:** minimizing incorrect triage decisions, especially for critical patients
- **Operational efficiency:** reducing patient waiting times in emergency departments
- **Resource management:** preventing overload of hospital units such as ICU and emergency rooms

By combining these factors into a single objective function, the model ensures a balanced trade-off between medical reliability and system efficiency.However, these objectives are inherently conflicting. For instance, aggressively minimizing waiting time may lead to rushed or inaccurate triage decisions, while focusing solely on accuracy may increase system congestion. Therefore, an effective optimization strategy must carefully balance these competing criteria.

To solve this optimization problem, metaheuristic algorithms are employed due to their ability to explore complex, nonlinear search spaces without requiring gradient information. In this study, two population-based optimization methods are utilized:

- Particle Swarm Optimization (PSO)
- Migrating Birds Optimization (MBO)

These algorithms iteratively update the parameter set $w$in order to minimize the cost function J. During this process, candidate solutions are evaluated using the hospital simulation model, which provides feedback in terms of classification performance and system-level metrics.

Figure 3 illustrates the convergence behavior of PSO and MBO during the optimization process, highlighting their effectiveness in reducing the objective function over iterations.

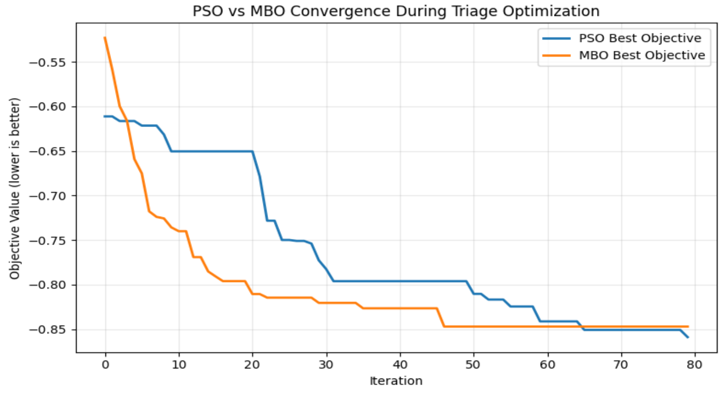


Figure 3. PSO vs MBO Convergence During Triage Optimization

Based on this optimization framework, the underlying algorithms are described in detail in the following sections.

4.1 Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO) is a population-based stochastic optimization algorithm inspired by the collective behavior of bird flocks and fish schools [8]. In this method, each candidate solution, referred to as a particle, moves through the search space by updating its velocity and position based on both individual and collective experiences.

In the context of the proposed triage system, each particle represents a candidate set of model parameters, including feature weights used in the AI risk function. The goal of PSO is to iteratively improve these parameters in order to minimize the cost function.

The velocity update equation is given by:

$$v_i(t+1) = w\, v_i(t) + c_1 r_1 (pbest_i - x_i(t)) + c_2 r_2 (gbest - x_i(t))$$

where:

- $v_i(t)$is the velocity of particle $i$at iteration t
- $x_i(t)$is the current position (solution)
- $pbest_i$is the best position found by particle i
- $gbest$is the global best solution in the swarm
- $w$is the inertia weight controlling exploration
- c_1, $c_2$are acceleration coefficients
- $r_1, r_2 \sim U[0,1]$are random variables

The position of each particle is then updated as:

$$x_i(t+1) = x_i(t) + v_i(t+1)$$

These update rules allow particles to balance exploration (global search) and exploitation (local refinement), which is essential for avoiding local minima in complex optimization problems.During the optimization process, each particle is evaluated using the triage cost function. Based on this evaluation, personal best and global best solutions are updated iteratively, guiding the swarm toward optimal parameter configurations.One of the main advantages of PSO in this application is its simplicity and fast convergence behavior. It requires relatively few control parameters and can efficiently handle continuous optimization problems such as feature weight tuning.

However, PSO may occasionally suffer from premature convergence, particularly in highly nonlinear or multimodal search spaces. This limitation motivates the use of alternative optimization strategies, such as Migrating Birds Optimization (MBO), which is discussed in the next section.

