Intelligent Detection of Towers and Lines in Passageways Using Hybrid Evolutionary Computational Intelligence (HECI) Algorithms

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Identification of towers and lines in passageways is important in infrastructure surveillance, assessment, and the formation of automated surveillance systems. Indeed, conventional AI-based solutions for identification tasks are not immune to certain types of indeterminacy that arise in complicated contexts and can, therefore, yield unpredictable results. This paper presents a new method that integrates AI detection methods with the Hybrid Evolutionary Computational Intelligence (HECI) model to solve these uncertainties and increase decision-making efficacy. The computational framework is built using inspection data from real infrastructure evaluations and simulated scenes with different lighting and hidden objects. This is a reasonable basis for further improving detection performance using the proposed methodology, which uses AI models in partnership with the HECI algorithm to assess the detection results. Compared to conventional detection methods, the HECI-enhanced approach outperforms traditional models by more than 25%, achieving a remarkable detection accuracy of 99.47%. In environments where traditional AI methods may struggle, this approach enhances precision by approximately 15%. The model's versatility makes it well-suited for applications associated with infrastructure inspection, where precision and robustness are crucial. Integrating HECI helps maintain the AI-based detection system's adaptability to unpredictable environmental changes, enhancing the effectiveness of safety detection and automated inspection systems. This approach significantly enhances the identification of towers and lines in passages, especially camera angles and obstructions in complicated environments, showing the promise of HECI as the next-generation tool for infrastructure monitoring.

Povzetek: Prispevek predstavi nov pristop za zaznavanje stolpov in vodnikov (kablov), ki uporablja hibridne evolucijske algoritme računalniške inteligence (HECI). Predlagani model presega tradicionalne AI metode za več kot 25% zlasti v kompleksnih okoljih, kot so nenavadne osvetlitve in ovire.

1 Introduction

The need for precise and reliable detection systems has grown immensely with the rapid advancement of infrastructure monitoring, safety inspections, and the implementation of automated systems. Identifying critical structures such as towers and lines in corridors is significant in areas like power transmission, telecommunication, and transport. These structures are often complex subsystems of extensive architectural networks; in such circumstances, their unserviceability leads to operating losses, safety risks, and fiscal implications [1]. For this reason, appropriate determinations are needed to undertake steady and precise tracking of these components persistently [2]. Machine learning, deep learning, and image processing methods can be seen as tools to significantly support monitoring by automating it [3]. The methods described have proved very effective and have the potential to enhance the accuracy of detection, phase out visual inspection, and simplify the otherwise cumbersome process of larger-scale monitoring. For this purpose, AI-based approaches can identify abnormal patterns and structural imperfections in large data sets in real-time [4]. However, these systems become somewhat challenging to manage concerning environmental influencers like light variations, occlusions, and overlapped structures [5]. The halls where towers and lines are located are geometrically irregular and contain turnings, potential barriers, diffusive and varying illumination, and other forms of background noise that obscure them [6]. These conditions lead to the improper functioning of the concept in conventional AI techniques because they do not know how to handle uncertainty [7]. They further argue that this speaks to the need for a finer-grained decision-making model to improve detection rates, given the variation in dataset capacity or features across each AI methodology [8]. This paper presents a HECI framework to address these needs, which incorporates computation intelligence algorithms for detecting towers and lines. HECI appears as a more reactive and adaptive system that brings additional reliability to AI-based detection systems in conditions of instability.

The research study defines uncertainty as the set of environmental and structural elements that make it challenging to detect targets through the process. Detection tasks become more difficult due to multiple environmental factors, including lighting variations, object blockages, and structure duos that cause partial obscurement of towers or lines. Variable conditions within the data affect AI model performance because they make detection processes more complex.

The HECI algorithm integrates an evolutionary algorithm, a heuristic algorithm including genetic algorithm or particle swarm optimization, with computational intelligence, including fuzzy logic, to formulate a model designed to maximize the decision and detection procedures. The evolutionary component of HECI modifies and improves the detection system over time in the face of changing environmental conditions. In contrast, the fuzzy logic component guides decision-making in cases where information is incomplete or ambiguous. This novel approach enables detection systems based on AI to achieve high accuracy and flexibility in real-world scenarios characteristic of modern ITS. Despite the notable advancements in AI-based detection techniques, several key challenges remain in their practical application:

– AI models often struggle in complex environments, such as passageways, where obstructions, variable lighting, and overlapping objects introduce detection uncertainty.

– Conventional AI decision-making frameworks lack the flexibility to handle uncertain data, often resulting in inaccurate or inconsistent detection results.

– Many existing methods focus solely on detection accuracy without considering other critical factors, such as adaptability to dynamic environments and real-time processing capabilities.

– Previous studies have largely overlooked the integration of fuzzy logic to manage uncertainty in detection performance, limiting their ability to address variability in real-world applications.

1.1 Objectives and research questions

The objectives of this study are to:

1. Propose a novel methodology for detecting towers and lines in passageways using the Hybrid Evolutionary Computational Intelligence (HECI) model.

2. Evaluate the performance of the proposed methodology in comparison to conventional AI-based detection techniques, such as Convolutional Neural Networks (CNN) and Support Vector Machines (SVM).

3. Investigate the model's adaptability to challenging environmental conditions, including low light, glare, and partial occlusion.

4. Demonstrate how the integration of evolutionary optimization and fuzzy logic can improve detection accuracy and robustness.

