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Lightweight and Interpretable Coin Recognition and Counting Using Geometric Detection and Fuzzy Score-Based Classification

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ABSTRACT

Deep learning-based coin recognition approaches typically require large, annotated datasets and substantial computational resources, yet offer limited interpretability. Such characteristics limit their applicability in lightweight, resource-constrained vision systems. Therefore, this study aims to develop and systematically evaluate a lightweight, interpretable coin recognition and counting method based on geometric detection and fuzzy-score-based classification. The main contribution of this work lies in integrating the Hough Circle Transform, contour-based circularity validation, and a weighted fuzzy score mechanism that aggregates diameter, circularity, and HSV color features without relying on data-driven model training. The proposed approach prioritizes computational efficiency and decision transparency, while maintaining robustness under varying lighting and object configurations. An experimental evaluation was performed on 40 test images containing 362 coins under both bright and dim lighting conditions, with aligned, scattered, and overlapping arrangements. The system achieved a detection rate of 87% and an object-level classification accuracy of 79%. Although image-level accuracy reached 50% under strict evaluation criteria, detailed error analysis indicates that performance degradation is primarily associated with segmentation limitations in overlapping configurations rather than instability in the fuzzy scoring mechanism. These findings demonstrate that a calibrated geometric and fuzzy-based approach can provide a transparent and computationally efficient alternative for small-scale vision applications without requiring large training datasets.

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1. INTRODUCTION

The rise of digital currency frameworks has dramatically altered the transaction dynamics in our present-day existence [1–3]. However, cash transactions, particularly those involving coin [3–5], remain commonplace in micro, small, and medium enterprises (MSMEs), where numerous minor exchanges necessitate the establishment of effective processing frameworks [6]. In Indonesia, rupiah coins are still widely circulated, although their utilization in daily transactions is often considered less practical [5].

However, despite the availability of various coin recognition approaches, their practical implementation remains limited in real-world scenarios. Across different micro, small, and medium enterprise (MSME) contexts, the act of counting coins is chiefly done through human efforts, causing operational difficulties and a substantial risk of mistakes made by people [7, 8]. Though existing techniques have their perks, they simultaneously uncover obvious gaps. Classic image processing strategies exhibit increased sensitivity to fluctuations in illumination and object arrangement. At the same time, deep learning frameworks require substantial computational power and extensive labeled datasets and often face interpretability challenges. These limitations indicate a gap between the performance of existing methods and the practical need for a system that is accurate, lightweight, reliable, and easy to interpret.

Multiple techniques have arisen in the sphere of computer vision intended to enhance the identification and counting of coins [9–11]. Recent studies predominantly employ deep learning techniques, specifically convolutional neural networks (CNNs) and models for object detection, which have exhibited high accuracy in intricate visual contexts [12–15]. Nonetheless, these methodologies typically necessitate expansive annotated datasets, protracted training periods, and substantial computational capabilities, thereby constraining their utility in lightweight and economically viable systems [7, 16, 17]. Additionally, the decision-making mechanisms embedded in these systems are often characterized by a notable lack of transparency, making them unsuitable for contexts that require significant interpretative depth.

Conversely, traditional image processing techniques, exemplified by the Hough Circle Transform and contour analysis, present a more straightforward implementation and reduced computational expense [18–21]. The methods rely on extracting geometric features and using decision-making rules based on specific thresholds. The layout of several items and the fluctuations in brightness significantly shape their relevance. To enhance adaptability in addressing such fluctuations, fuzzy-based methodologies have been introduced to encapsulate uncertainty in feature representation and classification [22, 10, 23–26].

Despite these advancements, the bulk of the available literature regards geometric detection and fuzzy classification as independent units [27–31], thereby overlooking their potential integration into a unified, clear framework. Additionally, previous studies often prioritize either achieving high accuracy in controlled environments or enhancing individual components, thereby overlooking a thorough investigation of robustness to varying real-world conditions, such as illumination fluctuations and overlapping objects. Thus, a vital obligation arises for an approach that can proficiently bridge this gap by intertwining straightforward processing, resilience, and transparent alternatives within a single, all-encompassing framework.

