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Surrogate-Assisted Multi-Objective Optimization of a 2.4 GHz Yagi Antenna Using Gaussian Process Regression and MOPSO

Joko Prasetyo[1], Akhmad Hairul Umam[2], Khoironi[1]*

[1,*]Department of Informatics and Computer Engineering, Politeknik Elektronika Negeri Surabaya, Surabaya, Indonesia

[2]Creative Multimedia Technology Department, Politeknik Elektronika Negeri Surabaya, Surabaya, Indonesia

*Corresponding Author: joko@pens.ac.id

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Abstract

This paper presents a surrogate-assisted multi-objective optimization approach for a 2.4 GHz Yagi–Uda antenna using Gaussian Process Regression (GPR) and Multi-Objective Particle Swarm Optimization (MOPSO). The antenna performance is evaluated in terms of maximum gain and minimum Voltage Standing Wave Ratio (VSWR). Three key physical parameters—inter-element spacing (gap), director length, and element diameter—are parametrically swept using CST Microwave Studio to generate training data. GPR models are employed as surrogate fitness estimators to approximate the nonlinear relationship between antenna geometry and performance metrics. These surrogate models are integrated into the MOPSO framework to efficiently explore the design space and obtain Pareto-optimal solutions. The results demonstrate that the proposed method significantly reduces the computational cost while effectively identifying optimal trade-offs between gain and VSWR. A maximum gain of 9.4 dBi with a VSWR of 1.18 is achieved at 2.4 GHz, validating the effectiveness of the proposed approach for practical WiFi antenna design.

1. Introduction

The Yagi–Uda antenna remains one of the most widely used directional antennas due to its high gain, simplicity, and ease of implementation. Since its introduction, it has been extensively applied in modern wireless communication systems, including broadcast, radar, and WLAN applications at 2.4 GHz. Recent research has further extended the Yagi–Uda structure toward advanced applications such as 5G communication and high-frequency directional systems, demonstrating its continued relevance in modern antenna engineering [1].

The design of a Yagi antenna involves determining optimal geometric parameters, including element lengths, inter-element spacing, and conductor dimensions. These parameters significantly influence gain, radiation pattern, bandwidth, and impedance matching, while exhibiting highly nonlinear and coupled relationships. As antenna requirements become increasingly complex, conventional empirical and analytical design approaches become insufficient for achieving optimal performance in modern systems [2].

To address these challenges, evolutionary optimization techniques have been widely adopted in antenna design. Among these, Particle Swarm Optimization (PSO), originally introduced as a population-based metaheuristic, has been extensively applied due to its simplicity, computational efficiency, and strong global search capability. PSO has been successfully implemented for antenna parameter tuning, radiation pattern synthesis, and array configuration optimization, demonstrating superior performance compared to traditional methods [3], [4].

However, real-world antenna design problems are inherently multi-objective in nature. For instance, improving antenna gain may negatively affect impedance matching or bandwidth. This necessitates the use of multi-objective optimization techniques capable of handling conflicting performance criteria. Multi-Objective Particle Swarm Optimization (MOPSO) extends the PSO framework to address such problems by generating a set of non-dominated solutions that represent the trade-off between competing objectives [5]. MOPSO has been widely applied in antenna design, including antenna array synthesis, radar system deployment, and wireless coverage optimization [6], [7].

In recent years, hybrid optimization approaches combining MOPSO with machine learning techniques have been proposed to address the computational complexity associated with antenna design. For example, advanced variants of multi-objective optimization algorithms with adaptive mechanisms have demonstrated enhanced performance in solving complex engineering problems [8].

Despite these advancements, a major limitation in antenna optimization remains the heavy computational burden associated with full-wave electromagnetic simulations. Each antenna configuration must be evaluated using numerical solvers such as CST or HFSS, which can be highly time-consuming, especially when integrated with population-based optimization methods. This issue becomes critical when addressing high-dimensional design problems or when large datasets are required for accurate optimization [9].

To overcome this limitation, surrogate modeling techniques have been introduced as efficient alternatives to replace expensive simulations. Surrogate models approximate the relationship between design parameters and antenna performance using a limited number of training samples, enabling fast evaluation during optimization. Among various surrogate modeling approaches, Gaussian Process Regression (GPR) has gained significant attention due to its strong theoretical foundation, high prediction accuracy, and capability to quantify uncertainty [10], [11].