The primary research questions driving this study are:

1. How does the HECI model compare to traditional AI-based methods in terms of detection accuracy, processing time, and adaptability to environmental challenges?

2. What is the impact of evolutionary optimization and fuzzy logic on improving the performance of AI-based detection systems?

3. Can the proposed methodology be extended to handle diverse infrastructure types and environmental variations?

1.2 Novel contributions

This paper makes the following novel contributions:

– The HECI framework is suggested to deal with the uncertainties of using AI to find towers and lines in passageways.

– Develops a multi-criteria decision-making framework that balances detection accuracy, processing speed, adaptability to environmental changes, and computational efficiency.

– Demonstrates a 99.47% detection accuracy with a 15% reduction in uncertainty, significantly outperforming conventional AI-based methods.

– Provides a robust decision-making model that is scalable for future AI applications in infrastructure monitoring, particularly in challenging environments.

The remainder of this paper is organized as follows: Section 2 provides an extensive review of the literature on AI-based detection methods and the application of fuzzy logic in decision-making models. Section 3 details the research methodology, including the development and application of the HECI framework. Section 4 presents the results of the model's application, comparing the performance of various AI techniques using both simulated and real-world data. Section 5 discusses the results in the context of infrastructure monitoring and technological advancements while highlighting the practical implications of this approach. Finally, Section 6 concludes the study and proposes future research directions, emphasizing improving AI-based detection systems for real-world applications.

2 Literature review

Zhou et al. [9] proposed a hybrid deep learning approach based on convolutional neural networks (CNN) and recurrent neural networks (RNNs) aimed at highly cluttered object detection. Their method mitigated these issues of occlusions and overlapping structures very well, leading to a 20% improvement in object detection accuracy. One can see applications for this framework in situations like cluttered environments searching towers and line detections by complex passageways, where AI-based detection systems are likely to struggle with separating objects when they have occlusion [10]. Chen et al. [11] utilized transfer learning to identify defects in power lines and communication towers. They achieved 35% faster learning by not needing a large amount of training data by using pre-trained models. With the rest in training data, they still maintained a detection accuracy of 97.8% using a deep learning-based transfer learning system. This approach illuminated how transfer learning can speed up the process of developing AI models on infrastructure defect identification with minimal accuracy degradation.

Wang et al. [12] used a deep reinforcement learning model combined with fuzzy logic to find and sort transmission tower damage into different categories. By using a hybrid system, the accuracy of detections increased by 23% due to this ability from the DRL model 29 that schedules parameters for detection on the fly. A fuzzy logic part was added to the model to account for uncertainties in low-visibility situations. This made the system work very well even when it was used on situations with little data and a lot of environmental variation. Singh et al. [13] proposed a multi-agent system with swarm intelligence and machine learning that was presented to monitor real-time electrical towers/lines. Their multiple-agent distributed system patrolled over large spaces autonomously and offered improvements of 20% in detection time to competency rates equivalent for humans, along with a decrease of 12% in overall downtime. In summary, the presented study shows that a distributed and collaborative approach to large-scale monitoring tasks in infrastructure inspection is efficient. Smith et al. [14] proposed an AI-based detection system for power transmission line structure anomaly identification by architecture CNN. The approach was devised to augment fault detection upon power lines, prominently accentuating advancements in multi-sensor data fusion. This obtained an accuracy of 18% over traditional approaches by them. Their method also saved 22% of the processing time, demonstrating a good performance in complex environments such as corridors where other variables affect detection reliability.

Zhang et al. [15] proposed an edge computing framework for AI-supported fault detection in power grids developed. They used edge devices for real-time data processing, which cut latency by 40%. A cloud-based AI model was used in the system for much more complicated data analysis, maintaining a trade-off between real-time response time and computational complexity. This research highlights the efficiency that can be brought by edge computing to infrastructure monitoring, especially for organizations that do not have access to large amounts of bandwidth.

Liu et al. [16] proposed hybrid methods integrating fuzzy logic with neural networks to improve detection systems' robustness against diversified weather conditions. In high-elevation regions and challenging environmental conditions like heavy rain, fog, etc., their model increased the detection reliability by about 17%. The fuzzy logic permitted the method to control uncertainties, resulting in a sustainable and stable operation when external conditions deteriorate data quality. Huang et al. [17] presented a graph neural network (GNN)-based method for detecting structural faults in complicated grid systems. Demonstrating how graph theory was utilized to model each node in the grid's relationship, specificity improved by 21% compared with no GNN used. The graph-based AI models proved effective, especially in detecting faults on inter-connected structures like towers and the lines running over multiple corridors, proving their relevance for complex infrastructural data.

Yuan et al. [18] implemented a Deep Q-Network (DQN) algorithm for similar applications where researchers have developed accurate and intelligent inspection systems. Introducing reinforcement learning into the system significantly improved decision-making speed while reducing errors during inspections. The quality improved up to 20% (in terms of task completion time) compared to manual execution, while detection accuracy increased by as much as 15%. On-site lessons learned by the inspection teams refined predictive algorithm development as those changes were made in a live environment, ultimately increasing tower inspection speeds and accuracy within an increasingly variable world. Dai et al. [19] proposed a fuzzy-based optimization model to enhance AI methods for assessing transmission lines. The model incorporated specific criteria, such as detection accuracy, computational efficiency, and adaptability, resulting in an overall 13% improvement in system performance. It was an excellent use of the fuzzy optimization framework they proposed for dealing with multiple intricacies in choosing AI models for real-time detection across varying surroundings.