To mitigate this existing gap, the present study proposes an automated framework for the recognition and enumeration of Rupiah coins by combining the Hough Circle Transform, contour-based geometric validation, and a fuzzy-score-based classification methodology that leverages HSV color and geometric attributes. The proposed method emphasizes a balance between performance and practicality, without relying on data-driven model training. The principal contributions of this research can be delineated as follows: (1) the formulation of a weighted fuzzy score-based classification mechanism that is methodically integrated with geometric validation, (2) a thorough assessment of system efficacy under varying illumination conditions (both bright and dim) as well as diverse object configurations (aligned, dispersed, and stacked), and (3) the creation of a streamlined and interpretable solution that is appropriate for practical application in environments with limited resources.

2. RESEARCH METHOD

This study is applied research with an experimental, quantitative approach aimed at developing an automated system for recognizing and counting Rupiah coins using digital image processing. The system is evaluated based on its coin detection and classification performance under various lighting conditions and object configurations.

2.1. System Overview

The proposed system is designed in a modular manner, from image acquisition to classification result evaluation. The general system workflow includes (1) image acquisition, (2) preprocessing, (3) coin object segmentation, (4) feature extraction, (5) fuzzy score-based classification, and (6) system performance evaluation. The preprocessing stage is divided into two parallel paths: intensity-based processing for coin segmentation and HSV-based processing for color feature extraction. This strategy preserves color information that would otherwise be lost during grayscale conversion while ensuring robust geometric segmentation. The system block diagram is shown in Figure 1.

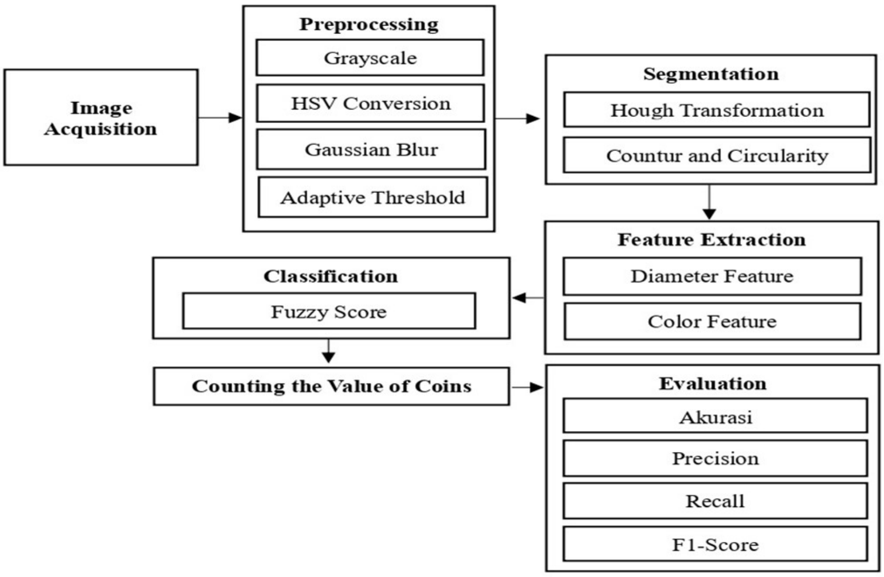


Figure 1. Block diagram of the proposed rupiah coin recognition and counting system

2.2. Image Acquisition

The dataset used consists of Rupiah coin images in JPG format with a resolution of 900×900 pixels. The data includes five denominations: Rp100, Rp200, Rp500 gold, Rp500 silver, and Rp1,000. The dataset consists of 60 images, divided into 20 for parameter estimation and 40 for system testing. Each image contains 4 to 20 coins with varying lighting conditions (bright and low-light) and object arrangements (rowed, scattered, and stacked). Although the dataset size is relatively small, it is methodologically justified because the proposed system does not rely on data-driven model training. Instead, it applies deterministic geometric detection and rule-based fuzzy score evaluation, where robustness is assessed through environmental variation rather than statistical generalization.

2.3. Image Preprocessing

The image preprocessing stage aims to improve image quality and facilitate robust coin segmentation under various lighting conditions [20, 21]. Initially, the acquired RGB image is converted to a grayscale image to simplify the intensity information. Then, a Gaussian blur is applied to reduce noise caused by uneven lighting and camera sensor artifacts. Next, adaptive thresholding is applied to generate a binary image that effectively separates the coin from the background, especially in non-uniform lighting conditions.

In parallel, the original RGB image is converted to the HSV (Hue, Saturation, Value) color space for color feature extraction. This parallel processing strategy allows intensity-based segmentation and color-based feature analysis to be performed independently, thus preserving color information that would otherwise be lost during grayscale conversion and thresholding. The segmented coin region is then used as a mask to extract color features from the HSV image.

