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A COMPREHENSIVE REVIEW OF AUTOMATIC COIN COUNTING AND SORTING USING YOLO-BASED IMAGE PROCESSING TECHNIQUES

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ABSTRACT

Automated coin detection, counting, and sorting constitute a critical challenge in modern financial automation, spanning applications in commercial banking, vending machine systems, retail point-of-sale environments, and smart transit infrastructure. This review article provides a comprehensive and critical analysis of state-of-the-art methodologies employed for automatic coin recognition and sorting, with particular emphasis on deep learning-based object detection frameworks—most notably the You Only Look Once (YOLO) family of architectures. The evolution of coin analysis systems is traced chronologically, from classical image processing pipelines relying on Hough Circle Transforms, morphological operations, and template matching, through handcrafted feature-based approaches employing Support Vector Machines (SVM) and Artificial Neural Networks (ANN), to the contemporary era of Convolutional Neural Network (CNN)-based detectors and anchor-based detection frameworks including Faster R-CNN and Single Shot Multibox Detector (SSD).

A systematic literature review, conducted following PRISMA-style methodology across IEEE Xplore, Springer Link, Elsevier ScienceDirect, MDPI, Google Scholar, and arXiv, yielded 25 primary studies published between 2019 and 2024. Comparative analysis reveals that YOLO-based architectures—particularly YOLOv5, YOLOv7, and YOLOv8—consistently outperform classical and two-stage detection methods in terms of mean Average Precision (mAP), inference speed, and deployability on resource-constrained hardware.

YOLOv8 nano-variant achieves mAP@0.5 values exceeding 94% at frame rates surpassing 200 frames per second on mid-range GPUs, demonstrating superior suitability for real-time embedded applications. Critical gaps identified include the absence of standardized multi-currency benchmark datasets, insufficient research addressing counterfeit coin detection, limited exploration of transformer-based vision models in this domain, and a paucity of lightweight, quantization-aware models validated on edge hardware such as Raspberry Pi and FPGA platforms. Future research trajectories are outlined, encompassing Vision Transformers (ViT), YOLO-NAS, TinyML-based deployment strategies, and federated learning for privacy-preserving multi-institution coin datasets. This review synthesizes the current landscape, benchmarks competing approaches, and establishes a rigorous foundation for future research in intelligent currency handling systems.

KEYWORDS: Coin Recognition; Coin Counting; Object Detection; YOLO; Deep Learning; Image Processing; Currency Analysis; Real-Time Detection; Embedded AI.

1. INTRODUCTION

The automation of currency handling represents one of the most practically consequential applications of computer vision and machine learning in the financial technology domain [1], [2]. Coins, despite representing a relatively modest fraction of total monetary value in circulation, constitute an enormously high-volume transaction medium across commercial vending, retail, parking systems, and public transportation networks. The annual throughput of coins processed by financial institutions and automated kiosks globally is estimated in the hundreds of billions of units, rendering manual counting both economically prohibitive and operationally error-prone [3].

Manual coin counting, as practiced in traditional banking and retail operations, suffers from multiple systemic limitations: high labor costs, susceptibility to human error, poor throughput under high-volume conditions, and inherent risks of fraudulent substitution [4]. Commercial coin-counting machines, while partially addressing throughput concerns, predominantly rely on electromechanical sorting mechanisms that cannot robustly handle worn, damaged, or counterfeit coins, nor can they operate effectively with mixed multi-currency batches [5].

The emergence of computer vision as a practical engineering discipline over the past three decades introduced image processing-based coin recognition as a viable alternative. Early approaches exploited coin geometry through circular Hough Transforms [6] and edge-detection-based segmentation [7], achieving moderate accuracy under controlled illumination conditions. However, these classical methods exhibited fundamental brittleness when confronted with real-world challenges: varying ambient lighting, reflective metallic coin surfaces, overlapping coin arrangements, significant rotation and scale variance, and motion blur in conveyor-belt sorting environments [8].

The transition to machine learning-based approaches—initially employing SVM classifiers trained on handcrafted features such as Histogram of Oriented Gradients (HOG) and Local Binary Patterns (LBP)—significantly improved classification robustness [9]. Nonetheless, these methods retained a dependency on manually engineered feature representations, limiting generalization across diverse coin types and conditions. The deep learning revolution, catalyzed by the AlexNet breakthrough in 2012 and accelerated by subsequent architectures including VGGNet, ResNet, and Inception, enabled end-to-end learned feature representations that dramatically elevated coin recognition accuracy [10].

