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A transfer learning approach for real-time detection and classification of Indonesian coins

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ABSTRACT

Automated currency recognition plays an important role in banking automation, retail systems, and assistive technologies. While banknote recognition has been extensively studied, coin recognition remains challenging due to small object size, metallic reflectance, visual similarity across denominations, and circulation-induced wear. This study proposes a real-time system for detecting and classifying Indonesian coins using a transfer learning–based deep learning approach. A curated dataset was developed to address the lack of publicly available training data for this domain. The model was initialized with pretrained weights and fine-tuned to adapt to the specific coin classification task. Experimental evaluation on an unseen test set demonstrates high detection accuracy while maintaining real-time inference performance. Qualitative analysis under challenging conditions—including glare, low illumination, occlusion, and coin wear—reveals operational limitations and defines robustness boundaries. The findings confirm that frozen-backbone transfer learning provides an effective and computationally efficient strategy for adapting state-of-the-art object detectors to low-resource, domain-specific currency recognition tasks.

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1. INTRODUCTION

Automated systems are becoming more prevalent, driving the rapid advancement of object detection technology for applications such as banknote detection in financial automation and retail self-checkout [1]. Although significant progress has been made in banknote recognition, coin recognition presents unique challenges due to small object size, varying light conditions, glare from metallic surfaces, and coin wear from circulation [2], [3].

This study focuses on detecting and classifying four Indonesian coins from the 2016 series: IDR 100, 200, 500, and 1000. These coins present significant challenges due to visual ambiguity—similar metallic finishes, marginal size differences, and the absence of publicly available reference datasets. The research gaps are: (i) absence of a curated annotated dataset of Indonesian coins, and (ii) lack of efficient real-time detection models capable of handling visual ambiguities with limited data.

Deep learning solutions, specifically Convolutional Neural Networks (CNNs), deliver efficient object detection [4]. Single-stage detectors define coin detection as a single regression problem [5], [6]. YOLO delivers strong performance, offering excellent balance between speed and accuracy in real-time [7], [8]. YOLOv8, the most advanced iteration, provides enhanced network architecture for state-of-the-art performance [9], [10].

Training deep learning models from scratch requires enormous annotated data, typically unavailable for domain-specific tasks. Therefore, we employ transfer learning, reusing a model developed for one task as the starting point for a related task. Transfer learning leverages pre-trained feature representations, enabling better knowledge acquisition with less data [11], [12]. This study employs transfer learning with frozen backbone layers to enable high-accuracy Indonesian coin recognition despite a small dataset, while maintaining robustness under real-world variations in lighting, occlusion, and coin wear.

The primary contributions are to: (i) implement a real-time coin detection model using transfer learning with YOLOv8; (ii) develop a newly constructed annotated dataset of 2016 Indonesian coins; (3) conduct comprehensive evaluation to quantify performance and highlight limitations.

Early computer vision approaches relied on hand-crafted features like SIFT or HOG combined with SVM classifiers [13], [14]. These methods were effective but computationally cumbersome and lacked robustness to real-world variability [15], [16]. The advent of deep learning revolutionized object detection [17]. Two-stage detectors like Faster R-CNN achieved high precision but introduced computational overhead unsuitable for real-time deployment [18], [19]. This catalyzed single-stage detectors, with the YOLO family becoming the defining architecture. YOLOv8 provides optimal balance for real-time applications through its single-stage, end-to-end framework [20].

Recent advances highlight the importance of large-scale pre-training for data-scarce settings. Xu *et al.* [21] demonstrate the effectiveness of pre-trained backbones in reducing reliance on extensive annotations, motivating our frozen-backbone transfer learning strategy. Lin *et al.* [22] show single-stage detectors remain dominant for real-time applications due to efficient end-to-end design.

Several studies have applied these models to currency recognition. Prabu *et al.* [23] demonstrated YOLOv5 for detecting and recognizing Indian coins. Rosalina [24] applied YOLOv8 to ancient Indonesian coins, proving the model's efficiency while noting differences from modern circulated coins. Another study implemented YOLOv8 to detect Indonesian banknote denominations [25], validating the model's efficacy while acknowledging different visual challenges compared to metallic coin surfaces.