2.4. Coin Object Segmentation

Object segmentation is performed using a combination of the Hough Transform and contour analysis. The Hough Transform identifies candidate circles based on center and radius parameters, while contour analysis ensures that detected objects exhibit geometric characteristics resembling those of coins. Shape validation is performed using circularity values [32], where objects with circularity values above a certain threshold are considered valid coins. Circularity is computed as shown in Equation 1.

$$Circularity(C) = 4\phi \times \frac{Area}{Parameter^2} \tag{1}$$

A perfect circle has a circularity value of 1.0. Lower values indicate shape deviation. In this study, a circularity threshold of 0.85 was empirically selected based on preliminary experiments to balance false-positive rejections and the preservation of valid coins under realistic imaging conditions. Objects with a circularity value > 0.85 were considered valid coin candidates and proceeded to the feature extraction stage.

2.5. Feature Extraction

Each validated coin object is then characterized using geometric and color features. Geometric features include diameter and circularity, while color features are derived from the HSV (Hue, Saturation, and Value) color space. The HSV color space was chosen for its ability to separate color information from light intensity, making it more stable on the coin's reflective surface.

2.6. Fuzzy Score-Based Classification

In this study, fuzzy logic is employed as a weighted, score-based rule assessment framework, rather than a comprehensive Mamdani or Sugeno fuzzy inference system. The coin object is evaluated using five features, and each extracted feature fi (diameter, hue, saturation, value, and circularity) contributes to the final classification score according to its relative importance. Let fi denote the observed feature value and Rij denote the predefined acceptable range for feature i in class j. For each denomination class j, feature membership is defined as shown in Equation 2.

$$\mu_{ij} = \begin{cases} \omega_i, & \text{if } f_i \in R_{ij} \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

where: Rij is the empirically determined valid range of feature i for class j, wi is the feature weight obtained through calibration experiments. The total fuzzy score for class j is computed as shown in Equation 3.

$$S_j = \sum_{i=1}^{5} \mu_{ij} \tag{3}$$

A coin is classified as a denomination j if as shown in Equation 4.

$$\begin{gathered} S_j = max(S_1, S_2, \ldots, S_k) \\ and \\ S_j \geq 0.70 \end{gathered} \tag{4}$$

The classification threshold of 0.70 was experimentally determined to reduce ambiguous assignments while preserving detection sensitivity. An object is assigned to the denomination corresponding to the highest score Sj, provided that the maximum score satisfies the minimum classification threshold $Sj \geq 0.70$. If the score is below this threshold, the object is labeled as "Unknown" to prevent unreliable classification. When two classes produce identical scores, priority is assigned according to calibration order to ensure deterministic decision behavior.

2.7. System Evaluation

The system was evaluated on 40 test images containing 362 coins under varying lighting conditions and object arrangements. System performance was critically assessed through its coin detection and classification capabilities using metrics such as accuracy, precision, recall, and F1-score. Additionally, image-level accuracy is computed using a strict criterion: a test image is considered successful only if all coins within it are correctly detected and classified. This evaluation provides insight into system robustness in complete transactional scenarios.

3. RESULT AND ANALYSIS

System testing was conducted to evaluate the detection and classification capabilities of Rupiah coins across diverse lighting conditions and object layouts. This review was painstakingly crafted to determine performance at the object level (specific coin spotting and categorization) and the image level (overall success of the image being tested). The investigation underscores not only quantitative performance indicators but also error characteristics and environmental sensitivity, aiming to provide a holistic understanding of system resilience.

3.1. System Testing Results

A systematic evaluation of the proposed framework was conducted to assess its ability to identify and categorize Rupiah coins under diverse lighting conditions and object arrangements. The experimental design was structured to simulate real-world conditions, incorporating variations in illumination intensity and distinct coin configurations within the test images. The performance assessment was conducted comprehensively across two distinct tiers: the object (coin) level to quantify detection and classification precision, and the test image level to evaluate the system's ability to process the entire image accurately.

3.1.1. Test Dataset Characteristics

The test dataset consists of 40 images of Rupiah coins, totaling 362 coins, spanning five denomination classes: Rp100, Rp200, Rp500 gold, Rp500 silver, and Rp1,000. Each image contains between 4 and 20 coins, with varying lighting conditions, including bright and low-light, as well as arrays of objects arranged in rows, scattered, and stacked. This variation is designed to represent real-world conditions in which lighting and object positioning cannot be strictly controlled. Examples of test images under bright and low-light conditions are shown in Figures 2 and 3.