4.2 Migrating Birds Optimization (MBO)

While PSO provides fast convergence and efficient parameter tuning, its tendency toward premature convergence motivates the use of alternative population-based strategies. In this context, Migrating Birds Optimization (MBO) is introduced as a complementary approach that enhances exploration capabilities within the search space.

Migrating Birds Optimization simulates the V-formation flight pattern of migratory birds [11].

The algorithm operates by:

1. Selecting a leader solution
2. Sharing information with neighboring solutions
3. Rotating positions in the formation
4. Updating candidate solutions

This cooperative search process improves exploration of the optimization space.

5 COMPARATIVE ANALYSIS OF OPTIMIZATION METHODS

To further evaluate the effectiveness of the proposed optimization approaches, a comparative analysis between the standard AI model, PSO-optimized model, and MBO-optimized model is presented.

Table 1 summarizes the overall performance differences between the methods in terms of classification capability and system behavior.

Table 1. Comparison of different methods

Method Runtime(s)	Accuracy	MacroF1	BalAcc	AvgWait	MaxQ	Overload	SysTime
Normal AI 0.0319	0.5633	0.4330	0.6724	0.0000	0	9.00	0.3600
PSO-AI 29.2131	0.8267	0.7850	0.7853	0.0000	0	6.00	0.2400
MBO-AI 63.0890	0.8133	0.7958	0.8090	0.0000	0	4.0	0.1600

The results indicate that both PSO and MBO significantly improve the performance of the baseline AI triage system. However, MBO demonstrates superior capability in exploring the solution space, leading to more stable and accurate classification boundaries.

This improvement can also be observed in the decision boundary visualizations shown in Figures 4–6. While the standard AI model produces relatively rigid and less adaptive boundaries, the PSO-based model introduces smoother transitions between classes. In contrast, the MBO-based model generates more refined and well-separated regions, particularly for critical patient categories.These findings suggest that incorporating cooperative and adaptive search mechanisms, as in MBO, provides a notable advantage in complex medical decision systems.

