A Hybrid MCDM Framework for Selecting Optimal AI Algorithms in Real-Time Infrared Signal Detection Systems

Nikola GLIGORIJEVIĆ[1], Dejan VIDUKA[2]*, Stefan POPOVIĆ[2], Danilo STRUGAREVIĆ[3], Vladimir ČABRIĆ[1]

[1] Faculty of Information Technologies, Alfa BK University, Bulevar marsala Tolbuhin 8, 1100 Belgrade, Serbia
nikola.gligorijevic@alfa.edu.rs, vladimir.cabric@alfa.edu.rs

[2] Faculty of Mathematics and Computer Sciences, Alfa BK University, Bulevar marsala Tolbuhin 8, 1100 Belgrade, Serbia
dejan.viduka@alfa.edu.rs, stefan.popovic@alfa.edu.rs

[3] Academy of Applied Preschool Teaching and Health Studies, Balkanska 18, 37000 Kruševac, Serbia
strugarevic@avmss.edu.rs

Abstract: This paper proposes a hybrid multi-criteria decision-making (MCDM) framework for selecting the optimal AI algorithms in the context of real-time infrared signal detection systems. Five performance criteria were considered, namely the processing speed, detection accuracy, segmentation efficiency, noise robustness and energy efficiency, reflecting the requirements of real-time image processing and embedded computer vision systems. This framework integrates the SWARA method for expert-based criteria weighting with Net Worth Analysis (NWA) for algorithm ranking, enabling a transparent and systematic evaluation. The experimental results show that the Fast R-CNN algorithm achieves the highest overall performance, while algorithms such as EfficientDet obtain lower scores and require further refinement to be effectively used in real-time infrared signal detection applications. To sum up, the proposed method addresses the current lack of structured decision-support tools for selecting among various AI-based infrared signal detection models under operational constraints. The research findings provide actionable guidance for researchers and practitioners developing embedded AI, surveillance and automated monitoring systems.

Keywords: Multi-criteria decision making (MCDM), SWARA method, Net Worth Analysis (NWA), Artificial intelligence, Image processing algorithms, Computer vision, Algorithm evaluation.

1. Introduction

In today's digital landscape, real-time infrared (IR) detection is vital in security, surveillance, autonomous control and industrial automation (Javaid et al., 2021). Real-time infrared (IR) detection refers to the immediate sensing or imaging of heat radiation emitted by objects without noticeable delay. In practice, IR detection enables the instant recognition of thermal signatures using IR cameras or sensors, which is essential for surveillance, autonomous navigation, industrial safety and embedded computer vision systems (Hou et al., 2022).

IR image-processing algorithms enable a fast, accurate object identification under variable conditions, supporting critical decisions in dynamic settings (Varshney & Arora, 2004). Traditional approaches often lacked robustness in complex environments, whereas AI, particularly convolutional neural network (CNN)-based deep learning models, demonstrated an enhanced capability for hierarchical feature extraction and nonlinear pattern modeling from high-dimensional infrared data. Architectures such as U-Net, YOLO and Fast R-CNN improve the precision, processing speed and segmentation efficiency through end-to-end feature learning and adaptive representation of thermal patterns.(Alotaibi et al., 2022; Mokari et al., 2023).

Yet selecting the best algorithm for IR detection remains challenging: performance varies across speed, accuracy, noise robustness and energy efficiency (Rogers et al., 1995), and prior work rarely offers structured frameworks uniting expert insight with objective aggregation. To address this gap, a hybrid MCDM model combining SWARA for criteria weights and Net Worth Analysis (NWA) for ranking was applied, yielding a transparent, expert-driven evaluation (Martyushev et al., 2023). The framework evaluates nine AI-based algorithms against five expert-defined performance criteria, integrating expert judgment with quantitative aggregation for real-time decision support. Despite the availability of numerous AI architectures for infrared image analysis, including convolutional neural network (CNN)-based detection and segmentation models such as U-Net, YOLO variants, Faster R-CNN, lightweight MobileNet-based networks, and optimized real-time detection frameworks, comprehensive and reproducible evaluation frameworks tailored specifically to real-time operational constraints remain limited (Rehman et al., 2021).

https://doi.org/10.24846/v35i1y202604 ICI Bucharest © Copyright 2012-2025. All rights reserved

Accordingly, the research question guiding this study is which AI algorithms provide optimal trade-offs across multiple performance dimensions for infrared signal detection under real-time operational constraints.

The remainder of this paper is structured as follows. Section 2 presents the previous research relevant to IR detection and the multi-criteria evaluation of AI models. Section 3 introduces the proposed hybrid SWARA-NWA methodology. Further on, Section 4 describes the employed evaluation criteria and selected AI algorithms, while Section 5 presents the obtained results and a sensitivity analysis. Section 6 discusses the obtained ranking results, the comparative performance of the evaluated algorithms across the defined criteria, the methodological implications of the SWARA-NWA framework, and its practical relevance for real-time infrared detection systems. Finally, Section 7 concludes this paper and outlines possible directions for future research (Gligorijević et al., 2025).

2. Previous Research

Recent work on selecting AI algorithms for real-time use largely emphasizes technical benchmarks for single models, while fewer studies adopt structured, multi-criteria frameworks that combine expert judgment with quantitative scoring. Decision-theoretic approaches to algorithm assessment are reviewed, with an emphasis on MCDM techniques: SWARA and Net Worth Analysis (NWA) that underpin the proposed hybrid framework.