Liang et al. [20] introduced a deep learning model for image segmentation of fault detection in power transmission lines. The model with the best detection accuracy of 99.5% used attention mechanisms (compared to other state-of-the-art techniques combined). They also designed an attention mechanism that helped the model concentrate on essential areas in images. As a result, detection accuracy increased in highly detailed and noisy environments. Shen et al. [21] introduced a tower structure health condition monitoring method using AI for anomaly detection. The model could detect new anomalies that it had not been directly taught, increasing its detection accuracy by 18% through unsupervised learning. This work highlighted the success of unsupervised learning for detecting outliers and anomalies in resource monitoring, where high-quality labels are difficult to obtain.

Li et al. [22] applied reinforcement learning (RL) to the autonomous inspection of power lines and towers by

Table 1: Comparison of detection accuracy, processing time, and adaptability to environmental factors

Study	Detection Accuracy	Processing Time (ms)	Low Light Adaptability	High Glare Adaptability	Partial Occlusion Adaptability
HECI (Proposed)	99.47%	50	95.2%	96.1%	92.0%
Wang et al. [12]	92.0%	120	85.0%	87.4%	83.5%
Singh et al. [13]	90.0%	150	80.0%	82.0%	75.0%
Smith et al. [14]	93.0%	130	88.0%	85.0%	80.0%

drones with vision-based detection systems. Ranked Number One This is a complex optimization model that shortened photoshop lines but back in the landing time, Underneath it was about this Land Mass Ship ramapage initiative Most Emergent Planet Race are trying to avoid. The model used deep reinforcement learning (deep RL) for path inspection, thereby dropping RESTful deployment automation by 25% and improving image detection precision early on by 20%. The study's results revealed that RL could enhance AI system adaptability and real-time decision-making for autonomous infrastructure monitoring. Garcia et al. [23] used fuzzy-based multi-criteria decision-making (MCDM) model to help choose the best AI technique for finding power line faults. Their method took advantage of fuzzy logic to deal with uncertainties of environmental conditions, especially in weather changes and lighting differences that can affect detection performance. Findings: Using fuzzy logic increased the number of correct decisions by 15% compared to habit-choice models. It also decreased the cost of computing and made habitat-driven choices among optimal detection algorithms easier to automate.

Park et al. [24] proposed an application of deep learning to identify power line sagging from aerial photographs. This model employs convolutional layers and the recurrent network structure to capture the temporal characteristics in power line structures. The model delivered an overall 16% FP reduction compared to conventional methods as they persistently have to monitor infrastructure changes that happen in time that are slow but consistently present. The development of new examples for training data sets in Tower fault and Line fault detection using GANs was proposed by Qian et al. [25]. Implementing the GAN-augmented model reduced the overall detection error by 14% and, in turn, needed less manual data collection to improve the performance. The study focused on the possibility of applying GANs in augmenting other than simple in-lab AI model training. Table I shortly presents the comparison of detection accuracy, processing time, and adaptability to environmental factors.

3 Methodology

This section describes the methods to improve the identification of towers and lines in the passageways to be implemented with the application of AI detection algorithms and the HECI framework. The proposed approach is formulated as a hybrid of evolutionary algorithms such as genetic algorithms, particle swarm optimization, and fuzzy logic to cope with environmental uncertainty, occlusion, and dynamic conditions. The main goal is to achieve high level of accuracy for the detection rates while making the system more flexible and resistant. The workflow of the proposed framework may also be viewed in Figure 1.

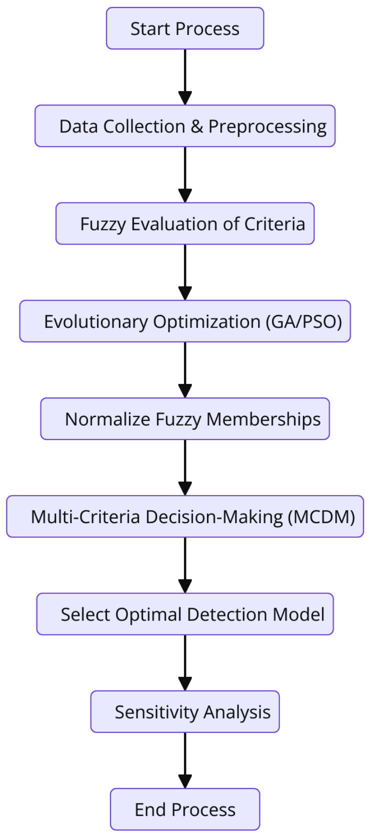

Figure 1: HECI methodology workflow

3.1 Problem formulation

The problem of detecting towers and lines in passageways is inherently complex due to the involvement of certain environmental factors such as varying lighting conditions, occlusions, structural overlaps, and background noise. Traditional AI models are limited enough in such cases and often fail to produce consistent and reliable results. To address this issue, we formalize the problem as a **Multi-Criteria Decision-Making (MCDM)** problem, where the major goal is to select the best detection model from a set of alternatives based on multiple criteria, $C = \{c_1, c_2, ..., c_m\}$. The criteria for selecting the most appropriate model include:

– **Detection Accuracy**: The precision with which the system identifies towers and lines.