Table 1 presents a comparison between our approach and related studies. Unlike prior works focusing on Indian coins [23], ancient Indonesian coins [24], or Indonesian banknotes [25], this study targets modern Indonesian coins from the 2016 series, which pose distinct challenges due to metallic reflectance, visual similarity across denominations, and circulation-induced wear. A key contribution is explicit use of transfer learning with frozen backbone layers—a strategy not adopted in compared studies. By leveraging pre-trained representations, our method achieves high accuracy with limited data while maintaining real-time performance.

This study presents the first application of YOLOv8 with frozen-backbone transfer learning for modern Indonesian coin recognition. Comparative analysis confirms existing studies do not employ transfer learning on limited coin datasets. Our approach demonstrates that leveraging pre-trained features enables high accuracy and robustness while reducing training time and computational cost.

Table 1. Comparison of relevant works

Feature	Indian coin detection and recognition [23]	Detection of ancient indonesian coins [24]	Denomination detection [25]	This research
Core model	YOLOv5	YOLOv8	YOLOv8	YOLOv8
Use of transfer learning frozen layers	No	No	No	Yes
Real-time detection	No	No	Yes	Yes
Target currency	Indian coins currency (Rupee)	Ancient indonesian coins	Indonesian banknotes currency issued from 2009 to 2023	2016 series indonesian coins currency

2. METHOD

We adopted a structured methodology using YOLOv8 with transfer learning, encompassing system design, dataset creation, model configuration, and training setup.

2.1. System overview

The system is a desktop application providing an end-to-end pipeline processing real-time video streams to detect and count coins. Users launch the application and activate the camera feed. The core is a detection loop: the camera captures continuous frames passed to our tuned YOLOv8 model in inference mode. The model processes each frame in a single forward pass, generating predictions for detection, classification, and denomination. For each detection, the model outputs bounding box coordinates, class labels, and confidence scores. The application counts each detection and accumulates total value.

The process begins with coins positioned within the camera's field of view. The system detects each coin based on visual features, determines denomination, verifies all coins are identified, calculates a subtotal, and either repeats for additional coins or computes the grand total.

Figure 1 illustrates the complete system workflow. The flowchart begins with camera input capturing continuous frames, followed by the YOLOv8 model processing each frame to predict bounding boxes and class labels. Detected coins are counted per frame and accumulated in a running total, with annotated frames and totals displayed to the user in real-time. The loop continues until the user stops the detection process, at which point final reports can be generated.

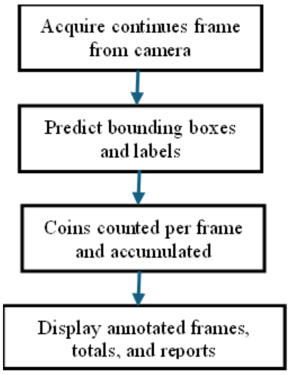


Figure 1. System workflow

2.2. Dataset preparation

A significant contribution is developing the first annotated dataset of 2016 Indonesian coins. The final dataset consists of 1,500 high-resolution images representing four denominations: IDR 100, 200, 500, and 1,000 (approximately 375 images per class). The dataset was curated to capture representative variations in lighting, occlusion, and coin wear.

To ensure the model could effectively generalize to real-world scenarios, data collection was intentionally diversified across several dimensions:

- Light conditions: images were captured in a range of lighting conditions, from bright sunlight producing glare to dark indoor ambient light creating shadows.
- Backgrounds and surfaces: coins were presented on flat, textured, and multi-colored backgrounds to teach recognition in cluttered environments.
- Angles: many images captured coins from overhead and angled perspectives.
- Coin conditions: the dataset includes coins from freshly minted to heavily circulated with visible scratches and tarnish.