2.1 Decision - Theoretic Framework and the Relevance of the Hybrid SWARA-NWA Model

Decision theory provides a foundation for comparing alternatives across conflicting criteria aligned with application constraints such as accuracy, speed, and robustness (Burggräf et al., 2020). Among the common multi-criteria decision-making (MCDM) methods, AHP, TOPSIS, PIPRECIA, and SWARA are frequently applied (Ulutaș et al., 2020); AHP supports pairwise structuring in imaging tasks (Lin et al., 2020), while TOPSIS and VIKOR are popular in engineering and infrastructure planning (Siddique et al., 2021). SWARA, proposed by Keršulienė et al. (2010), assigns criterion weights through stepwise expert adjustment, offering a faster and more intuitive process than AHP (Stanujkic et al., 2015), and has demonstrated adaptability in diverse domains such as packaging design, personnel selection, and supplier evaluation (Alimardani et al., 2013). However, SWARA alone does not provide a final aggregation or ranking, which is effectively addressed by Net Worth Analysis (NWA), a method that transparently aggregates weighted criteria into the overall scores (Rong &Yu, 2023), with successful applications in diagnostics, environmental decisions, and airline performance (Uzun et al., 2021). Despite the individual uses of SWARA and NWA, their combined implementation for evaluating AI algorithms remains limited, as prior studies have favored other hybrids such as SWARA-VIKOR or PIPRECIA-OCRA (Popović et al., 2025). To bridge this gap, this study integrates SWARA and NWA into a unified framework for ranking AI algorithms in real-time infrared detection, where expert intuition and quantitative performance must be jointly considered. Such an approach responds to the lack of reproducible, transparent decision models in IR detection research (Manolakis & Shaw, 2002), contributing to the development of structured, energy-efficient, and scalable evaluation frameworks suitable for safety-critical applications.

3. Methodology

In order to address the research objective of identifying the most suitable artificial intelligence algorithm for real-time infrared signal detection, this study employs a hybrid multi-criteria decision-making (MCDM) approach. This methodology integrates the SWARA method for deriving the relative importance of the evaluation criteria and the NWA for aggregating algorithm performance scores. This combination enables a structured, expert-informed, and transparent evaluation process that reflects both thesubjective judgments and quantitative assessments. The following subsections describe each component of the proposed framework in detail.

3.1 Research Design Overview

The research design is based on a structured two-stage decision framework in which SWARA is first employed to determine the relative importance of the evaluation criteria, followed by NWA for aggregating the algorithm performance scores and generating the final ranking. The research aims to identify the algorithm that provides the best balance of performance across five criteria: processing speed, detection accuracy, segmentation efficiency, robustness to noise, and energy efficiency.

The methodological framework was selected to address the research question defined in the introduction and is particularly suited for environments where both subjective expert opinion and objective scoring are required. The hybrid model allows for the translation of expert judgments into quantitative weights (SWARA), which are then used for aggregating and ranking the alternatives through NWA.

3.2 The Application of the SWARA Method

In this study, the SWARA methodology was applied to evaluate and rank algorithms for infrared signal detection. It enables a systematic weighting of the employed criteria based on their relative importance (Puška et al., 2023). Unlike pairwise comparison methods such as AHP, SWARA allows experts to express preferences sequentially, reducing the cognitive load and improving consistency in dynamic environments (Hashemkhani Zolfani et al., 2018). Originally introduced by Keršulienė et al. (2010), SWARA offers flexibility by letting decision-makers articulate judgments without fixed scales. Through expert-based weighting, it reconciles differing opinions and supports rational, transparent decision-making. As a decision-support tool, it is broadly applicable across practical and scientific contexts with competing objectives (Rong &Yu, 2023).

Below are the steps used in the research:

Step 1: Prioritization of criteria

Each decision maker determines the priorities of the criteria according to their importance. If there are l decision makers and n criteria, the grade assigned to the criterion j by decision maker k is marked as p_{kj}, where $j = 1,2,...,n$, and $k = 1,2,...,l$.

Step 2: Geometric mean of the decision maker's ratings

The individual ratings of all decision makers are combined using the geometric mean according to equation (1), where p_j denotes the combined relative importance of each criterion:

$$p_j = \left(\prod_{k=1}^{l} p_{k_j} \right)^{\frac{1}{l}}, \forall j \tag{1}$$

Step 3: Calculating the relative importance (comparative importance)

All criteria are ranked in a descending order according to their relative importance ratings. Then, starting from the second ranked criterion, the comparative importance of criterion j relative to the preceding criterion $j-1$ is denoted as s_j. This relative importance is calculated according to equation (2):

$$s_j = p_{j-1} - p_j \tag{2}$$

Step 4: Calculating the coefficients for each criterion

The coefficients for each criterion are obtained by pairwise comparison and are denoted as c_j. This coefficient shows how much the criterion $j+1$ is important in relation to the criterion j. The coefficients are calculated based on equation (3):

$$c_j = \{1, j = 1; s_{j+1}, j = 2, ..., n\} \tag{3}$$

Step 5: Calculating the adjusted weights for all criteria

The corrected weights s'_j for all criteria are calculated according to equation (4):

$$s_j = \{1, j = 1; s_{j-1}, j = 2, ..., n\} \tag{4}$$

Step 6: Calculating the final criteria weights

The final weights w_j for each criterion are calculated using equation (5):

$$w_j = \frac{s'_j}{\sum_{k=1}^{n} s'_k} \tag{5}$$

3.3 Net Worth Analysis (NWA)

NWA is a key component of multi-criteria decision-making (MCDM) used for evaluating alternatives based on predefined criteria (Bakir et al., 2020). It is particularly effective when multiple, potentially conflicting factors must be assessed simultaneously, as it assigns numerical scores reflecting the overall desirability of each option (Zangemeister, 2014). In complex contexts such as AI algorithm evaluation, where diverse performance indicators are considered, NWA

ICI Bucharest © Copyright 2012-2025. All rights reserved

provides a transparent and easily interpretable ranking mechanism. By summing up the the weighted values of all the relevant criteria, it yields cumulative scores that clearly identify the most suitable alternative (Čupić et al., 2003).