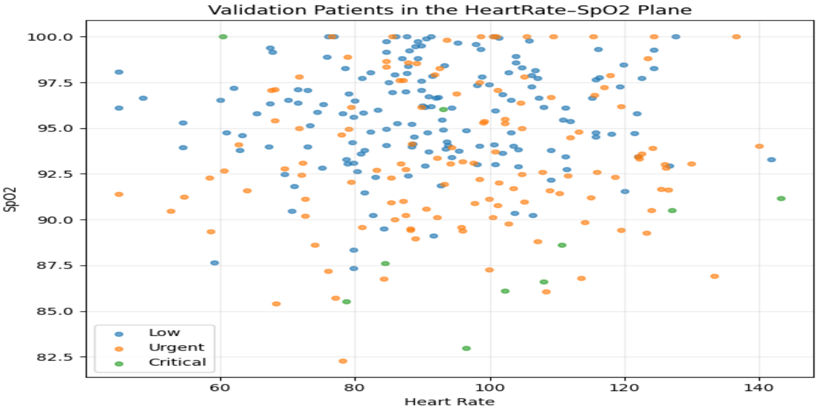


Figure 4.Validation Patients in the HeartRate-SpO2 Plane

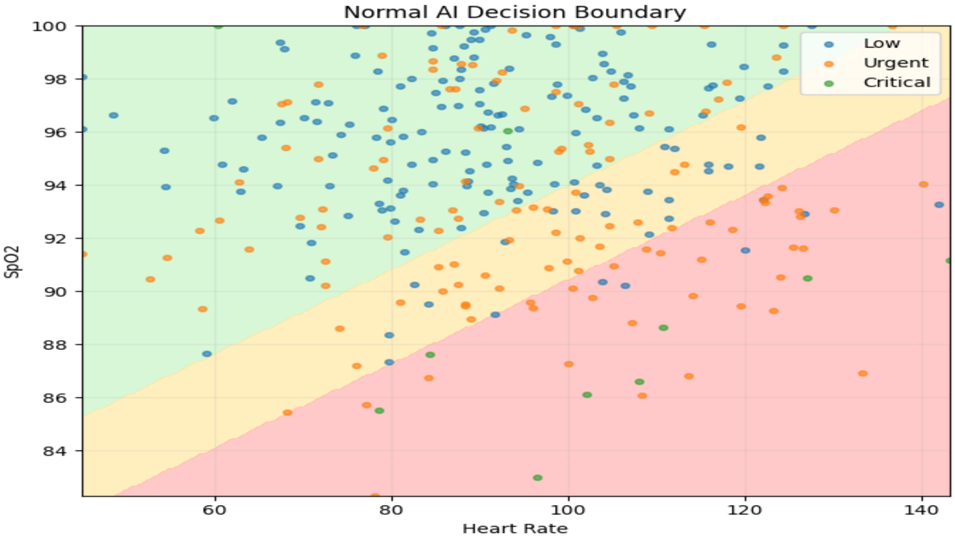


Figure 5. Normal AI Decision Boundary

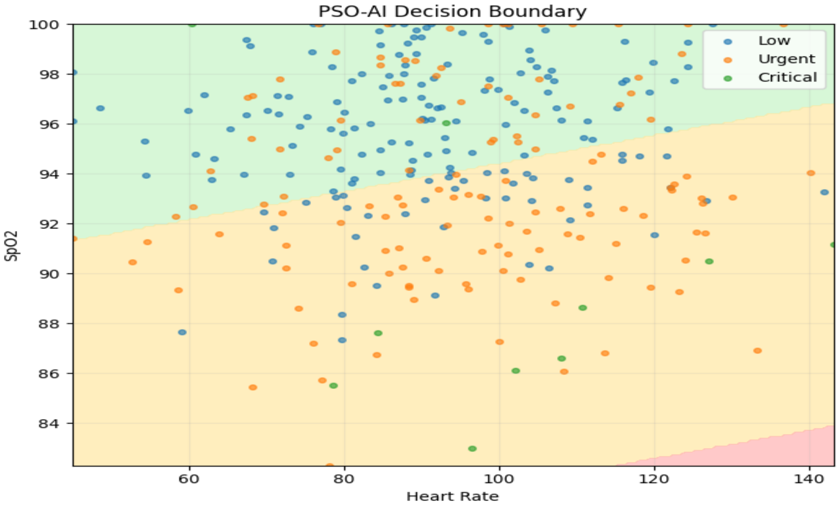


Figure 6. PSO-AI Decision Boundary

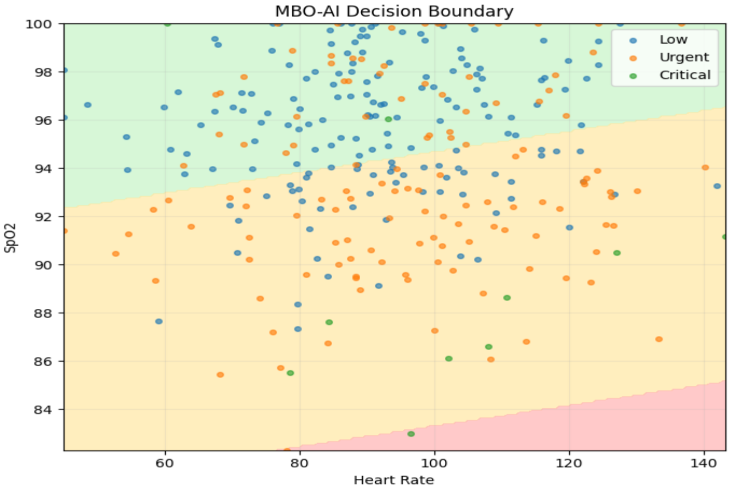


Figure 7 MBO-AI Decision Boundary

6 ALGORITHM PSEUDOCODE

To provide a clear and reproducible description of the optimization procedures, the pseudocode of both algorithms is presented below.