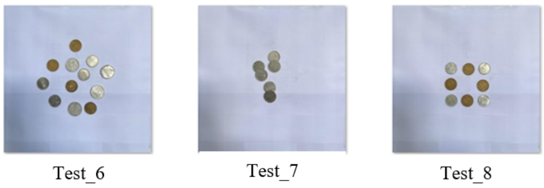


Figure 2. Bright condition test dataset sample

Figure 3. Low light test dataset sample

3.1.2. Pre-Processing and Segmentation Results

The preprocessing phase consisted of grayscale conversion, Gaussian blur filtering, and adaptive thresholding. These steps were implemented to improve image quality and to enhance the separation between the coin and the background. As a result, the contrast between the coin and the background significantly increased, as illustrated in Figure 4, facilitating more accurate segmentation.

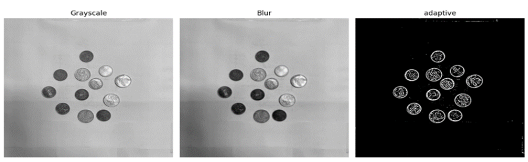
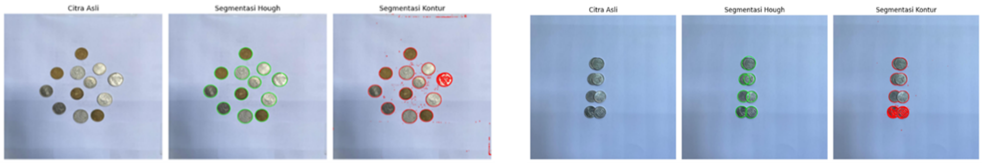


Figure 4. Pre-Processing Result Sample

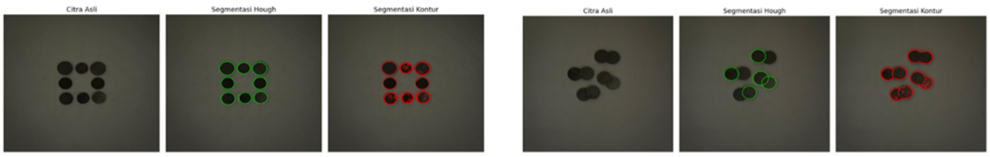
The segmentation results show that the combination of the Hough Transform and contour analysis accurately detected most coins under bright lighting conditions and in non-overlapping object arrangements. However, under stacked coins, the segmentation process encountered difficulties due to overlapping contours and the loss of some object edges, resulting in some coins being missed or detected as a single object. An example of the segmentation results is shown in Figure 5.



(a) Successful (b) Failed

Figure 5. Image segmentation results in bright conditions

Under low-light conditions, the segmentation pattern showed noticeable differences compared to bright lighting. Under these conditions, scattered coins tended to yield better detection rates than lined coins, indicating that contour separation remained distinguishable despite reduced lighting. In contrast, stacked coins still performed poorly, as shown in Figure 6. This limitation was primarily caused by contour merging and partial boundary loss, which prevented accurate circular validation when coins overlapped. These findings indicate that the segmentation method used is robust enough to handle variations in lighting and object arrangement but remains sensitive to coin overlap, a major factor in detection failures.



(a) Successful (b) Failed

Figure 6. Image segmentation results in low light conditions

3.1.3. Detection and Classification Results

Table 1 summarizes the detection and classification performance of the proposed system across the entire test dataset. Out of 362 coins, the system successfully detected 317, for a detection rate of 87%. Furthermore, among the detected coins, 286 were correctly classified into their respective denominations, indicating a reliable classification performance at the object level. The majority of detection failures occurred in stacked configurations, where overlapping contours led to multiple coins being interpreted as a single object or to rejection during circularity validation.