The final score for each algorithm is calculated using the following equation:

$$NWA_i = \sum_{j=1}^{n} q_j x_{ij} \tag{6}$$

where:

- NWA_i denotes the final cumulative score of algorithm *i*,
- q_j is the normalized final weight of the criterion *j* (from SWARA),
- x_{ij} represents the performance value of algorithm *i* with respect to the criterion *j*,
- *n* denotes the total number of criteria.

Since the SWARA method is applied to the alternatives for each criterion, the variable x_{ij} corresponds directly to the SWARA-derived performance weight w_{ij}. This notation was clarified in order to ensure consistency with the numerical example.

This approach provides a holistic evaluation of alternatives, taking into account both the importance of each criterion and the algorithm's performance under that criterion. In this study, a simplified form of NWA was applied, in which the final scores represent the sum of the normalized SWARA-derived performance weights for each algorithm across all criteria. This approach is consistent with NWA's additive structure and is widely used in MCDM applications where expert-based relative evaluations are available instead of raw numerical performance data.

3.4 The Integration of SWARA-NWA and Expert Consensus

The integration of SWARA and NWA was performed sequentially to ensure methodological consistency and reliability. Initially, SWARA was applied for determining the relative importance of the evaluation criteria through an expert-based, stepwise comparison, generating a normalized weight vector that captured the collective expert judgment (Demirci, 2022). These weights were then used as inputs for the NWA stage, where the algorithm performance values were aggregated into final net scores. To enhance their validity, the expert assessments were refined through a two-round Delphi process, enabling the convergence of opinions via anonymous feedback and iterative refinement (Hsu & Sandford, 2007). This hybrid procedure combines SWARA's consensus-driven weighting with NWA's objective aggregation, ensuring that the expert-defined priorities are mathematically embedded in the final ranking. Consequently, the framework achieves transparency, robustness, and scalability, making it suitable for real-world AI evaluation contexts such as embedded systems and surveillance technologies. It is important to clarify that SWARA was applied at two levels, namely to determine the relative importance of the employed criteria and to derive the relative performance weights of the evaluated algorithms for each individual criterion.

This layered application enables experts to express comparative judgments both across criteria and across alternatives, ensuring the consistent integration of expert knowledge throughout the evaluation process.

4. Evaluation Criteria and Algorithms

In line with the objective of selecting the most suitable AI algorithm for infrared signal detection under real-time constraints, the evaluation was based on five carefully chosen criteria. These criteria reflect both the technical performance metrics and operational constraints commonly encountered in embedded and surveillance systems. The selection was informed by domain-specific literature (Martyushev et al., 2023) and refined through expert consensus using the Delphi method.

4.1 Defining the Criteria

The criteria and their weights are defined below, which are crucial for the selection of algorithms for the detection of infrared signals. This methodology allows experts to express their opinions and evaluate the importance of the employed criteria in a simpler way.

The five evaluation criteria considered in this study are defined as follows.

Processing speed: This criterion measures how quickly algorithms can process data and make decisions. Processing speed is crucial for real-time applications, where a fast response is required (Habeeb et al., 2019);

Detection accuracy: This criterion evaluates the algorithm's ability to accurately recognize and classify infrared signals. High precision is essential for reducing false positive and negative detections (Rogers et al., 1995);

Segmentation efficiency: This criterion measures how accurately algorithms can separate objects within an image. An effective segmentation allows the accurate identification of the boundaries between objects (Clinton et al., 2010);

Robustness to noise: This criterion assesses how well algorithms can perform in the presence of noise and other disturbances. Robustness is a key performance criterion under varying imaging and environmental conditions (Souffi et al., 2021);

Energy efficiency: This criterion measures how much energy the algorithms consume during processing. Energy efficiency is especially important for battery-powered devices (Martyushev et al., 2023);

Collectively, these five criteria provide a comprehensive framework for assessing the trade-offs between performance, responsiveness and resource usage across various algorithms.

4.2 Defining the Priority of the Criteria

The priority of the employed criteria is defined in Table 1 and it is the task of the researcher. Researchers define priorities in accordance with the specific requirements of the analysis, and with the technical requirements and available resources. The goal is to enable researchers to systematically determine the weight coefficients of the criteria through a simple process of comparison based on importance, which would enable the efficient selection of algorithms for the detection of infrared signals. The weights derived through the SWARA method ensure that the final rankings are grounded on expert-informed priorities, enhancing the interpretability and transparency of the decision-making process.