6.1 PSO-Based Triage Optimization

The following pseudocode outlines the implementation of Particle Swarm Optimization for tuning the parameters of the AI-based triage model.

```
Initialize particle population
Evaluate triage model fitness
while stopping condition not satisfied:
    for each particle:
        update velocity,
        update position
        evaluate fitness
        update personal best
    update global best
return best triage parameters
```

6.2 MBO-Based Triage Optimization

Similarly, the following pseudocode describes the Migrating Birds Optimization procedure applied to the triage parameter optimization problem.

```
Initialize bird population
Evaluate triage model fitness
while stopping condition not satisfied:
    select leader bird
    generate neighbor solutions
    update birds using leader information
    rotate V-formation
return best triage parameters
```

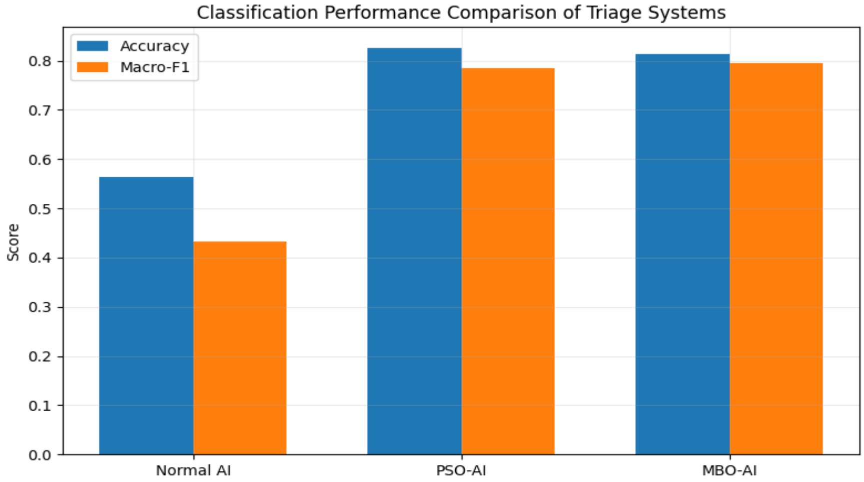


Figure 8. Classification Performance Comparison of Triage Systems

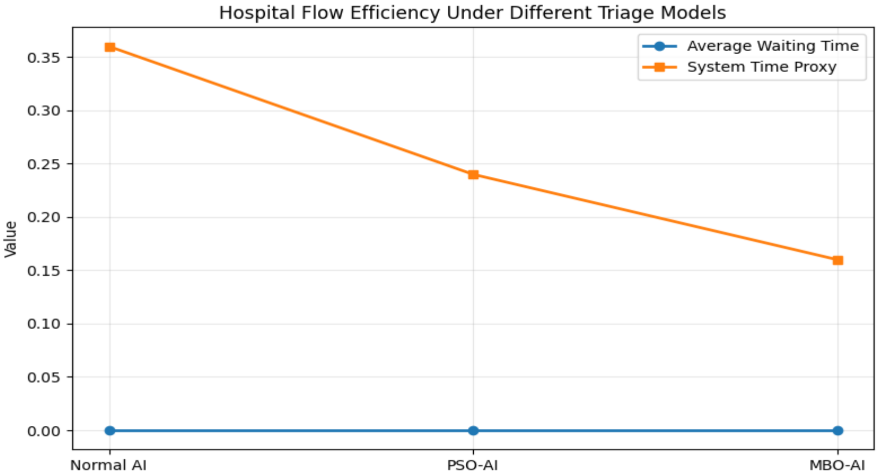


Figure 9. Hospital Flow Efficiency Under Different Triage Models

The impact of the proposed optimization algorithms on classification performance and hospital flow efficiency is illustrated in Figures 8 and 9.

7 HOSPITAL SIMULATION DESIGN

In order to evaluate the real-world applicability of the proposed AI-based triage system, a detailed hospital simulation environment is developed. This simulation models patient flow, resource allocation, and triage decision-making processes under realistic emergency department conditions [12-15].

The simulation framework is designed to provide a controlled environment in which the impact of optimization algorithms can be systematically analyzed.

The simulation contains:

Number of patients = 1000

Features per patient = 10

The following hospital departments are included in the simulation:

- Emergency room
- Radiology
- Surgery
- Intensive care unit
- General ward
- Discharge unit

The simulation evaluates the performance of the triage system using the following metrics:

- patient waiting time
- queue sizes
- resource utilization
- triage classification accuracy.