Figure 2 shows a representative sample of annotated coins from the dataset. Each coin is enclosed within a bounding box with its corresponding class label (IDR 100, 200, 500, or 1,000). The image demonstrates the variety of lighting conditions, backgrounds, and coin orientations captured in the dataset, as well as the precision of the bounding box annotations that tightly enclose each coin.

Figure 2. Sample of annotated coins from dataset

2.3. YOLOv8 and transfer learning approach

YOLOv8 was selected for its balance of fast inference and high detection accuracy. The architecture implements significant improvements including an anchor-free detection head and a C2f module enabling efficient processing [26].

To minimize training complexity with a small specialized dataset, we employed transfer learning:

- Model initialization: we initialized with yolov8m.pt, pre-trained on the comprehensive MS COCO dataset.
- Freezing backbone layers: we froze the weights of the first ten layers detecting low-level features (edges, corners, textures)—fundamental and transferable across visual tasks. This preserved generalized knowledge while reducing trainable parameters, preventing overfitting.
- Fine-tuning: the remaining layers learning task-specific features were trained on our custom coin dataset, adapting to visual characteristics like engravings, numbers, and reflective surfaces.

Using this transfer learning approach, we achieved significant training time savings and maintained high accuracy unattainable if trained from scratch.

2.4. Training environment and parameters

Training used an NVIDIA A100 GPU via Google Colab Pro. A PyTorch pipeline with Ultralytics' YOLOv8 implementation was built. Key parameters:

- Epochs: up to 100 with early stopping (patience=10) monitoring validation loss.
- Batch size: 16 balancing memory efficiency and stable convergence.
- Image resolution: 640×640 pixels matching YOLOv8 input dimensions.
- Optimizer: AdamW selected for effective weight decay properties.
- Learning rate: 0.001, widely accepted for fine-tuning tasks.

3. RESULTS AND DISCUSSION

3.1. Evaluation metric

Model performance was assessed using widely adopted object detection metrics: precision, recall, and mean average precision (mAP).

- Precision = TP/(TP+FP): proportion of correct positive predictions.
- Recall = TP/(TP+FN): ability to detect all relevant instances.
- mAP@0.5: mAP at IoU threshold 0.5.
- mAP@0.5:0.95: mAP across IoU thresholds 0.5 to 0.95.

3.2. Quantitative results

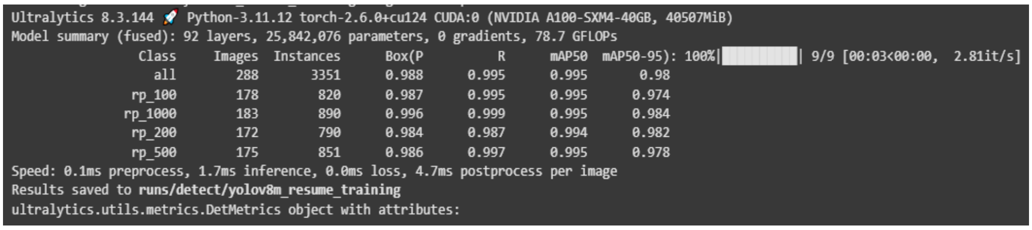
The model was evaluated on the unseen test set (150 images, approximately 300-coin instances). Early stopping halted training at epoch 39; weights from epoch 29 (lowest validation loss) were retained as the final model.

Figure 3 presents the final performance metrics. Overall mAP@0.5 of 0.995 and mAP@0.5:0.95 of 0.98 demonstrate near-perfect classification and highly accurate localization. Per-class analysis showed consistent performance across all denominations, with mAP@0.5 exceeding 0.99 for each class. The most similar denominations (IDR 100 and 200) achieved mAP@0.5:0.95 scores of 0.97 and 0.98 respectively, confirming the model successfully learned distinguishing characteristics despite similar appearances. The relatively high performance can be attributed to the constrained problem scope involving only four visually distinct classes under static single-coin scenarios.