Table 1. The relative importance of the ranked criteria for algorithm selection

Criterion	s_j	k_j	w_j	q_j
Processing speed	0.20	1.12	1.000	0.245
Detection accuracy	0.15	1.15	0.870	0.213
Segmentation efficiency	0.10	1.10	0.791	0.193
Robustness to noise	0.08	1.08	0.732	0.178
Energy efficiency	0.12	1.12	0.654	0.160

Table 1 follows the definitions in subsection 3.2, where s_j, k_j, w_j and q_j correspond to the SWARA parameters described in Steps 3 to 6.

4.3 Algorithms for the Detection of Infrared Signals

The selection of the algorithms for this study was guided by their broad application in image processing and artificial intelligence, as well as their proven efficiency in pattern recognition and classification. The chosen models encompass both lightweight architectures optimized for constrained environments and deep networks focused on high accuracy, providing a comprehensive comparative basis. Binary Segmentation enables a rapid separation of objects from the background using contrast and brightness, making it suitable for real-time detection (Sarraf, 2017). U-Net, a convolutional architecture, achieves a high segmentation accuracy even under low contrast, proving effective in infrared analysis (Siddique et al., 2021). YOLO (You Only Look Once) offers real-time object detection by processing entire images simultaneously, which is valuable in surveillance contexts (Yin et al., 2020). FCNs (Fully Convolutional Networks) perform pixel-level segmentation for a detailed object boundary recognition, while ResNet's residual architecture facilitates deep feature learning and avoids overfitting in classification and detection tasks (He et al., 2016). EfficientDet combines speed and accuracy through an optimized model scaling, being ideal for resource-limited applications (Jia et al., 2022). DeepLab employs dilated convolutions for a multi-scale segmentation, improving the detection accuracy in complex infrared scenes (Liu et al., 2022). Fast R-CNN combines high detection accuracy with efficient object localization, enabling precise real-time detection. Finally, MobileNet, a compact CNN

ICI Bucharest © Copyright 2012-2025. All rights reserved

model for embedded systems, balances speed and accuracy, which makes it suitable for low-power infrared sensors (Yuan et al., 2022). Collectively, these algorithms address diverse challenges in infrared signal detection and form a robust foundation for identifying optimal approaches across varying operational contexts.

4.4 The Selection and Work of Experts

The selection and engagement of experts were essential for the MCDM process (Fei et al., 2019). Seven experts were chosen based on their professional background in artificial intelligence, image processing, computer vision and cybersecurity, each with over seven years of domain-specific experience to ensure a multidisciplinary perspective. In order to minimize potential bias, the Delphi method was employed to structure the assessment process (Bećirović et al., 2023). In the first phase, the experts independently rated the importance of predefined criteria, and their inputs were aggregated via geometric mean as required by SWARA. In the second phase, they reviewed the collective results and refined their judgments, achieving consensus while avoiding a dominant influence (Harvey & Mueller, 2021). Anonymous evaluations and standardized guidelines further supported impartiality. The experts performed two main tasks: defining the relative importance of criteria and assessing algorithm performance.

Their consensus formed the basis for the SWARA-NWA weighting, ensuring methodological transparency and grounding the obtained results on real-world expertise.

5. Research Results

This section presents the results of the multi-criteria evaluation of nine AI algorithms used for real-time infrared signal detection. The results are structured around the five evaluation criteria defined earlier, namely the processing speed, detection accuracy, segmentation efficiency, robustness to noise and energy efficiency. Using the SWARA method, expert-based weights were calculated for each criterion, and the NWA method was applied for computing the final performance scores for each algorithm. These findings address the research question posed in the introduction and provide actionable insights into which algorithms provide the most balanced performance under real-time operational constraints.

All nine algorithms listed in subsection 4.3 were evaluated in the study. Figures 1-5 illustrate the performance distributions for a subset of five algorithms for improved visual clarity, while the complete results for all nine evaluated algorithms are summarized in the final aggregated results table (Table 2). The values shown in Figures 1 to 5 correspond to the SWARA-derived normalized performance weights for each algorithm and criterion.

5.1 Evaluation of the Algorithms According to the Processing Speed Criterion

The results for processing speed are presented in Figure 1 and Table 2. Fast R-CNN and Binary Segmentation achieved the highest scores (0.245),

Table 2. Evaluation of algorithms - final results

Algorithm	Processing speed (q_j)	Detection accuracy (q_j)	Segmentation efficiency (q_j)	Robustness to noise (q_j)	Energy efficiency (q_j)	NWA (Sum of final weights)
Binary Segmentation	0.245	0.213	0.193	0.178	0.160	1.079
U-Net	0.213	0.245	0.213	0.160	0.213	1.058
YOLO	0.193	0.193	0.245	0.193	0.193	1.017
FCN	0.178	0.178	0.178	0.213	0.178	0.925
ResNet	0.160	0.160	0.160	0.245	0.245	0.970
EfficientDet	0.160	0.160	0.160	0.160	0.160	0.800
DeepLab	0.213	0.245	0.213	0.213	0.213	1.107
Fast R-CNN	0.245	0.213	0.245	0.245	0.245	1.193
MobileNet	0.193	0.193	0.245	0.193	0.193	1.017

indicating their suitability for time-sensitive applications. U-Net followed with 0.213, while YOLO and MobileNet demonstrated a moderate performance (0.193). Lower processing speed scores were observed for FCN, ResNet, and EfficientDet, suggesting a reduced suitability for real-time scenarios.