Table 1. Test Dataset Processing Results

Dataset	**Position**	**Number of Coins**	**Detected**	**Classified**	**Description**
Test_1.jpg	Aligned	9	9	9	Successful
Test_2.jpg	Aligned	8	8	8	Successful
Test_3.jpg	Scattered	8	8	8	Successful
Test_4.jpg	Aligned	8	8	8	Successful
Test_5.jpg	Aligned	9	9	8	Failed
Test_6.jpg	Scattered	12	13	12	Successful
Test_7.jpg	Overlapping	6	6	6	Successful
Test_8.jpg	Aligned	8	8	8	Successful
Test_9.jpg	Scattered	9	9	9	Successful
Test_10.jpg	Aligned	4	4	4	Successful
Test_11.jpg	Aligned	8	8	8	Successful
Test_12.jpg	Scattered	16	16	10	Failed
Test_13.jpg	Scattered	8	8	8	Successful
Test_14.jpg	Scattered	9	9	9	Successful
Test_15.jpg	Overlapping	7	7	7	Successful

(dilanjutkan di halaman berikutnya)

Tabel 1 (lanjutan)

Dataset	Position	Number of Coins	Detected	Classified	Description
Test_16.jpg	Scattered	4	4	4	Successful
Test_17.jpg	Overlapping	15	10	9	Failed
Test_18.jpg	Overlapping	10	6	3	Failed
Test_19.jpg	Overlapping	8	4	2	Failed
Test_20.jpg	Overlapping	15	9	5	Failed
Test_21.jpg	Overlapping	10	10	7	Failed
Test_22.jpg	Aligned	8	6	6	Failed
Test_23.jpg	Scattered	8	8	8	Successful
Test_24.jpg	Overlapping	8	5	5	Failed
Test_25.jpg	Aligned	8	8	8	Successful
Test_26.jpg	Scattered	6	6	6	Successful
Test_27.jpg	Overlapping	9	5	5	Failed
Test_28.jpg	Aligned	8	8	7	Failed
Test_29.jpg	Scattered	15	12	12	Failed
Test_30.jpg	Overlapping	9	5	4	Failed
Test_31.jpg	Aligned	9	9	9	Successful
Test_32.jpg	Scattered	7	7	7	Successful
Test_33.jpg	Overlapping	10	9	8	Failed
Test_34.jpg	Aligned	6	5	5	Failed
Test_35.jpg	Scattered	15	13	11	Failed
Test_36.jpg	Overlapping	9	7	6	Failed
Test_37.jpg	Aligned	6	4	4	Failed
Test_38.jpg	Scattered	14	14	14	Successful
Test_39.jpg	Overlapping	8	6	4	Failed
Test_40.jpg	Overlapping	8	8	5	Failed
	Total	362	317	286	

Based on the lighting conditions summarized in Table 2, the proposed system exhibited relatively balanced performance under both bright and low-light scenarios. The number of coins correctly classified in bright images was slightly higher than that obtained under low-light conditions. This difference can be attributed to variations in illumination intensity, which influenced the stability of color-related features, particularly the hue component.

Table 2. Results Based on Lighting Conditions

Condition	Number of Coins	Detected	Undetected	Classified	Unclassified
Bright	181	162	19	145	17
Low-light	181	155	26	141	14
Total	362	317	45	286	31

Based on object arrangement (Table 3), the best performance was achieved in rows and scattered coins, with high detection and classification rates. Conversely, stacked coins produced the lowest performance, with the highest number of undetected coins and misclassifications. This indicates that segmentation quality is a dominant factor in the system's success.

Table 3. Results Based on Object Position

Condition	Number of Coins	Detected	Undetected	Classified	Unclassified
Aligned	99	94	5	92	2
Scattered	131	126	5	118	8
Overlapping	132	97	35	76	21
Total	362	317	45	286	31

Analysis per coin denomination (Table 4) shows that the Rp500 gold and Rp500 silver coins had the most stable classification rates. This is due to the more distinct differences in color and size characteristics compared to other denominations. In contrast, the Rp100 and Rp200 coins showed a higher misclassification rate due to their similar sizes and surface colors.

Table 4. Statistical Classification Results by Denomination

Condition	Number of Coins	Detected	Undetected	Classified	Unclassified
IDR 100	65	50	15	43	7
IDR 200	61	51	10	38	13
IDR 500 (gold)	61	59	2	59	0
IDR 500 (silver)	94	84	10	84	0
IDR 1000	81	73	8	62	11
Total	362	317	45	286	31

3.1.4. Performance Evaluation

System performance was evaluated using accuracy, precision, recall, and F1-score metrics. A summary of the evaluation results is shown in Table 5. Overall, the system achieved an average precision of 90%, a recall of 86%, and an F1-score of 88%, with an object classification accuracy of 79%.