Direct comparison validates our transfer learning approach. Prabu et al. [23] achieved mAP@0.5 of 0.98 on Indian coins using YOLOv5 trained from scratch on 2,000 images. Our method achieves 0.995 with 25% less data (1,500 images) and reduced training time due to frozen backbone transfer learning. Rosalina [24] achieved 0.94 on ancient coins with full fine-tuning on 1,200 images, reflecting the additional challenges of irregular shapes and extreme degradation. Made et al. [25] reported 0.99 on banknotes using YOLOv8 on 1,800 images, but banknotes benefit from distinct color patterns while our model handles more difficult metallic coins with subtle relief features. These comparisons confirm that frozen-backbone transfer learning reduces data requirements while maintaining competitive accuracy.

3.3. Qualitative analysis

We evaluated practical detection capabilities through qualitative tests involving different real-world factors. Figure 4 shows detection results under ideal conditions—diffuse lighting, minimal background clutter, and clearly separated coins. The model performed optimally with confidence scores exceeding 0.95, establishing a strong performance baseline.



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Ultralytics 8.3.144 🚀 Python-3.11.12 torch-2.6.0+cu124 CUDA:0 (NVIDIA A100-SXM4-40GB, 40507MiB)
Model summary (fused): 92 layers, 25,842,076 parameters, 0 gradients, 78.7 GFLOPs
                 Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100%|██████████| 9/9 [00:03<00:00,  2.81it/s]
                   all        288       3351      0.988      0.995      0.995       0.98
                rp_100        178        820      0.987      0.995      0.995      0.974
               rp_1000        183        890      0.996      0.999      0.995      0.984
                rp_200        172        790      0.984      0.987      0.994      0.982
                rp_500        175        851      0.986      0.997      0.995      0.978
Speed: 0.1ms preprocess, 1.7ms inference, 0.0ms loss, 4.7ms postprocess per image
Results saved to runs/detect/yolov8m_resume_training
ultralytics.utils.metrics.DetMetrics object with attributes:
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Figure 3. Final model performance metric

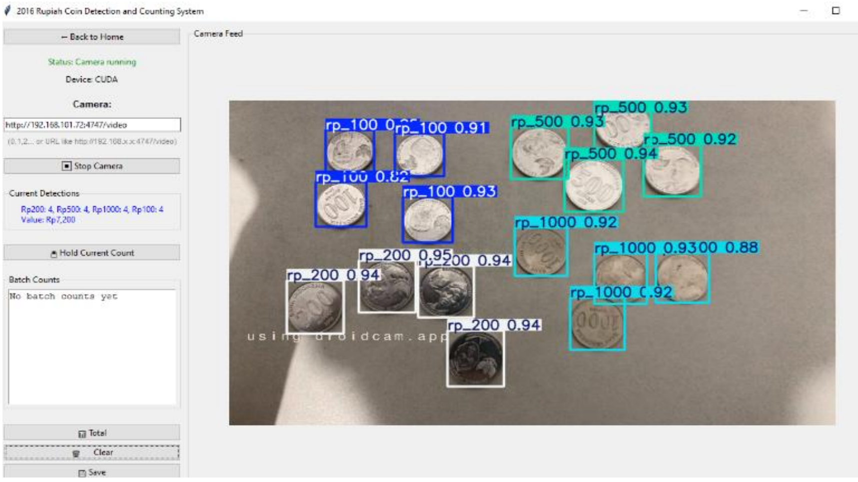

Figure 4. Detection objects in an ideal condition

3.4. Real-world conditions:
3.4.1. Glare and direct light

Strong specular reflections caused by direct lighting occasionally obscured surface details, leading to sporadic misclassifications (Figure 5). The most common confusion observed was between IDR 500 and IDR 1000 coins, as both have similar diameters and the reflective highlights tended to appear in the central region where denomination numerals are located. When glare covered more than approximately 30% of the coin’s surface area, classification accuracy dropped noticeably while detection confidence remained above 0.90. This indicates that the model relies more heavily on fine surface details for classification than for initial detection. The model generally retained detection capability despite reduced classification reliability, suggesting that low-level shape features are more robust to lighting variations than the high-frequency textural details required for fine-grained denomination discrimination.