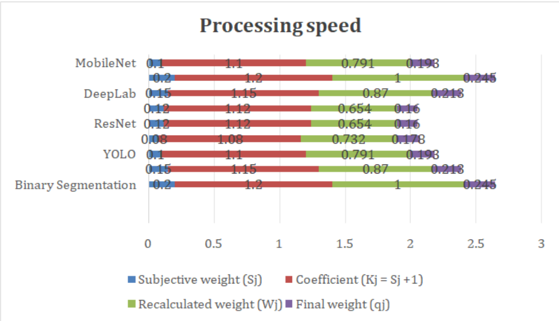

Figure 1. Evaluation of the algorithms in accordance with the Processing speed criterion

5.2 Evaluation of the Algorithms According to the Detection Accuracy Criterion

In terms of detection accuracy (Figure 2 and Table 2), U-Net and DeepLab achieved the highest scores (0.245), followed by Fast R-CNN and Binary Segmentation (0.213). A moderate accuracy was observed for YOLO and MobileNet (0.193), whereas ResNet, FCN, and EfficientDet obtained the lowest scores.

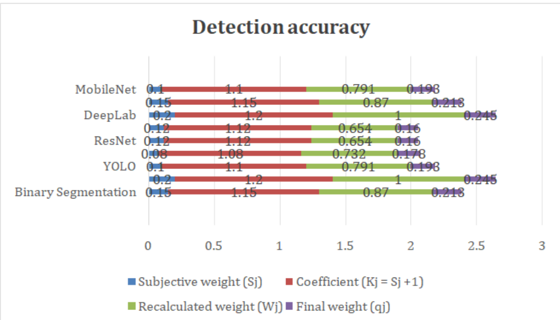

Figure 2. Evaluation of the algorithms in accordance with Accuracy of detection criterion

5.3 Evaluation of the Algorithms According to the Segmentation Efficiency Criterion

Figure 3 and Table 2 present the results for segmentation efficiency. YOLO, MobileNet, U-Net, and DeepLab achieved the highest scores (0.245 or 0.213), which are consistent with their architectural design for semantic segmentation tasks. A moderate segmentation performance was observed for Fast R-CNN, Binary Segmentation, and FCN (in the range from 0.178 to 0.193), whereas ResNet and EfficientDet recorded the lowest scores for this criterion.

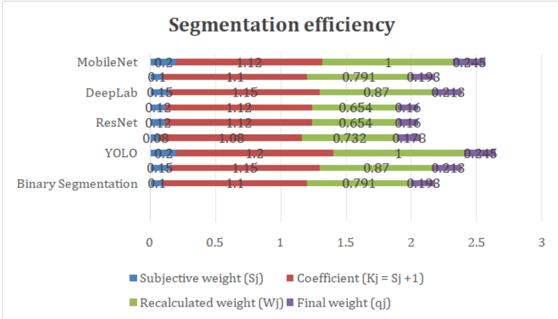

Figure 3. Evaluation of the algorithms in accordance with the Segmentation efficiency criterion

Future research may incorporate additional robustness analyses using alternative MCDM methods or independent expert panels to further confirm the stability and reliability of the obtained results.

5.4 Evaluation of the Algorithms According to the Robustness to Noise Criterion

When robustness to noise was considered (Figure 4 and Table 2), ResNet and Fast R-CNN achieved the highest scores (0.245). FCN, U-Net, and DeepLab followed with scores of 0.213. Lower scores were observed for YOLO, MobileNet, Binary Segmentation, and EfficientDet, indicating potential limitations in noisy environments.

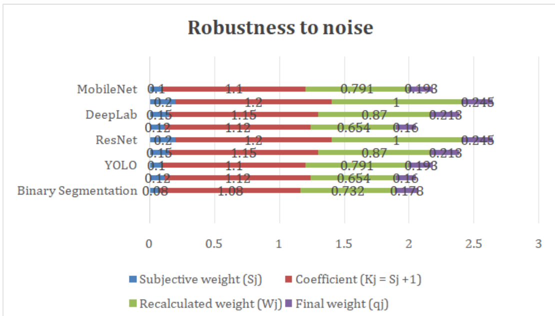

Figure 4. Evaluation of the algorithms in accordance with the robustness to noise criterion

ICI Bucharest © Copyright 2012-2025. All rights reserved

5.5 Evaluation of the Algorithms According to the Criterion Energy Efficiency

Regarding energy efficiency (Figure 5 and Table 2), Fast R-CNN and ResNet achieved the highest scores (0.245), followed by U-Net and DeepLab (0.213). A moderate energy performance was observed for YOLO, MobileNet, and FCN, whereas Binary Segmentation and EfficientDet obtained the lowest efficiency ratings (0.160).

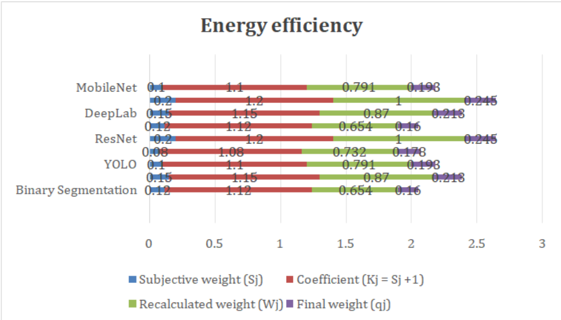

Figure 5. Evaluation of the algorithms in accordance with the Energy efficiency criterion

5.6 Sensitivity Analysis for the Criteria Weights

To test the robustness of the obtained rankings, a sensitivity analysis was performed by varying the weights for each criterion by ±10%, while keeping the remaining criteria weights proportionally adjusted to maintain a sum of 1. This analysis (Table 3) evaluates the impact of weight changes on the final algorithm rankings. The results of the sensitivity analysis indicate that Fast R-CNN consistently preserved its top rank under all scenarios, suggesting a strong robustness of its overall performance. In contrast, Binary Segmentation and YOLO were more sensitive to changes in the processing speed and segmentation efficiency weights, indicating their rankings are more context-dependent.