GPR has been successfully applied in antenna optimization problems, including modeling impedance characteristics, radiation behavior, and resonant frequencies.

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Studies have shown that GPR-based surrogate models can significantly reduce the number of required simulations while maintaining high accuracy, making them suitable for complex electromagnetic design tasks [12], [13].

Recent works have also investigated alternative machine learning approaches, including neural networks and deep learning models, for antenna design optimization. These models have demonstrated promising results in predicting antenna performance across wide parameter spaces and enabling efficient design exploration [14], [15]. Additionally, advanced surrogate-assisted multi-objective optimization frameworks have been proposed, integrating evolutionary algorithms with machine learning models to achieve faster convergence and improved solution quality [16].

Moreover, emerging techniques such as reduced-dimensionality surrogate modeling and hybrid optimization frameworks have further improved the efficiency of antenna optimization processes. These approaches focus on identifying dominant design variables and reducing problem dimensionality, thereby enabling faster surrogate model training and improved optimization performance [17].

Despite extensive research in antenna optimization, several challenges remain. Many existing studies focus on microstrip or planar antennas, while fewer works address Yagi–Uda antenna optimization using surrogate-assisted multi-objective techniques. Furthermore, most previous studies rely on direct electromagnetic simulations during optimization or focus on single-objective formulations, limiting their ability to capture trade-offs between conflicting performance metrics such as gain and VSWR.

Therefore, this study proposes a surrogate-assisted optimization approach combining Gaussian Process Regression and Multi-Objective Particle Swarm Optimization for the design of a 2.4 GHz Yagi–Uda antenna. The proposed framework integrates CST-based parameter sweep data with GPR models to provide fast and accurate predictions of antenna performance. These surrogate models are then embedded within the MOPSO algorithm to efficiently explore the design space and generate Pareto-optimal solutions representing the trade-off between gain and VSWR.

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2. Methods

This study employs a surrogate-assisted multi-objective optimization framework combining electromagnetic simulation, machine learning, and evolutionary optimization techniques to design a high-performance 2.4 GHz Yagi–Uda antenna. The methodology integrates CST-based parameter sweeping, Gaussian Process Regression (GPR) modeling, and Multi-Objective Particle Swarm Optimization (MOPSO) to efficiently explore the antenna design space while minimizing computational cost. Such hybrid approaches have been widely adopted in antenna design due to their ability to handle nonlinear relationships and reduce expensive full-wave simulation requirements [18], [19].

2.1 Antenna Configuration and Design Variables

The antenna considered in this work is a five-element Yagi–Uda antenna operating at a frequency of 2.4 GHz, which is commonly used for WiFi communication systems. The antenna structure consists of one reflector, one driven element, and three directors arranged linearly along a supporting boom. Yagi–Uda antennas are known for their high directivity and relatively simple geometry, making them suitable for optimization studies involving geometric parameter variations [20].

To enable systematic optimization, the antenna geometry is parameterized using a design vector defined as:

$$\mathbf{x}_i = [g, l_d, d] \tag{1}$$

where g represents the inter-element spacing normalized to wavelength, l_d denotes the director length normalized to wavelength, and d is the diameter of the antenna elements expressed in millimeters. These variables are selected because they have a significant influence on the antenna's electromagnetic behavior, particularly in terms of gain, impedance matching, and bandwidth.

The inter-element gap $g$primarily controls mutual coupling between antenna elements, which affects radiation pattern shaping and impedance characteristics. The director length $l_d$plays a critical role in determining the resonant condition of the antenna and thus has a strong impact on gain performance. Meanwhile, the element diameter d influences current distribution and contributes to bandwidth enhancement and improved impedance matching, which directly affects the VSWR [20], [18].

The design variables are constrained within realistic ranges based on established antenna design guidelines to ensure physical feasibility and manufacturability. These bounds are summarized in Table 1 and define the feasible search space explored by the optimization algorithm.