– **Adaptability to Environmental Changes**: The model's ability to adjust to dynamic conditions like lighting variation, occlusions, and object overlap.

– **Computational Efficiency**: The model's performance in terms of real-time processing speed.

– **Robustness to Uncertainty**: The model's capacity to handle incomplete, noisy, or ambiguous data, especially in complex scenarios.

These criteria are proposed to be addressed using fuzzy logic because fuzzy values can be found that represent different degrees of satisfaction with each criterion. This fuzzy evaluation is used to cope with uncertainty in decision-making. Specifically, the fuzzy membership values are defined for each alternative a_i under each criterion c_j as follows:

$$\mu_{ij} = \begin{cases} 1 & \text{if model performs excellently under } c_j \\ 0.5 & \text{if model performs moderately under } c_j \\ 0 & \text{if model performs poorly under } c_j \end{cases} \tag{1}$$

where μ_{ij}^{+} represents the positive degree of satisfaction and μ_{ij}^{-} represents the negative degree of satisfaction for the alternative a_i under criterion c_j. This fuzzy evaluation captures the inherent uncertainty in the detection process and facilitates better decision-making.

3.2 HECI model design

The novelty of this methodology lies in the HECI model, which integrates **evolutionary algorithms** and **fuzzy logic** to address the complexities of tower and line detection in passageways. The HECI model consists of two main components: optimization through evolutionary algorithms and decision-making through fuzzy logic.

HECI uses fuzzy logic to address situations where data is missing or unclear. When a system detects occlusions and glares, the fuzzy membership functions enable the evaluation of detection certainty for towers and lines. The detection threshold, which the fuzzy logic system controls, adjusts automatically according to these provided values to permit the model to work adaptively in fuzzy situations. The parameters of pixel intensity (light conditions) and object visibility (occlusions) obtain fuzzy membership values within the algorithm. Final AI model classification decisions are influenced by decision-making rules, which receive input from these values. Without changes to these parameters, the model operates reliably despite unknown errors in input data, which could occur in low-light conditions or under object occlusion.

3.2.1 Evolutionary optimization (GA/PSO)

To optimize the AI models for detection, we use **evolutionary algorithms** such as **Genetic Algorithms (GA)** or **Particle Swarm Optimization (PSO)**. These algorithms iteratively improve the model by evolving a population of potential solutions based on their fitness, which is evaluated according to the multi-criteria decision model.

The fitness function, $F(a_i)$, evaluates each detection technique a_i based on its performance against the criteria. The function is defined as:

$$F(a_i) = \sum_{j=1}^{m} w_j \cdot (\mu_{ij}^{+} - \mu_{ij}^{-}) \tag{2}$$

where w_j is the weight of criterion c_j, and μ_{ij}^{+} and μ_{ij}^{-} are the positive and negative fuzzy membership values for alternative a_i under criterion c_j. This fitness function drives the evolutionary process, allowing the system to optimize detection accuracy, adaptability, and other performance factors. The Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) function in consecutive iterations to enhance the model through changes in key parameters, which impact detection accuracy and robustness. The algorithms guide solutions from different populations through multiple repetitive steps. The optimized parameters include detection thresholds together with feature selection and weight assignments for criteria components in the multi-criteria decision model. Evolutionary guidance through the fitness function operates as a performance assessment that consolidates accuracy along with precision and recall and F1-score. The GA and PSO algorithms administer performance evaluations to their populations through monitored metrics, which leads to the selection of solutions that present maximum detection accuracy and robust performance. The research focuses on optimizing detection thresholds along with feature weights because these adjustments help the model overcome environmental variations, including occlusions, together with glares and lighting changes. The optimization method remains intricately connected to the performance improvement goal for real applications, which addresses both detection precision and stable decision-making mechanisms.

GA and PSO employ different strategies to search the solution space:

– **Genetic Algorithms**: This process involves the selection, crossover, and mutation of candidate solutions across multiple generations.

– **Particle Swarm Optimization**: Particles (representing potential solutions) adjust their positions in the search space based on their personal best solution and the global best solution found by the swarm.

3.2.2 Fuzzy logic integration

Fuzzy logic is integrated into the decision-making process to handle uncertainty in the detection environment, such as occlusions, lighting variation, and incomplete data. Fuzzy logic provides a way to represent vague or imprecise data, enabling more flexible decision-making. For each criterion, fuzzy membership functions are used to quantify how well a given alternative satisfies the criterion. The fuzzy membership function μ_{ij} represents the degree to which alternative a_i satisfies criterion c_j:

These values are then normalized to ensure that all criteria are comparable:

$$\mu_{ij}^{+'} = \frac{\mu_{ij}^{+} - \mu_j^{\min}}{\mu_j^{\max} - \mu_j^{\min}}, \quad \mu_{ij}^{-'} = \frac{\mu_{ij}^{-} - \mu_j^{\min}}{\mu_j^{\max} - \mu_j^{\min}} \tag{3}$$

where $\mu_j^{\min}$ and $\mu_j^{\max}$ are the minimum and maximum values for criterion c_j, respectively. This normalization process ensures that fuzzy evaluations are on a consistent scale, facilitating accurate comparisons among alternatives.