This analysis confirms that the proposed hybrid SWARA-NWA decision-making framework demonstrates stability under minor weight perturbations; however, decision-makers should

Table 3. Sensitivity Analysis Results

Scenario	Rank	Algorithm	Score
Processing speed (−10%)	1	Fast R-CNN	0.238
	2	DeepLab	0.220
	3	U-Net	0.210
Processing speed (+10%)	1	Fast R-CNN	0.238
	2	DeepLab	0.220
	3	U-Net	0.210
Detection accuracy (−10%)	1	Fast R-CNN	0.233
	2	DeepLab	0.220
	3	Binary Segmentation	0.211
Detection accuracy (+10%)	1	Fast R-CNN	0.237
	2	DeepLab	0.224
	3	Binary Segmentation	0.216
Segmentation efficiency (−10%)	1	Fast R-CNN	0.235
	2	DeepLab	0.223
	3	Binary Segmentation	0.213
Segmentation efficiency (+10%)	1	Fast R-CNN	0.239
	2	DeepLab	0.221
	3	Binary Segmentation	0.212
Robustness to noise (−10%)	1	Fast R-CNN	0.234
	2	DeepLab	0.222
	3	Binary Segmentation	0.212
Robustness to noise (+10%)	1	Fast R-CNN	0.240
	2	DeepLab	0.219
	3	Binary Segmentation	0.210
Energy efficiency (−10%)	1	Fast R-CNN	0.234
	2	DeepLab	0.223
	3	Binary Segmentation	0.214
Energy efficiency (+10%)	1	Fast R-CNN	0.239
	2	DeepLab	0.220
	3	Binary Segmentation	0.210

remain aware of contextual dependencies when applying this framework to real-world environments.

5.7 Final Results and the Risk of Expert Bias

Despite employing the Delphi method for mitigating individual biases and achieving expert consensus, certain risks such as selection bias, confirmation bias, and anchoring effects could not be fully eliminated. Anonymity during scoring and aggregation via geometric means were applied for reducing these influences, though future studies should complement expert input with empirical benchmark data in order to enhance objectivity. The integrated SWARA-NWA based evaluation revealed that Fast R-CNN achieved the highest overall ranking, demonstrating a consistent performance across all the five criteria, while DeepLab and Binary Segmentation also performed strongly with regard to certain evaluation criteria. In contrast, algorithms such as EfficientDet and FCN ranked lower, indicating a limited suitability for real-time or resource-constrained applications. These findings confirm that the optimal algorithm selection depends on contextual priorities and highlight the robustness of the proposed hybrid decision framework in balancing expert judgment with a quantitative evaluation.

6. Discussion

The hybrid SWARA-NWA-based analysis revealed distinct performance differences among the evaluated AI algorithms with regard to infrared signal detection. In order to avoid redundancy, the discussion synthesizes the key findings without rendering the previously presented numerical values. Fast R-CNN achieved the highest overall scores across all the five criteria, confirming its suitability for real-time, resource-constrained environments. DeepLab and Binary Segmentation also performed strongly, with DeepLab excelling in precision and segmentation, while Binary Segmentation prioritized speed and energy efficiency. No single algorithm proved to be universally superior: YOLO and MobileNet offered balanced trade-offs, whereas EfficientDet and FCN ranked lower across most criteria. The adaptability of the proposed framework allows recalibration for diverse contexts such as surveillance, embedded AI or industrial monitoring, where priorities like speed, precision or energy use may shift.

By combining Delphi-based expert consensus with complementary MCDM methods, the proposed approach strengthens methodological rigor while remaining scalable and practical, a valuable decision-support tool for AI system evaluation and deployment.

7. Conclusion

This study introduced a hybrid MCDM framework integrating SWARA for criteria weighting and NWA for the final ranking in order to evaluate AI algorithms with regard to real-time infrared signal detection. This model effectively combines expert judgment with quantitative aggregation, enabling a transparent and structured decision-making. The analysis identified Fast R-CNN as the top-performing algorithm, followed by the DeepLab and Binary Segmentation algorithms, highlighting that algorithm suitability depends on operational priorities such as accuracy, speed, and energy efficiency, while no single model dominates across all contexts.

The research proposes a reproducible, adaptable evaluation framework applicable beyond infrared processing, supported by Delphi-based expert consensus and rigorous hybrid modeling. Practically, it offers actionable guidance for selecting AI components in real-time and embedded systems, with potential use for autonomous vehicles, industrial monitoring and security applications. The limitations include the reliance on expert-derived weights and evaluations rather than empirical benchmarking and the focus on five expert-defined criteria. Future work should incorporate factors like scalability, cost and explainability, extend this framework to other domains, and also explore fuzzy or probabilistic enhancements. The validation of the proposed hybrid SWARA-NWA framework using real-time infrared datasets, combined with comparative analyses involving other MCDM techniques (e.g. AHP, PIPRECIA, TOPSIS), would further enhance its methodological robustness and external generalizability.