Table 1. Design Variables and Parameter Ranges

No	Variable	Symbol	Unit	Range
1	Inter-element gap	g	λ	0.10 – 0.30
2	Director length	l_d	λ	0.44 – 0.48
3	Element diameter	d	mm	1 – 6
4	Reflector	l_r	λ	fixed 0.52
5	Driven element	l_{dr}	λ	fixed 0.47

2.2 CST-Based Parameter Sweep and Dataset Generation

To accurately characterize the relationship between antenna geometry and performance metrics, a parameter sweep is conducted using CST Microwave Studio. CST is a widely used full-wave electromagnetic simulation tool capable of accurately modeling antenna radiation behavior under realistic conditions. In this study, the Time Domain Solver with open (add space) boundary conditions is employed to capture the far-field radiation characteristics of the antenna.

For each design configuration defined by $\mathbf{x}_i$, the antenna is simulated to evaluate its performance at 2.4 GHz. The output of each simulation consists of two key metrics: gain and VSWR, which form the objective function vector:

$$\mathbf{f}(\mathbf{x}_i) = [f_1(\mathbf{x}_i), f_2(\mathbf{x}_i)] \tag{2}$$

where $f_1(\mathbf{x}_i)$represents the realized gain in dBi and $f_2(\mathbf{x}_i)$represents the VSWR. The gain is maximized to improve signal strength and directivity, while the VSWR is minimized to ensure efficient impedance matching between the antenna and transmission line.

The parameter sweep generates a dataset consisting of input–output pairs:

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$$\{(\mathbf{x}_i, \mathbf{f}(\mathbf{x}_i))\}, i = 1,2, \ldots, N \quad (3)$$

This dataset captures the nonlinear and coupled relationship between antenna design parameters and performance metrics. Such relationships are difficult to model using analytical expressions due to the complexity of electromagnetic interactions; therefore, data-driven models are required [19].

Table 2. Sample CST Simulation Dataset

No	Gap $g(\lambda)$	Director $l_d(\lambda)$	Diameter d(mm)	Gain (dBi)	VSWR
1	0.10	0.46	3	8.10	1.85
2	0.15	0.46	3	8.90	1.45
3	0.20	0.44	3	8.60	1.55
4	0.20	0.45	3	9.00	1.35
5	0.20	0.46	3	9.40	1.22
6	0.20	0.47	3	9.20	1.30
7	0.20	0.46	4	9.40	1.18
8	0.20	0.46	6	9.30	1.15
9	0.25	0.46	3	8.80	1.35
10	0.30	0.46	3	8.00	1.70

The dataset demonstrates that the antenna response is highly nonlinear, where small variations in director length or gap spacing can lead to significant changes in gain and VSWR. This complexity motivates the use of surrogate modeling techniques such as GPR to approximate the response surface efficiently [19].

2.3 Gaussian Process Regression Surrogate Model

To reduce the computational cost associated with repeated CST simulations, Gaussian Process Regression is employed as a surrogate model. GPR is a nonparametric Bayesian approach that models the antenna response as a Gaussian process defined by a mean function and a covariance kernel [11].

The model is expressed as:

$$y(\mathbf{x}) \sim \mathcal{GP}(\mu(\mathbf{x}), k(\mathbf{x}, \mathbf{x}')) \quad (4)$$

where $\mu(\mathbf{x})$ is the mean function and $k(\mathbf{x}, \mathbf{x}')$ represents the covariance kernel that measures similarity between two input vectors. The squared exponential kernel is used due to its smoothness and effectiveness in modeling nonlinear physical systems:

$$k(\mathbf{x}, \mathbf{x}') = \sigma^2 \exp\left(-\frac{\|\mathbf{x}-\mathbf{x}'\|^2}{2l^2}\right) \quad (5)$$

where $\sigma^2$is the signal variance and $l$is the length scale controlling sensitivity to input variations.

Two independent GPR models are trained:

- $\hat{G}(\mathbf{x})$ for gain prediction
- $\hat{V}(\mathbf{x})$ for VSWR prediction

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These models provide fast and continuous approximations of the objective functions, enabling efficient optimization without repeated electromagnetic simulations [11], [19].