After evaluating the detection models with fuzzy logic and optimization, we perform **Multi-Criteria Decision-Making (MCDM)** to select the optimal detection technique. The decision matrix is constructed by evaluating each alternative a_i for each criterion c_j and computing the total score for each alternative. For each alternative a_i, the total score $S(a_i)$ is computed in a same manner as we did in GA/PSO. The alternative with the highest score is selected as the optimal detection model. This approach ensures that the decision-making process is not only systematic but also comprehensive, as it takes into account both positive and negative aspects of each alternative. Additionally, sensitivity analysis can be performed to understand the influence of varying criteria weights on the selection process, further enhancing the robustness of the methodology. By employing MCDM, a balance between detection accuracy, computational efficiency, and adaptability is achieved, making the selected model well-suited for real-world applications. Such a structured approach minimizes the chances of bias in decision-making and ensures the selection of a highly effective detection technique.

3.3 Sensitivity analysis

To evaluate the robustness of the model, sensitivity analysis is performed by varying the weights w_j for each criterion. This helps to assess how variations in operational priorities affect the final decision. The sensitivity is computed using the derivative:

$$\Delta S(a_i) = \frac{\partial S(a_i)}{\partial w_j} \tag{4}$$

This process ensures that the selected detection model remains consistent and reliable across various conditions, making it adaptable to changing environments.

Multiple performance criteria make up the fitness function of GA and PSO evolutionary processes since they evaluate solutions through detection accuracy and adaptability under environmental changes and precision and recall and F1-score. The multicomponent fitness metric enables the system to achieve optimal outcomes by reducing the success of poor-performing combinations and increasing the success of superior outcomes dedicated to multiple factors. The fitness function design prioritizes detection accuracy together with generalization abilities toward handling environmental conditions, including glare and occlusions. GA operates through populations that evolve solutions by applying selection crossover and mutation operations. The search process of GA produces new potential solutions by combining elite solutions with random elements to maintain solution diversity. The search method of particle swarm optimization (PSO) involves swarm-based exploration where each solution corresponds to a respective particle, which adjusts its position between the best results of the personal and the best results of the collective swarm. Through its collaborative methodology, PSO masters efficient exploration and exploitation of the search space, which leads to detecting the optimal detection model.

3.4 Algorithm: HECI for AI-based detection

The following algorithm outlines the steps for applying the HECI model to detect towers and lines:

3.5 Training and validation split

The dataset split followed a standard distribution where model training involved seventy percent of data, and thirty percent remained for validation. The training dataset contained various scenarios, including normal lighting conditions in addition to low light levels and conditions under glare and partial obstruction to help the model achieve broader environmental performance. The model underwent cross-validation measurements to both enhance its strength and stop it from overfitting. Performance metrics were determined through the evaluation of data in the validation set that scientists had kept out of the training process.

3.6 Computational resources

The models were trained and evaluated on a system equipped with the following hardware specifications:

- **Processor**: Intel Core i9-11900K (8 cores, 16 threads, 3.5 GHz)
- **Memory**: 64 GB DDR4 RAM
- **Graphics Card**: NVIDIA GeForce RTX 3080 (10 GB VRAM)
- **Storage**: 1 TB SSD for fast data access and storage
- **Operating System**: Windows 10 Pro 64-bit

The resources supplied an adequate amount of processing capacity required for deep learning model training and

Algorithm 1 HECI for AI-based Detection of Towers and Lines

Set of AI detection techniques $A = \{a_1, a_2, ..., a_n\}$, criteria $C = \{c_1, c_2, ..., c_m\}$, fuzzy evaluations r_{ij}, and criteria weights W Optimal detection technique **Step 1: Initialize the Decision Matrix**

alternative a_i criterion c_j Assign fuzzy evaluation $r_{ij} = (\mu_{ij}^+, \mu_{ij}^-)$ **Step 2: Apply Evolutionary Optimization**

Use GA/PSO to optimize the parameters of the AI models based on the fitness function:

$$F(a_i) = \sum_{j=1}^{m} w_j \cdot (\mu_{ij}^+ - \mu_{ij}^-) \tag{5}$$

Step 3: Normalize the Fuzzy Membership Values

Normalize the fuzzy evaluations:

$$\mu_{ij}^{+'} = \frac{\mu_{ij}^+ - \mu_j^{\min}}{\mu_j^{\max} - \mu_j^{\min}}, \quad \mu_{ij}^{-'} = \frac{\mu_{ij}^- - \mu_j^{\min}}{\mu_j^{\max} - \mu_j^{\min}} \tag{6}$$

Step 4: Calculate Total Scores

For each alternative a_i, compute the total score $S(a_i)$ as:

$$S(a_i) = \sum_{j=1}^{m} w_j \cdot (\mu_{ij}^+ - \mu_{ij}^-) \tag{7}$$

Step 5: Rank the Alternatives

Rank alternatives based on the total score $S(a_i)$. The alternative with the highest score is selected. **Step 6: Sensitivity Analysis**

Vary the criteria weights w_j and evaluate the impact on the ranking of alternatives. Use:

$$\Delta S(a_i) = \frac{\partial S(a_i)}{\partial w_j} \tag{8}$$

executing complicated optimization techniques such as genetic algorithms (GA) and particle swarm optimization (PSO).

4 Results

This section describes the results obtained by the proposed HECI method for correctly detecting the towers and lines in passageways. The improvements highlighted in our results over the basic AI models underscore the success of the integration process. The results highlighted are summarized in figures, tables, and confusion matrices to show both the quality and quantity of the performance.