Acknowledgement

The research presented in this paper was carried out within the framework of the project No. 1760, “Multi-criteria analysis modeling for decision optimization in computer sciences” at Alfa BK University, the Faculty of Mathematics and Computer Sciences.

ICI Bucharest © Copyright 2012-2025. All rights reserved

REFERENCES

Alimardani, M., Hashemkhani Zolfani, S., Aghdaie, M.H. et al. (2013) A novel hybrid SWARA and VIKOR methodology for supplier selection in an agile environment. Technological and Economic Development of Economy. 19(3), 533–548. https://doi.org/10.3846/20294913.2013.814606.

Alotaibi, G., Awawdeh, M., Farook, F. F. et al. (2022) Artificial intelligence (AI) diagnostic tools: Utilizing a convolutional neural network (CNN) to assess periodontal bone level radiographically-A retrospective study. *BMC Oral Health*. 22(1), Art. ID 399. https://doi.org/10.1186/s12903-022-02436-3.

Bakir, M., Akan, Ş., Kiraci, K., et al. (2020) Multiple-criteria approach of the operational performance evaluation in the airline industry: Evidence from the emerging markets. *Romanian Journal of Economic Forecasting*, 23(2), 149–172.

Bećirović, S., Marinković, V. & Lakić, D. (2023) Assessment of the suitability of the Delphi method for assessing the needs of pharmacoeconomic studies in the decision-making process. *Indian Journal of Pharmaceutical Education and Research*, 57(4), pp.1232–1241. https://doi.org/10.5530/ijper.57.4.147.

Burggräf, P., Wagner, J., Koke, B. et al. (2020) Performance assessment methodology for AI-supported decision-making in production management. *Procedia CIRP*, 93, 891–896. https://doi.org/10.1016/j.procir.2020.03.047.

Clinton, N., Holt, A., Scarborough, J. et al. (2010) Accuracy assessment measures for object-based image segmentation goodness. Photogrammetric Engineering & Remote Sensing. 76(3), 289–299. https://doi.org/10.14358/PERS.76.3.289.

Čupić, M., Tummala, R. & Suknović, M. (2003) *Odlučivanje: formalni pristup* [*Decision Making: A Formal Approach*]. Belgrade, Faculty of Organizational Sciences.

Demirci, A. (2022) The application of SWARA based COPRAS and OCRA methods to supplier selection problem. *Ege Stratejik Araştırmalar Dergisi* [*Ege Strategic Research Journal*]. 13(2), pp.43–55. https://doi.org/10.18354/esam.1120887.

Fei, L., Deng, Y. & Hu, Y. (2019) DS-VIKOR: A new multi-criteria decision-making method for supplier selection. International Journal of Fuzzy Systems, 21, 157–175. https://doi.org/10.1007/s40815-018-0543-y.

Gligorijević, N., Djukić Popović, S., Nikolić et al. (2025) A hybrid SWARA-NWA framework for evaluating AI-based image recognition algorithms in educational technology applications. International Journal of Cognitive Research in Science, Engineering and Education, 13(3), 19–735. https://doi.org/10.23947/2334-8496-2025-13-3-719-735.

Habeeb R.A.A., Nasaruddin F., Gani A. et al. (2019) Real-time big data processing for anomaly detection: A survey. International Journal of Information Management. 45(C), 289–307. https://doi.org/10.1016/j.ijinfomgt.2018.08.006.

Harvey, S. & Mueller, J.S. (2021) Staying alive: Toward a diverging consensus model of overcoming a bias against novelty in groups. Organization Science, 32(2), 293–314. https://doi.org/10.1287/orsc.2020.1384.

Hashemkhani Zolfani, S., Yazdani, M. & Zavadskas, E.K., (2018) An extended stepwise weight assessment ratio analysis (SWARA) method for improving criteria prioritization process. Soft Computing. 22, 7399–7405. https://doi.org/10.1007/s00500-018-3092-2.

He, K., Zhang, X., Ren, S. et al. (2016) Deep residual learning for image recognition. In: Proceedings of the 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), *27-30 June 2016*, *Las Vegas, USA*. New York, USA, IEEE. pp.770–778.

Hou, F., Zhang, Y., Zhou, Y. et al. (2022) Review on infrared imaging technology. Sustainability, 14(18), Art. ID 11161. https://doi.org/10.3390/su141811161.

Hsu, C.C. & Sandford, B.A. (2007) The Delphi technique: Making sense of consensus. Practical Assessment, Research & Evaluation, 12(1), 10. https://doi.org/10.7275/pdz9-th90.

Javaid, M., Haleem, A., Rab, S. et al. (2021) Sensors for daily life: A review. *Sensors International*. 2, Art. ID 100121. https://doi.org/10.1016/j.sintl.2021.100121.

Jia, J., Fu, M., Liu, X. et al. (2022) Underwater object detection based on improved EfficientDet. *Remote Sensing*, 14(18), Art. ID 4487. https://doi.org/10.3390/rs14184487.

Keršulienė, V., Zavadskas, E.K. & Turskis, Z. (2010) Selection of rational dispute resolution method by applying new step-wise weight assessment ratio analysis (SWARA). Journal of Business Economics and Management. 11(2), 243–258. https://doi.org/10.3846/jbem.2010.12.