2.4 Multi-Objective Particle Swarm Optimization (MOPSO)

The optimization problem is formulated as a multi-objective problem:

$$\begin{aligned} &\text{maximize} \quad f_1(\mathbf{x}) = \hat{G}(\mathbf{x}) \\ &\text{minimize} \quad f_2(\mathbf{x}) = \hat{V}(\mathbf{x}) \end{aligned} \tag{6}$$

MOPSO is employed to solve this problem by simulating the collective behavior of particles in the search space [3]. Each particle updates its velocity and position according to:

$$\mathbf{v}_i^{t+1} = \omega \mathbf{v}_i^t + c_1 r_1 (\mathbf{p}_i - \mathbf{x}_i^t) + c_2 r_2 (\mathbf{g}_i - \mathbf{x}_i^t) \tag{7}$$

$$\mathbf{x}_i^{t+1} = \mathbf{x}_i^t + \mathbf{v}_i^{t+1} \tag{8}$$

where $\mathbf{p}_i$is the personal best and $\mathbf{g}_i$is a leader selected from the Pareto archive. The parameter settings or the inertia weight ω is fixed at 0.5 to balance exploration and exploitation, while the cognitive and social coefficients c_1 and c_2 are set to 1.5. Pareto dominance, defined in eq. 9, is used to determine optimality:

$$\begin{cases} f_1(\mathbf{x}_a) \geq f_1(\mathbf{x}_b) \\ f_2(\mathbf{x}_a) \leq f_2(\mathbf{x}_b) \end{cases} \tag{9}$$

The algorithm maintains an external archive to store non-dominated solutions, representing the Pareto front. This allows the algorithm to capture trade-offs between conflicting objectives efficiently [2].

3. Results and Discussion

The performance of the proposed surrogate-assisted optimization framework is evaluated through two main aspects, namely the quality of the Pareto-optimal antenna designs obtained using MOPSO and the predictive accuracy of the Gaussian Process Regression (GPR) surrogate model. Visualization of the results is carried out to provide a clear understanding of the relationship between antenna design variables and performance metrics, as well as the effectiveness of the optimization process.

3.1 Gaussian Process Regression Performance

The GPR surrogate model is evaluated by comparing its predicted values with the actual results obtained from CST simulations. This validation ensures that the surrogate model accurately represents the nonlinear mapping between antenna design variables and performance metrics.

3.1.1 Prediction Accuracy Visualization

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The relationship between predicted gain and actual CST gain is illustrated in Fig. 1. Ideally, the predicted values should align along the diagonal line, indicating perfect prediction accuracy.