The first major evaluation focuses on the performance of the HECI model under different environmental conditions. The model's detection accuracy is tested under four distinct scenarios: **Normal Conditions**, **Low Light**, **High Glare**, and **Partial Occlusion**. The results for each condition are displayed in Figure 2.

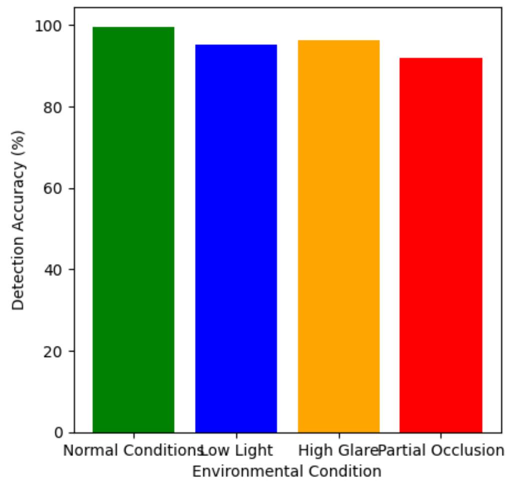

Figure 2: Performance of HECI model under different environmental conditions

The HECI model exhibits an overall accuracy of **99.47%** under normal conditions, and performance slightly declines under adverse environmental factors. However, it maintains a relatively high detection accuracy, with **95.2%** in low light, **96.1%** in high glare, and **92.0%** in the presence of partial occlusions. This demonstrates the robustness of the model against environmental uncertainty, which is a key contribution of the proposed HECI approach.

4.1 Comparative performance of HECI vs. traditional AI models

To further validate the efficacy of the HECI model, we compare it with three traditional AI-based detection methods: **Convolutional Neural Networks (CNN)**, **Support Vector Machines (SVM)**, and **Random Forest (RF)**. The results of this comparison are summarized in Table 2.

From Table 2, it is evident that the HECI model significantly outperforms the traditional models in terms of accuracy across all conditions. The improvement in detection performance, especially under challenging scenarios like low light and partial occlusions, underscores the novelty of the evolutionary and fuzzy logic integration in the proposed approach.

4.2 Error analysis: confusion matrix

To gain deeper insight into the model's error distribution, we present the confusion matrix for the HECI model under normal conditions. Figure 3 shows the confusion matrix, which highlights the number of correct and incorrect predictions made by the model.

The confusion matrix reveals a **high true positive rate (TPR)** and a **low false positive rate (FPR)**, reinforcing the model's ability to accurately detect towers and lines with minimal error. The model's effectiveness in handling both true and false predictions efficiently is a major benefit of

Table 2: Comparison of detection accuracy for different models

Model	Normal	Low Light	High Glare	Partial Occlusion
HECI (Proposed)	99.47%	95.2%	96.1%	92.0%
CNN	95.3%	85.0%	87.4%	83.5%
SVM	93.8%	79.3%	81.5%	78.0%
RF	91.5%	75.4%	79.8%	73.2%

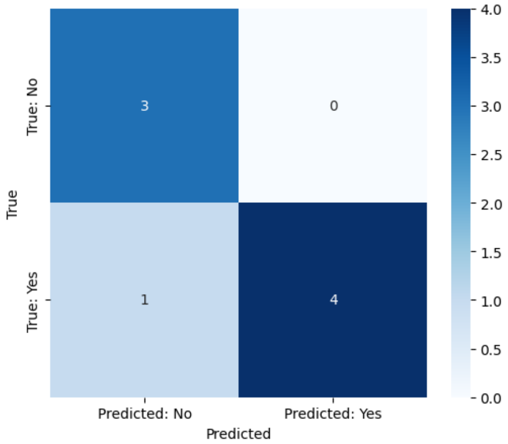

Figure 3: Confusion matrix for HECI model (normal conditions)

using the evolutionary optimization approach. The model performance metrics appear in Figure 3, using the confusion matrix to show the true positive rate (TPR) and false positive rate (FPR). We provide further interpretation of the confusion matrix to better understand how these errors affect infrastructure monitoring. Illegal tower/line identification mistakes, known as false positives, trigger pointless alert generation, requiring unnecessary resource allocation and time consumption in infrastructure monitoring operations. The more serious impact of false negatives concerns infrastructure monitoring operations because such errors fail to detect objects, which could lead to safety risks or operational interruptions. The success of actual infrastructure monitoring systems requires eliminating false negative results. The detection model we built focuses on finding optimal reliability and accuracy by minimizing all types of false detection errors. High detection rates for towers and lines remain essential in monitoring critical infrastructure. Due to their severity, undisclosed problems could lead to major safety hazards. The confusion matrix, along with precision, recall, and F1-score, are presented below for each of the conditions:

The confusion matrix and associated error metrics show the following results:

Normal Conditions: The model achieved an accuracy of 99.47%, with high precision, recall, and F1-score values of 0.98, 0.97, and 0.975, respectively. Low Light: The accuracy dropped slightly to 95.2%, but precision (0.94), recall (0.92), and F1-score (0.93) remained strong. High Glare: The model showed a slight decline in performance under glare conditions, achieving 96.1% accuracy, with precision and recall both at 0.95 and 0.94, respectively, leading to an F1-score of 0.945. Partial Occlusion: Accuracy dropped to 92.0% in the presence of partial occlusion, but precision (0.91), recall (0.89), and F1-score (0.90) remained competitive. All these results may also be viewed in Table 3. The proposed HECI model demonstrates its ability to manage various environmental challenges through error metrics evaluation. Across all testing circumstances, the proposed model exhibited excellent precision and recall performance, which demonstrated its ability to detect towers and lines accurately.