Lin, K., Chen, H., Xu, C.-Y. et al. (2020) Assessment of flash flood risk based on improved analytic hierarchy process method and integrated maximum likelihood clustering algorithm. *Journal of Hydrology*. 584, Art. ID 124696. https://doi.org/10.1016/j.jhydrol.2020.124696.

Liu, Y., Zhu, M., Wang, J. et al. (2022) Multi-scale deep neural network based on dilated convolution for spacecraft image segmentation. Sensors, 22(11), Art. ID 4222. https://doi.org/10.3390/s22114222.

Manolakis, D. & Shaw, G. (2002) Detection algorithms for hyperspectral imaging applications. IEEE Signal Processing Magazine. 19(1), 29–43. https://doi.org/10.1109/79.974724.

Martyushev, N. V., Boris V. Malozyomov, B. V., Khalikov, I. H. et al. (2023) Review of methods for improving the energy efficiency of electrified ground transport by optimizing battery consumption. Energies, 16(2), Art. ID 729. https://doi.org/10.3390/en16020729.

Mokari, A., Guo, S. & Bocklitz, T. (2023) Exploring the steps of infrared (IR) spectral analysis: Pre-processing, classical data modelling, and deep learning. Molecules, 28(19), Art. ID 6886. https://doi.org/10.3390/molecules28196886.

Popović, S., Viduka, D., Bašić, A., et al. (2025) Optimization of artificial intelligence algorithm selection: PIPRECIA-S model and multi-criteria analysis. Electronics, 14(3), Art. ID 562. https://doi.org/10.3390/electronics14030562.

Puška, A., Nedeljković, M., Stojanović, I. et al. (2023) Application of fuzzy TRUST CRADIS method for selection of sustainable suppliers in agribusiness. Sustainability, 15(3), Art. ID 2578. https://doi.org/10.3390/su15032578.

Rehman, S., Rehman, N., Naz, M. et al. (2021) Application of Grey-based SWARA and COPRAS techniques in disease mortality risk assessment. Journal of Healthcare Engineering, 2021, Art. ID 7302157. https://doi.org/10.1155/2021/7302157.

Rong, Y. & Yu, L. (2023) Decision support system for prioritization of offshore wind farm site by utilizing picture fuzzy combined compromise solution group decision method. Entropy, 25(7), Art. ID 1081. https://doi.org/10.3390/e25071081.

Rogers S.K., Colombi J.M., Martin C.E. et al. (1995) Neural networks for automatic target recognition. Neural Networks, 8(7–8), pp.1153–1184. https://doi.org/10.1016/0893-6080(95)00050-X.

Siddique, N., Paheding, S., Elkin, C. P. et al. (2021) U-Net and its variants for medical image segmentation: A review of theory and applications. IEEE Access, 9, pp.82031–82057. https://doi.org/10.1109/ACCESS.2021.3086020.

Stanujkic, D., Karabasevic, D. & Zavadskas, E.K. (2015) A framework for the selection of a packaging design based on the SWARA method. Engineering Economics, 26(2), pp.181–187. https://doi.org/10.5755/j01.ee.26.2.8820.

Souffi, S., Lorenzi, C., Huetz, C. et al. (2021) Robustness to noise in the auditory system: A distributed and predictable property. eNeuro, 8(2). https://doi.org/10.1523/ENEURO.0043-21.2021.

Sarraf, S. (2017) Binary image segmentation using classification methods: Support vector machines, artificial neural networks and k-th nearest neighbours. International Journal of Computer, 24(1), pp.56–79. https://doi.org/10.53896/ijc.v24i1.832.

Ulutaş, A., Popovic, G., Stanujkic, D. et al. (2020) A new hybrid MCDM model for personnel selection based on a novel grey PIPRECIA and grey OCRA methods. Mathematics, 8(10), Art. ID 1698. https://doi.org/10.3390/math8101698.

Uzun, B., Taiwo, M., Syidanova, A. et al. (2021) The technique for order of preference by similarity to ideal solution (TOPSIS). In: Uzun Ozsahin, Gökçekuş, H., Uzun, B. & LaMoreaux, J. (eds.) *Application of Multi-Criteria Decision Analysis in Environmental and Civil Engineering. Professional Practice in Earth Sciences*. Cham, Switzerland, Springer, pp. 25–30.

Varshney, P.K. & Arora, M.K. (2004) *Advanced image processing techniques for remotely sensed hyperspectral data*. New York:, USA, Springer.

Yin, Y., Li, H. & Fu, W. (2020) Faster-YOLO: An accurate and faster object detection method. Digital Signal Processing, 102, Art. ID 102756. https://doi.org/10.1016/j.dsp.2020.102756.

Yuan, H., Cheng, J., Wu, Y. et al. (2022) Low-res MobileNet: An efficient lightweight network for low-resolution image classification in resource-constrained scenarios. Multimedia Tools and Applications, 81(27), pp.38513-38530. https://doi.org/10.1007/s11042-022-13157-8.

Zangemeister, C. (2014) *Nutzwertanalyse in der Systemtechnik: Eine Methodik zur multidimensionalen Bewertung und Auswahl von Projektalternativen* [*Utility Analysis in Systems Engineering: A Method for Multidimensional Evaluation and Selection of Project Alternatives*]. Winnemark, Germany, Zangemeister & Partner.

ICI Bucharest © Copyright 2012-2025. All rights reserved

This is an open access article distributed under the terms and conditions of the
Creative Commons Attribution-NonCommercial 4.0 International License.