Table 5. Summary of Evaluation Results

Evaluation Metric	Scope	Value
Average Precision	All denominations	90%
Average Recall	All denominations	86%
Average F1-Score	All denominations	88%
Overall System Accuracy	All denominations	79%
Total System Error Rate	-	20%
Image-Level Accuracy	All test images	50%

Notably, image-level accuracy reached 50% under a strict evaluation criterion, in which an image was considered successful only if all coins within it were correctly detected and classified. This relatively moderate image-level accuracy does not necessarily indicate poor object-level performance. Instead, it reflects the cumulative sensitivity of segmentation errors in multi-object scenarios, where a single misclassification results in total image failure.

3.2. Comparative Analysis with Baseline Approaches

To facilitate a more thorough assessment, the efficacy of the proposed methodology is juxtaposed with emblematic baseline techniques, including a traditional threshold-centric method and learning-based strategies commonly employed in prior research. The traditional method is based on geometric detection followed by static threshold classification and lacks adaptive decision-making. In contrast, learning-based methodologies employ trained models to autonomously extract and categorize features.

Table 6. Comparative Analysis of Proposed Method and Baseline Approaches

Aspect	Proposed Method	Classical Threshold-Based	Learning-Based
Accuracy	Moderate - High	Moderate	High
Interpretability	High	High	Low
Computational Cost	Low	Low	High
Training Requirement	None	None	Required
Robustness	Moderate - High	Low	High

In applied scenarios, the usual threshold-based approach offers ease and minimal computational expense; however, its unyielding decisions limit its efficacy in accommodating differences in lighting and object shapes. This limitation often leads to inconsistent results, especially when feature values overlap across various coin classifications. Conversely, approaches grounded in learning tend to demonstrate greater robustness in managing these variations, attributable to their capacity for acquiring intricate feature representations. Yet, this boosted resilience aligns with escalating computational challenges, reliance on substantial labeled data sets, and opacity in the primary decision-making process.

The proposed method overcomes those challenges by establishing a structure that integrates a weighted fuzzy score alongside geometric validation. In contrast to rigid thresholding, the fuzzy score facilitates a progressive assessment of feature contributions, thereby enabling a more adaptable decision-making process in situations where feature values are not clearly separated. Alongside this, the framework aims for low computational load and does not require model training, making it highly suitable for lightweight applications.

As summarized in Table 6, the proposed method achieves a balance between flexibility and efficiency. Although it may not achieve the utmost accuracy typically associated with data-driven methodologies, it offers a more pragmatic and comprehensible solution for practical applications where computational resources and data accessibility are constrained.

3.3. Error Analysis

An exhaustive assessment was conducted to clearly define the limitations of the proposed system, focusing on detection errors, misclassification patterns, and image-level denials. The analysis delineates three principal categories of error:

1. Omissions in detection are attributable to the merging of contours in stacked coin configurations.
2. Misclassification occurs between visually analogous denominations in conditions of reduced illumination.
3. Rejection of objects resulting from stringent geometric validation criteria.

The predominant source of error was identified as segmentation failure rather than misclassification attributable to fuzzy scoring.

3.3.1. Segmentation-Related Errors

The most significant performance degradation occurred in stacked coin configurations. In such cases, partial overlap between coins caused contour merging, leading the Hough Circle Transform to detect either incomplete circles or combined regions interpreted as a single object. As a consequence, some coins were not detected or were detected with distorted geometric parameters.

Although the circularity criterion was established at 0.85 to guarantee robust geometric validation, this rigorous filtering also led to the rejection of detections in instances where the peripheries of coins were partially obscured. Coins exhibiting minor deformation or incomplete outlines yielded circularity values that fell beneath the established threshold and were consequently omitted from subsequent analysis. This finding indicates that geometric validation, while effective in reducing false positives, becomes sensitive under overlapping conditions. Thus, segmentation robustness plays a more critical role in overall system performance than the fuzzy classification stage.

3.3.2. Misclassification Patterns

Misclassification inaccuracies were predominantly identified among denominations exhibiting analogous geometric and chromatic attributes, especially between the Rp100 and Rp200 coins. In low-light environments, fluctuations in illumination significantly affected hue and saturation constancy, leading to convergence of feature ranges across these dimensions. In instances of this nature, the weighted fuzzy scoring system assigned similar scores to the various categories. When score differences were minimal but above the classification threshold (0.70), the system chose the category with the highest score, which at times led to erroneous labeling. However, it is important to note that these errors were less frequent compared to detection failures. This suggests that the fuzzy score-based decision mechanism remains relatively stable when valid geometric segmentation is achieved.