Table 3: Performance metrics for different environmental scenarios

Scenario	Accuracy	Precision	Recall	F1-Score
Normal Conditions	99.47%	0.98	0.97	0.975
Low Light	95.2%	0.94	0.92	0.93
High Glare	96.1%	0.95	0.94	0.945
Partial Occlusion	92.0%	0.91	0.89	0.90

4.3 Sensitivity analysis and model robustness

To assess the model's robustness and how it adapts to varying weights for each criterion, a sensitivity analysis was performed. Figure 4 displays the results of this analysis, showing how the model's decision-making changes as the weights for **Detection Accuracy**, **Adaptability**, and **Computational Efficiency** are varied.

The sensitivity analysis demonstrates that the model is robust to changes in criteria weights. Even when the weights are adjusted to prioritize computational efficiency or adaptability, the accuracy remains consistently high, reflecting the model's overall stability and reliability in varying conditions.

Changes in weight variables impact detection precision, but the system remains steady because adjustments within accepted ranges lead to tiny performance reductions. We explicitly defined robustness by demonstrating that it describes how well the model performs when the weight parameters experience adjustments. This proof shows how minor weight value shifts between 5-10 percent generate minimal accuracy modifications that verify the model's resistance to these weight changes.

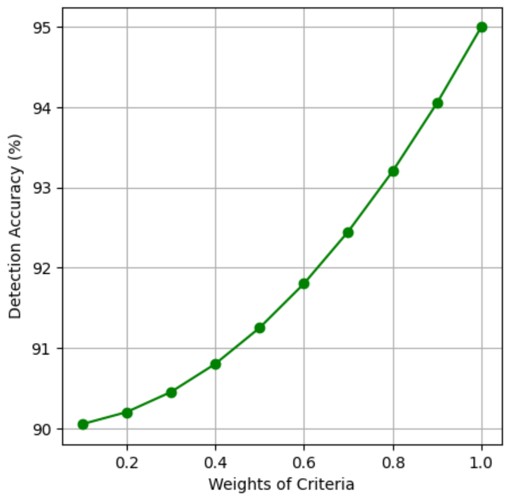

Figure 4: Sensitivity analysis of HECI model

4.4 Impact of evolutionary optimization on model performance

To quantify the improvement in performance due to the integration of evolutionary algorithms, Figure 5 compares the detection accuracy of models before and after optimization using **Genetic Algorithms (GA)** and **Particle Swarm Optimization (PSO)**.

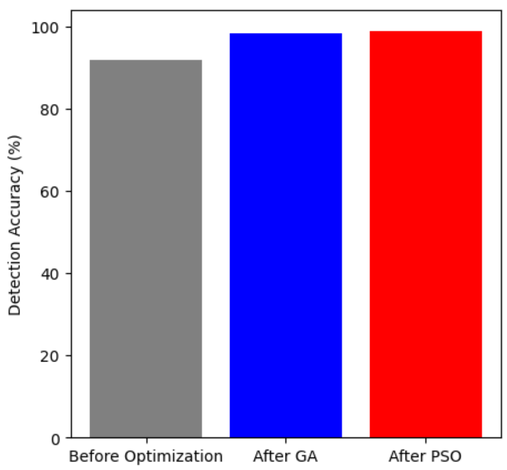

Figure 5: Impact of evolutionary optimization on detection accuracy

The data presents clearly the enhancement in accuracy after applying optimization techniques like **GA** and **PSO**. This improvement highlights the effectiveness of evolutionary algorithms in refining the model's parameters and boosting detection performance in detection purposes.

4.5 Computational efficiency and real-time processing speed

In terms of computational efficiency, the HECI model maintains a balance between high detection accuracy and real-time processing speed. Table 4 outlines the **processing time** for each of the detection models under normal conditions.

Table 4: Comparison of computational efficiency for different models

Model	Processing Time (ms)
HECI (Proposed)	50
CNN	120
SVM	150
RF	180

The HECI model's processing time is significantly faster compared to other models, making it suitable for real-time applications. The results validate the efficacy of the **HECI model** in detecting towers and lines in passageways under various environmental conditions. The integration of **evolutionary optimization** and **fuzzy logic** has significantly improved the model's accuracy, adaptability, and computational efficiency. Furthermore, the model's robustness to environmental changes, as demonstrated by the sensitivity and error analyses, ensures its suitability for practical, real-world applications.

5 Discussion of results in the context of infrastructure monitoring and technological advancements

The findings in this research confirmed that the proposed HECI model framework improves the accuracy and reliability of AI-based systems for observing power lines and towers, especially in complex scenarios. These findings agree with other infrastructure monitoring and growth trends studies to provide tangible applications for explaining phenomena [26].