Figure 5. Misclassification due to glare

3.4.2. Poor light environment

In low-light environments with illumination levels below 50 lux, reduced visual contrast and loss of fine-grained features significantly affected performance. Image analysis showed compressed dynamic ranges with most pixel values concentrated in the lower intensity spectrum. While detection remained possible in some cases, misclassifications increased noticeably compared to ideal lighting conditions compared to ideal lighting conditions. Confidence scores fell to 0.70-0.85 even for correct classifications (Figure 6), indicating reduced model certainty. The primary cause was insufficient illumination failing to reveal critical engravings and denomination markers, particularly for the IDR 100 and IDR 200 coins which rely on subtle surface relief for discrimination.

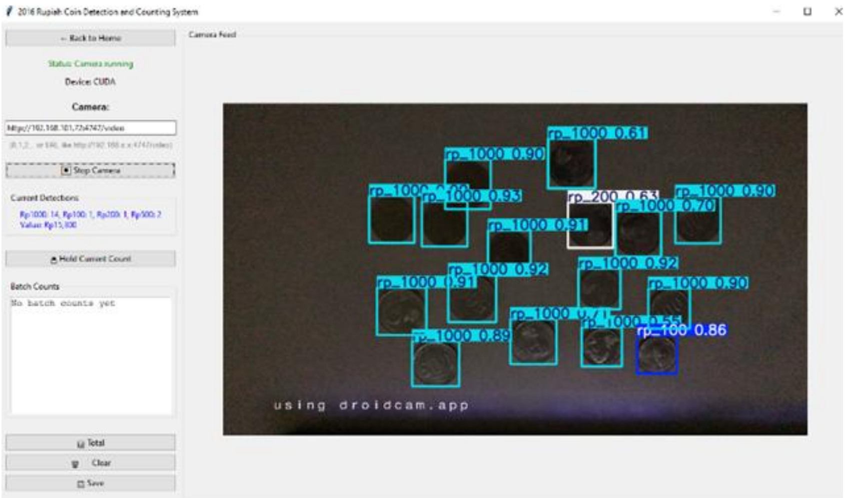

Figure 6. Misclassification due to poor lighting

3.4.3. Overlapping and cluttered coins

Heavily overlapping or clustered coins posed significant challenges for instance separation, resulting in missed detections or incorrect classifications when overlap exceeded approximately 30% (Figure 7). Quantitative analysis revealed that recall dropped from 0.99 to 0.82 when overlap exceeded this threshold. In cases where three or more coins were clustered, the model frequently detected only two of the three, merging the third with an adjacent detection. This limitation stems from the non-maximum suppression algorithm used in YOLOv8, which eliminates redundant bounding boxes based on overlap thresholds. When coins are physically stacked, the overlap creates genuine ambiguity about object boundaries that cannot be resolved without additional contextual information or multi-view analysis.

Figure 7. Missed object detection

3.4.4. Coin wear and degradation

Heavily tarnished or damaged coins exhibited degraded surface features, adversely affecting classification accuracy. Analysis of worn coins showed that when surface relief depth decreased significantly, classification accuracy dropped from 0.99 to approximately 0.76. Coins with extensive wear were most commonly misclassified as the next smaller denomination—for example, worn IDR 500 coins were often classified as IDR 200 (Figure 8). This confusion pattern suggests that when numeric digits are degraded, the model defaults to size-based classification, which can be ambiguous given the small size differences between denominations. This limitation is particularly relevant for real-world deployment, as circulated coins inevitably show varying degrees of wear, and any practical system must maintain reasonable accuracy across the full spectrum of coin conditions.

Overall, experimental results confirm the system delivers high accuracy under typical operating conditions but shows limitations under extreme lighting, significant occlusion, and severe coin wear, defining operational boundaries and future improvement areas.