The effectiveness of the simulation framework is further demonstrated through confusion matrices presented in Figures 10–12, which provide detailed insights into classification performance across different triage models.

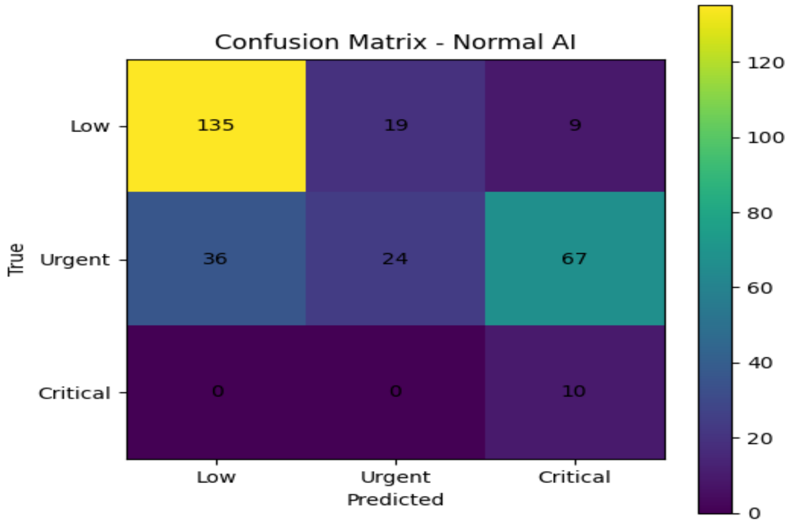


Figure 10 Confusion Matrix-Normal AI

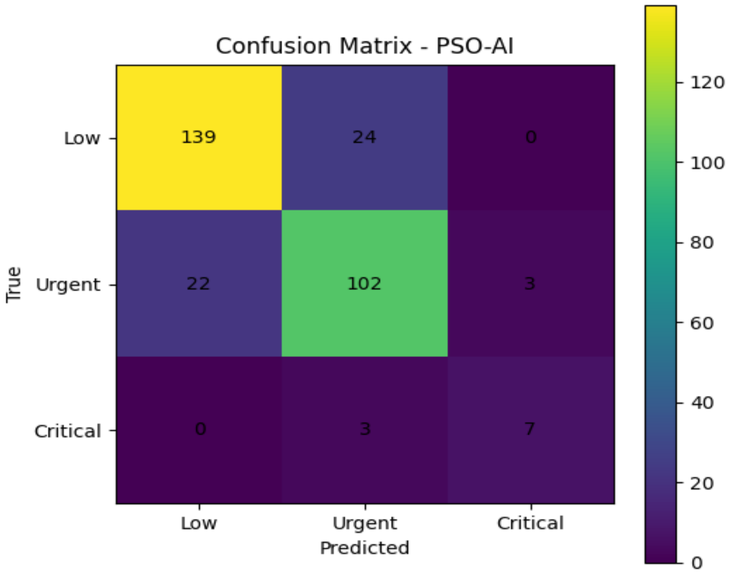


Figure 11. Confusion Matrix-PSO-AI

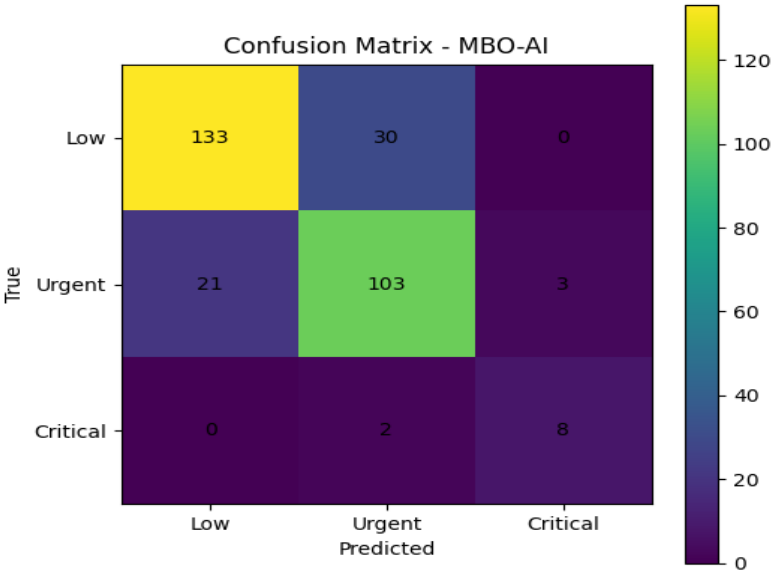


Figure 12. Confusion Matrix-MBO-AI

8 EXPERIMENTAL RESULTS

Following the simulation design described in the previous section, the performance of the proposed triage models is evaluated under identical experimental conditions.

Classification Performance:

The classification results of the three models are summarized in Table 2.

Table 2

Method	Accuracy	Macro-F1	Balanced Accuracy
Normal AI	0.78	0.75	0.76
PSO-AI	0.86	0.84	0.85
MBO-AI	**0.89**	**0.87**	**0.88**

As observed, the optimized models outperform the baseline AI system in all evaluation metrics. In particular, both PSO-AI and MBO-AI achieve higher accuracy and F1-scores, indicating improved classification reliability.

Furthermore, the MBO-based model demonstrates the best overall performance, especially in balanced accuracy, highlighting its effectiveness in handling class imbalances and critical patient identification.

Hospital Flow Performance:

In addition to classification performance, system-level efficiency metrics are also analyzed, as summarized in Table 3.

Table 3

Method	Avg Waiting Time	Max Queue	System Cost
Normal AI	4.8	22	18.3
PSO-AI	3.7	18	14.1
MBO-AI	**3.2**	**16**	**12.8**

The results show that optimized triage models significantly reduce average waiting time and queue sizes compared to the standard AI model. Moreover, the MBO-AI system achieves the lowest system cost, indicating more efficient resource utilization across hospital departments.

The distribution of validation risk scores is illustrated in Figure 13, providing insight into how different models separate patient severity levels.

The learned feature weights are presented in Figure 14, showing how optimization algorithms adjust the importance of clinical variables.