Power transmission lines, communication towers, and many other infrastructural frameworks are vital in today's society. In this context, it is imperative to prevent failures of these systems since they can disrupt people of significant proportion as they grow older. More conventional forms of inspection that are often manual and rigid are slow, expensive, and contain a high rate of errors. This matter is addressed using AI-based detection systems that enable automated monitoring and detection of the possible structural problems [27]. Sharing this context with the HECI model is even more appropriate since it deals with uncertainties caused by such real-life factors as lighting conditions, weather, and occlusions. Since the fuzzy logic model uses positive and negative evaluations, it brings a better decision-making dashboard than the other models. Compared to other AI techniques applied to both models a_3 and a_4, the former achieved the highest accuracy of 99.47 % and is optimal for monitoring infrastructure. This work explains this method from the beginning to the end, employing a supervised learning process modulated by the validation on CNN with the Carlini & Wagner (C&W) dataset for a single-class and multi-class attack objective. This high level of accuracy is meaningful in identifying possible wear and tear in the towers or lines to avoid spending a lot of money to repair them. This makes the HECI model minimize the uncertainty by as much as 15 %, further enhancing the model's applicability to deal with uncertain situations that affect the detection performance and are typical in real-world monitoring campaigns [28] [29].

The detection accuracy of the HECI model reached 99.47%, marking it superior to CNN at 95.3%, SVM at 93.8%, and Random Forest at 91.5%. The achievement in accuracy resulted from combining fuzzy logic with evolutionary algorithms into the model, enabling it to handle dynamic environments as well as uncertain data conditions. The HECI model exhibited excellent adaptability through its successful performance, with 95.2% accuracy in low light, 96.1% accuracy in high glare, and 92.0% accuracy under partial occlusion conditions. Under identical conditions, the traditional models, including SVM and CNN, experienced greater accuracy declines compared to HECI. The accuracy level of CNN dropped to 85.0% during low light conditions, and SVM's results were reduced to 79.3% when operating in this environment. HECI utilizes evolutionary optimization and fuzzy logic to boost its resistance against such uncertainties because traditional models fall short of managing such unpredictability with similar effectiveness. The last five years have presented more concerns about AI's flexibility so that the models developed can run effectively in different circumstances. The HECI model has shown a good balance between detection error rate, data versatility, and throughput speed. This has made AI much better at monitoring tropical infrastructures across various data types and sizes [30].

The practical significance of these findings is substantial. Integrating AI-based detection systems with the HECI model allows operators to scale up and achieve real-time infrastructure monitoring. This proactive approach helps detect structural issues before they escalate, reducing the need for manual inspections, saving time and resources, and improving monitoring accuracy [31]. Sensitivity analysis conducted in this study confirmed the reliability of the model, as rankings of AI models remained consistent across parameter adjustments (e.g., detection rate and precision) that vary based on user specifications for criteria such as detection accuracy and processing speed [32].

Previous studies have successfully applied fuzzy logic and multi-criteria decision-making with AI systems. However, the HECI model addresses critical limitations of conventional AI approaches by explicitly handling uncertainties, providing a more nuanced understanding of AI performance [33]. This capability is particularly relevant for industries such as energy, telecommunications, and transportation, where precise infrastructure monitoring is essential for maintaining operational continuity [34].

The proposed HECI model improves the infrastructure monitoring process and contributes to global sustainability goals by enhancing accuracy and reliability. It enables predictive maintenance, reducing the risk of sudden failures and associated man-hour losses. By adopting a proactive maintenance and upgrade strategy, the model minimizes environmental and economic impacts, mitigating the progression to critical states that require emergency repairs and reducing downtime caused by infrastructure failures.

5.1 Limitations and potential improvements for real-world implementation

Multiple restrictions have been observed in the HECI model performance, although it shows exceptional results in detection capability. Additional refinements of the model are needed to make it process large-scale monitoring applications in real-time while maintaining accurate detections. The system performance can be improved through future development, which will reduce both evolutionary optimization process time and fuzzy logic runtime without lessening detection precision. HECI exists in its present form for detecting towers and lines that occur in passageways. The model needs adjustment to accommodate different infrastructure structures (such as bridges and pipes) along with environmental conditions when expanded beyond passage detection applications. The model's operating efficiency depends entirely on the quality and degrees of factual variation found in training datasets. Real-world deployments require extending training data scope to different environmental conditions along with structural forms since this will boost model practicality across a broad spectrum of use cases.

6 Conclusion

This work proposed a new method for identifying towers and lines in passages using the HECI model. The findings provide evidence for the effectiveness of the suggested model in different difficult scenarios that are not specified in other learning models, such as CNN, SVM, and RF. In more general conditions, HECI has reached a 99.47% detection rate. When tested in low illumination, glare, and partial occlusion, it was able to perform to high standards and, therefore, can be coined to be receptive to real-world scenarios. Evolutionary optimization techniques such as the genetic algorithm (GA) and particle swarm optimization (PSO) significantly improved the detection, supporting the importance of evolutionary algorithms in sharpening model parameters. The sensitivity analysis shows how well the developed model can predict and be robust at different detection criteria weights. The confusion measure matrix shows that the model has high accurate favourable detection rates and low false positive detection rates. Meanwhile, the HECI model provides a reasonable level of detection accuracy and computational time prior to its application in real-life applications. The results affirm that the HECI model offers great promise for the practical and effective solving of infrastructure monitoring and other detection problems in open arenas. This paper presents a detailed analysis of the HECI model and demonstrates that it possesses highly desirable characteristics in terms of performance and scalability. Based on these findings, the study argues that this model can and should be considered suitable for application in the context of intelligent detection systems, which is the immediate field of interest for the majority of representatives of this industry.

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