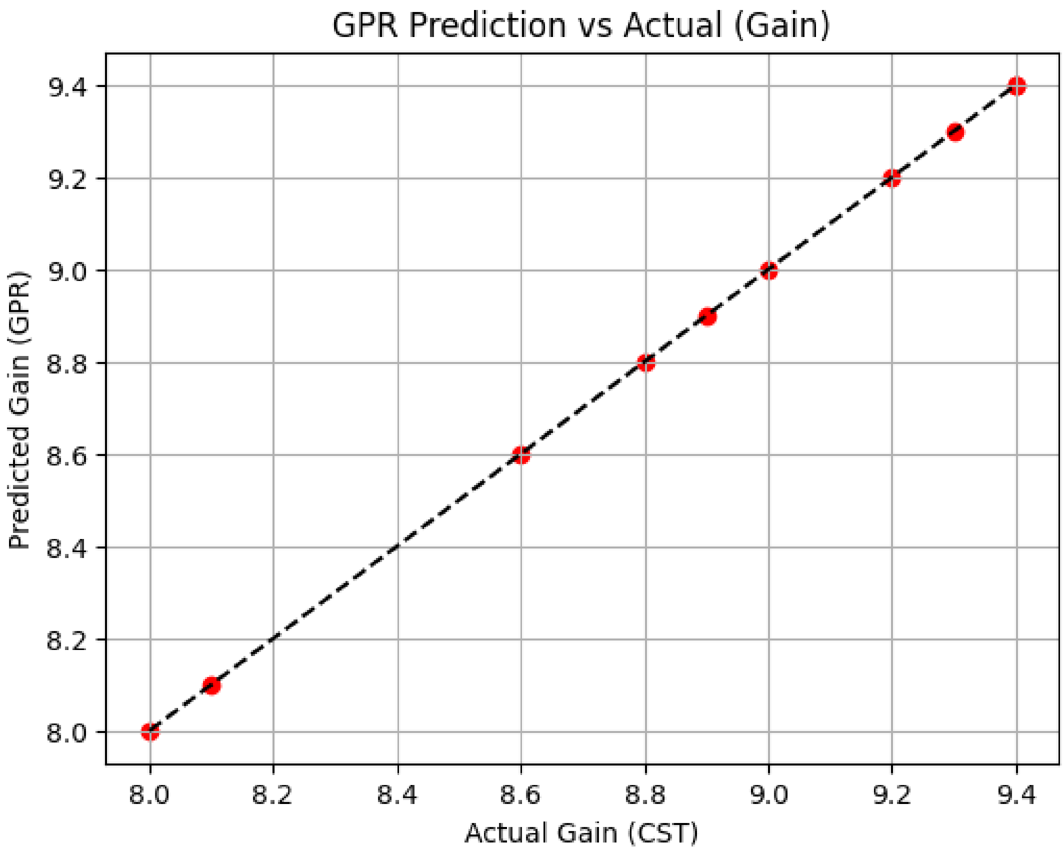

Figure 1. Relationship between predicted gain and actual CST gain

From Fig. 1, it can be observed that most data points lie close to the diagonal line, indicating a strong agreement between predicted and actual values. This demonstrates that the GPR model successfully captures the nonlinear behavior of the antenna system. Minor deviations from the diagonal may occur due to modeling approximation errors or limited training data.

The high prediction accuracy confirms that the surrogate model can effectively replace CST simulations during the optimization process, thereby significantly reducing computational time without sacrificing reliability.

3.2 Pareto Front Analysis

The MOPSO algorithm produces a set of non-dominated solutions that represent the trade-off between gain maximization and VSWR minimization. These solutions form the Pareto front, which is a key output in multi-objective optimization. The Pareto front illustrates how improving one objective typically leads to the degradation of the other, confirming the conflicting nature of antenna gain and impedance matching.

The distribution of Pareto-optimal solutions is visualized by plotting gain against VSWR, as shown in Fig. 2. Each point in the plot corresponds to a candidate antenna design obtained through the MOPSO process.

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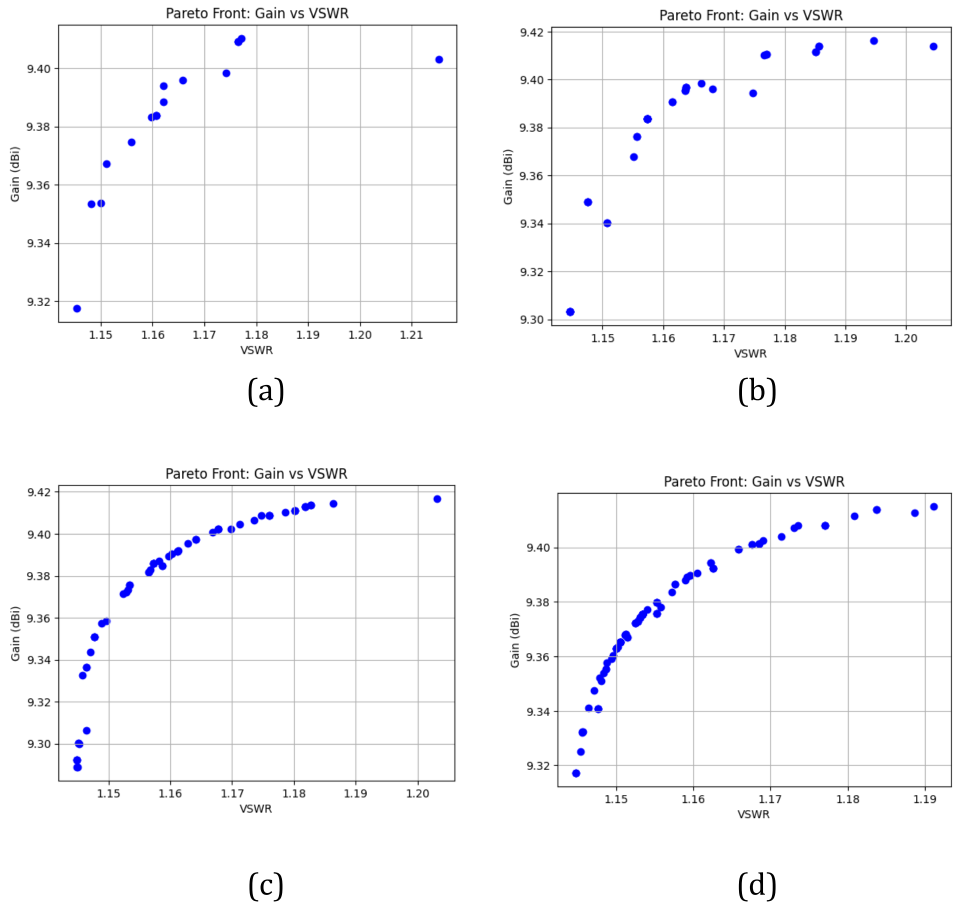