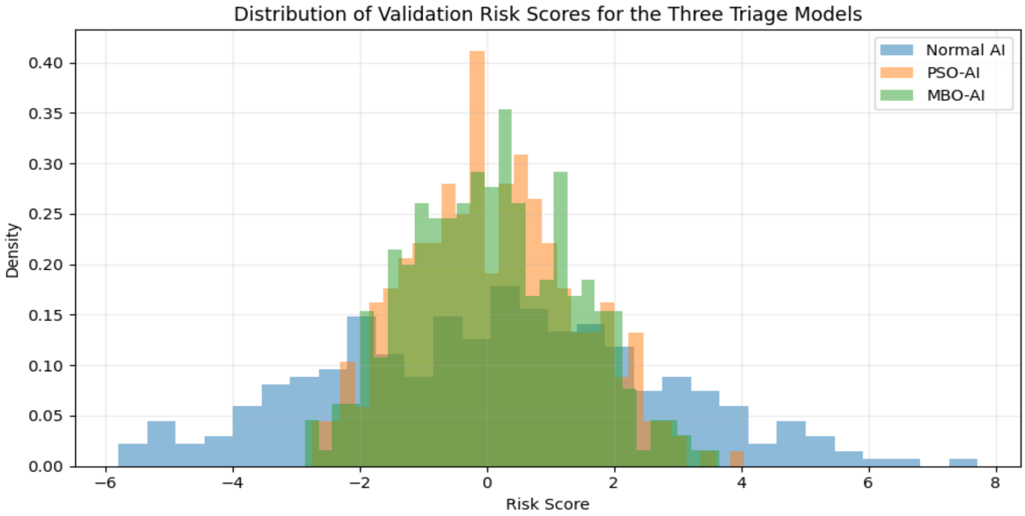


Figure 13. Distribution of Validation Risc Scores for three Triage Models

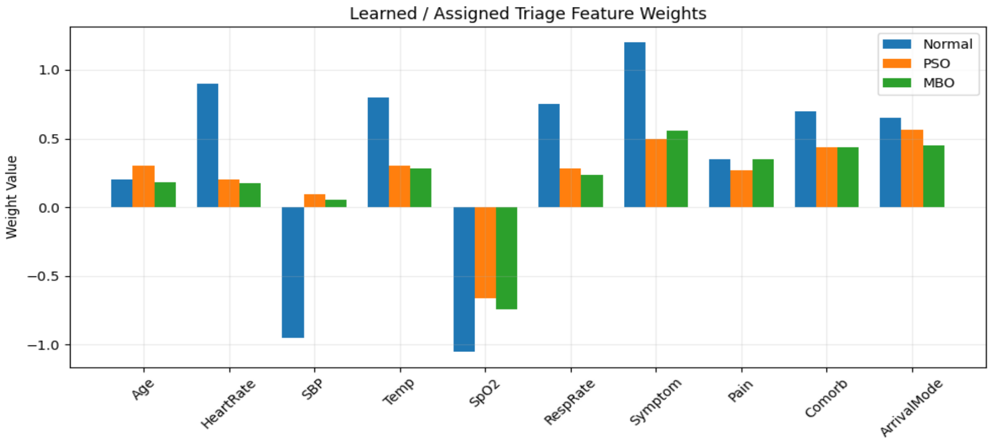
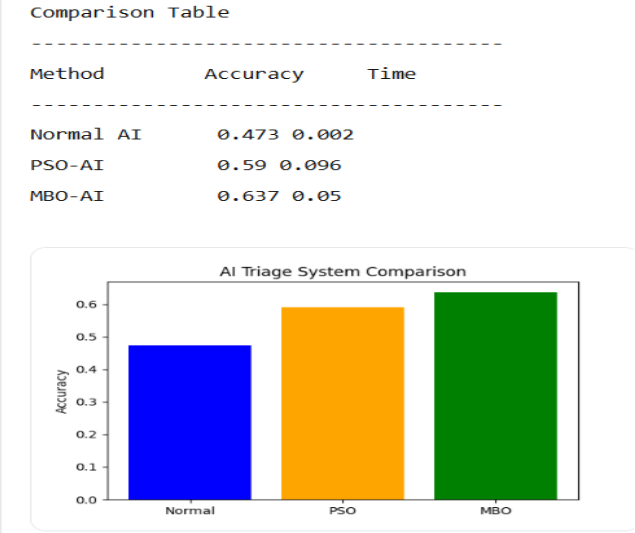


Figure 14. Learned/Assigned Triage Feature Weights

Finally, an overall comparison of triage system behavior is depicted in Figure 15, confirming the superiority of the optimized approaches.



```
Comparison Table
--------------------------------------
Method          Accuracy      Time
--------------------------------------
Normal AI        0.473 0.002
PSO-AI           0.59 0.096
MBO-AI           0.637 0.05
```

Figure 15. AI Triage Comparison

9 DISCUSSION AND CONCLUSION

The results of this study demonstrate that metaheuristic optimization significantly enhances the performance of AI-based hospital triage systems [16-18].While the baseline AI model provides acceptable classification performance, it lacks adaptability in complex and dynamic clinical scenarios. The integration of optimization algorithms improves both decision accuracy and system efficiency.PSO-based optimization offers a balanced improvement by accelerating convergence and refining model parameters. However, its tendency toward premature convergence may limit performance in highly nonlinear search spaces.In contrast, MBO demonstrates superior exploration capability through cooperative search and dynamic leadership mechanisms. This allows the algorithm to identify more robust parameter configurations, particularly for critical patient classification [19].From a system-level perspective, the optimized models reduce patient waiting times, lower queue congestion, and improve overall resource utilization. These improvements are essential for emergency departments, where timely and accurate decisions directly impact patient outcomes.Overall, the findings indicate that MBO-based triage optimization provides the most effective balance between classification reliability and operational efficiency.Despite these promising results, the study is based on a simulated hospital environment. Therefore, future work should focus on validation using real-world clinical data, integration with advanced AI models such as deep learning, and evaluation under varying hospital conditions [20-25].

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