3.3.3. Image-Level Failure Analysis

The overall image-level accuracy of 50% reflects the use of a strict evaluation criterion: a test image is considered successful only if all coins within it are correctly detected and classified. Most image-level failures were not due to a complete system breakdown but rather due to one or two undetected or misclassified coins within otherwise correctly processed images. In many of these cases, most coins in the image were accurately recognized. This analysis substantiates that performance deterioration is predominantly driven by segmentation constraints in intricate spatial configurations, rather than by instability within the fuzzy score classification system.

3.4. Conceptual Trade-Off Analysis with Learning-Based Approaches

Beyond empirical comparison, the following analysis focuses on the conceptual positioning of the proposed method. Although a direct experimental comparison was not undertaken, a conceptual analysis is presented to position the proposed method within a broader methodological perspective. Learning-based approaches are designed to optimize predictive performance through data-driven representation learning, enabling them to capture complex, non-linear feature relationships.

In contrast, the suggested methodology adheres to a deterministic, rule-governed framework, in which each classification decision is explicitly derived from discernible feature contributions. This setup focuses on openness and the ability to follow the process, encouraging extensive insight and organized assessment of decision-making. Rather than relying on implicit feature learning, the system is constructed based on explicit feature evaluation and domain-driven criteria.

This distinction reflects a fundamental conceptual trade-off between performance-oriented modeling and interpretability-oriented system design. Diverging from reliance on sophisticated, data-focused strategies that elevate precision through detailed internal constructs, the endorsed system fosters clarity, offers users greater power, and ensures straightforward interpretation. Such a positioning makes it especially appropriate for contexts in which comprehending the decision-making process is as significant as the resultant outcome.

4. CONCLUSION

This study endeavor established an automated system for the recognition and quantification of Rupiah coins, employing Hough Circle detection, contour-based geometric validation, and a fuzzy score-based classification framework that leverages both geometric and HSV color attributes. An experimental assessment on a dataset comprising 40 test images, totaling 362 coins, yielded a detection rate of 87% and an object-level classification accuracy of 79%, with optimal performance observed under bright illumination and orderly coin arrangements. The results suggest that segmentation quality is the principal determinant of the system's overall efficacy, particularly in stacked configurations where contour overlap compromises detection reliability. Although there were constraints, the fuzzy score-based classification method demonstrated consistent effectiveness across a range of lighting conditions, especially when the saturation and circularity features were properly weighted.

From a scientific standpoint, this investigation demonstrates that reliable object-level classification can be achieved without reliance on data-driven model training, facilitated by a systematic integration of geometric validation and fuzzy score-based decision-making. Compared with traditional threshold-based methodologies, the proposed technique offers greater flexibility in decision boundaries, while, unlike learning-based strategies, it maintains reduced computational complexity and comprehensive interpretability. This highlights a reasonable balance between predictive capability and elucidation, emphasizing transparency, governance, and performance rather than widespread statistical assumptions.

The primary contribution of this research is the development of a weighted fuzzy score mechanism integrated with empirically calibrated geometric constraints, yielding a transparent and reproducible classification framework for small-scale vision systems. Despite the system's constraints in addressing significant object overlap stemming from segmentation challenges, it maintains an admirable balance of accuracy, interpretability, and computational efficiency. Subsequent investigations may aim to bolster segmentation robustness in contexts with overlapping objects and to explore hybrid frameworks that integrate deterministic and machine-learning components to enhance system performance.

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6. DECLARATIONS

AI USAGE STATEMENT

During the development of this manuscript, the authors used ChatGPT (OpenAI) to improve the clarity and readability of the document. After using this tool, the authors carefully reviewed and revised the content as needed and assume full responsibility for the publication's content.

AUTHOR CONTIBUTION

Ni Gusti Ayu Dasriani conceived the research idea, designed the methodology, conducted the experiments, performed the analysis, and prepared the manuscript. I Gede Yoga Sudarma Yasa contributed to the system implementation and data preparation. Bambang Krismono Triwijoyo assisted in the analysis of the results and revised the manuscript. Dadang Priyanto supervised the study and reviewed the manuscript. Cong Dai Nguyen contributed to conceptual validation and manuscript editing.

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The authors declare that they have no competing interests.

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