Figure 2. Pareto Front Gain against VSWR, (a) 30 particles, and 100 iterations, (b) 30 particles, and 300 iterations, (c) 100 particles, and 100 iterations, (d) 100 particles and 300 iterations

As observed in Fig. 2, the Pareto front exhibits a clear trade-off curve, where solutions with lower VSWR generally correspond to slightly reduced gain, while higher gain values tend to be associated with higher VSWR. The upper-left region of the plot represents the most desirable solutions, where gain is maximized while VSWR remains low.

To further validate the performance of the proposed method, an additional experiment was conducted by varying the number of particles and iterations in the MOPSO algorithm. Four cases were considered, using 30, 100 particles, 100 iterations, and 300 iteration. The results show that increasing the number of particles and iterations improves the quality of the obtained Pareto front, particularly in achieving higher gain and lower VSWR.

The existence of such a Pareto front confirms that no single optimal solution exists for both objectives simultaneously. Instead, the decision of selecting the best antenna configuration depends on application requirements. For instance, communication systems prioritizing signal strength may select a design with higher gain, whereas systems requiring efficient power transfer may favor lower VSWR.

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4. Conclusion

. This paper has presented a surrogate-assisted MOPSO framework for optimizing a 2.4 GHz Yagi antenna using Gaussian Process Regression and CST-based parameter sweep data. The proposed approach efficiently identifies Pareto-optimal antenna designs with high gain and low VSWR while significantly reducing computational cost. The methodology is well suited for practical WiFi antenna design and can be extended to include additional objectives such as bandwidth and side-lobe level optimization in future work.

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Authors Biographies

Joko Prasetyo received his undergraduate degree in Informatics Engineering from Institut Teknologi Sepuluh Nopember (ITS), Surabaya, Indonesia. He is currently a lecturer at Politeknik Elektronika Negeri Surabaya (PENS), where he is actively involved in teaching and research in the field of computational science and engineering. His primary research interests focus on optimization techniques, including metaheuristic algorithms and intelligent optimization methods for solving complex engineering problems. His work spans various applications such as system optimization, algorithm development, and the integration of optimization methods with emerging technologies.
Email: joko@pens.ac.id
ORCID: 0009-0005-3131-9713

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Ahmad Khairul Umam received his undergraduate degree in Mathematics from Institut Teknologi Sepuluh Nopember (ITS), Surabaya, Indonesia. He is currently a lecturer at Politeknik Elektronika Negeri Surabaya (PENS), where he is actively engaged in teaching and research in the fields of computational mathematics and digital image processing. His research interests focus on image processing and enhancement techniques, including image restoration, noise reduction, filtering, and feature extraction. His work emphasizes improving image quality through the application of mathematical modeling and advanced computational algorithms, with practical applications in computer vision and digital imaging systems.
Email: akumam@pens.ac.id
ORCID: 0000-0003-2061-4926

Khoironi received his undergraduate degree in Informatics Engineering from Universitas AMIKOM, Indonesia. He is currently a lecturer at Politeknik Elektronika Negeri Surabaya (PENS), where he is actively involved in teaching and research in the field of computer science and artificial intelligence. His research interests focus on image processing and computer vision, particularly in image classification and object detection. His work involves the development of intelligent algorithms for recognizing patterns, detecting objects, and improving visual data interpretation using machine learning and deep learning techniques. He has conducted research on applying modern computational methods to enhance accuracy and efficiency in image-based systems across various real-world applications.
Email: khoironi@pens.ac.id
ORCID: 0009-0002-5526-9480

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