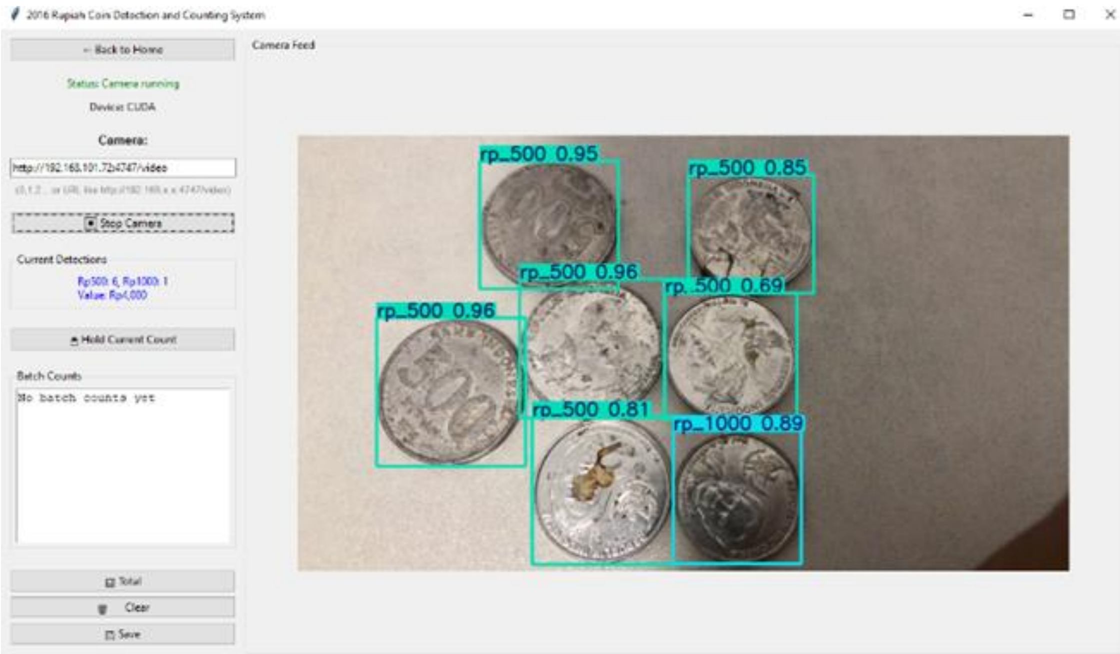

Figure 8. Misclassification of tarnished objects

4. CONCLUSION

This study proposes a real-time system for detecting and classifying 2016 Indonesian coins using a transfer learning-based YOLOv8 framework. By freezing backbone layers and fine-tuning higher-level features, the model achieves high detection accuracy (mAP@0.5 = 0.995) on an unseen test set despite limited dataset size. Results demonstrate transfer learning is an effective strategy for adapting general-purpose object detection models to specialized, low-resource domains. Qualitative evaluations reveal performance degradation under extreme lighting, severe occlusion, and heavy coin wear, providing transparent assessment of the system's practical limitations.

Scientifically, this work validates frozen-backbone transfer learning as a computationally efficient approach for domain-specific currency recognition and contributes a newly constructed annotated dataset for modern Indonesian coins, addressing a gap in existing research. From an application perspective, the proposed system is well-suited for banking automation, retail systems, and assistive technologies requiring real-time coin recognition. Future work will focus on expanding dataset diversity to include more challenging scenarios such as extreme lighting variations, severe occlusion, and heavily worn coins, and developing a lightweight mobile version for broader accessibility.

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The authors declare that no funding was received for conducting the research.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Nur Hadisukmana	✓	✓	✓	✓	✓	✓		✓	✓	✓		✓		
R. B. Wahyu	✓	✓			✓			✓		✓	✓			
Stewart Qiu		✓	✓	✓		✓	✓		✓	✓	✓			

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors state no conflict of interest related to this research.

DATA AVAILABILITY

The data that support the findings of this study are available on request from the corresponding author, [initials, NH]. The data, which contain information that could compromise the privacy of research participants, are not publicly available due to certain restrictions.

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