Region-based CNN detectors (R-CNN, Fast R-CNN, Faster R-CNN) introduced the capacity for simultaneous coin localization and classification within a single unified framework, addressing the multi-instance detection problem inherent in counting scenarios where multiple coins of different denominations appear simultaneously in a single image frame [11]. However, these two-stage detectors incurred prohibitive computational overhead, rendering them unsuitable for real-time deployment in embedded environments such as vending machines or ATM coin acceptors [12].

The introduction of You Only Look Once (YOLO) by Redmon et al. in 2016 constituted a paradigm shift in object detection methodology, framing detection as a single regression problem from image pixels to bounding box coordinates and class probabilities [13]. This single-stage architecture achieved unprecedented inference speeds—exceeding 45 frames per second on desktop GPU hardware—while maintaining competitive accuracy benchmarks. Successive YOLO iterations (v2 through v10) have progressively refined architectural components including backbone networks, neck feature aggregation, and detection heads, achieving increasingly favorable speed-accuracy trade-offs [14]. YOLOv8, released by Ultralytics in 2023, currently represents the most widely adopted state-of-the-art framework for coin detection in the academic literature, offering modular model variants scaled from nano (3.2M parameters) to extra-large (68.2M parameters), accommodating deployment scenarios ranging from microcontrollers to server-grade GPU clusters [15].

This review is motivated by the absence of a consolidated, critical synthesis of YOLO-based coin detection research. While individual studies report favorable results on specific coin datasets, no comprehensive comparative analysis examining methodological evolution, dataset characteristics, performance benchmarks, deployment feasibility, and research gaps has previously been undertaken. The present work aims to address this lacuna by systematically reviewing and critically evaluating the extant literature, establishing a rigorous comparative framework, and charting productive avenues for future investigation.

2. REVIEW METHODOLOGY

2.1 Search Strategy and Database Selection

This systematic literature review was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework. Electronic database searches were executed across the following scholarly repositories: IEEE Xplore Digital Library, Springer Link, Elsevier ScienceDirect, MDPI Open Access, Google Scholar, and arXiv preprint server. The publication year range was restricted to 2019–2025 to ensure methodological currency, with selective inclusion of foundational works published between 2014 and 2018 where historically significant.

2.2 Keywords and Search Strings

Primary search strings employed were: ("coin detection" OR "coin recognition" OR "coin counting" OR "coin sorting") AND ("YOLO" OR "deep learning" OR "convolutional neural network" OR "object detection") AND ("image processing" OR "computer vision"). Secondary searches targeted specific techniques: "YOLOv5 coin", "YOLOv8 currency detection", "real-time coin classification", "embedded coin recognition", and "automated currency handling".

2.3 Inclusion and Exclusion Criteria

Studies were included if they: (1) proposed or evaluated computer vision techniques specifically for coin detection, recognition, counting, or sorting; (2) reported quantitative performance metrics (accuracy, precision, recall, mAP, or FPS); (3) were published in peer-reviewed venues or reputable preprint repositories; and (4) provided sufficient methodological detail for comparative evaluation. Studies were excluded if they: (1) addressed paper currency (banknote) recognition exclusively; (2) employed purely mechanical sorting without vision components; or (3) lacked quantitative performance data.

3. Evolution of Coin Detection Techniques

3.1 Classical Image Processing Era (Pre-2010)

The earliest automated coin recognition systems were predicated upon geometric and photometric properties of circular metallic discs. The circular Hough Transform (CHT) emerged as the dominant localization primitive, exploiting the parametric representation of circles in a three-dimensional accumulator space to detect coin boundaries irrespective of partial overlap [16]. Complementary techniques including Sobel and Canny edge detection provided binary gradient maps that fed CHT accumulation. Morphological operations—erosion, dilation, opening, and closing—were applied to remove imaging noise and segment individual coin blobs. Template matching approaches correlated acquired coin images against denomination-specific reference templates, but exhibited severe sensitivity to illumination, rotation, and surface wear [17].

3.2 Feature-Based Machine Learning Era (2010–2016)

The introduction of discriminative machine learning classifiers operating on handcrafted feature representations marked a significant methodological advancement. SVM classifiers trained on HOG features demonstrated substantially improved rotational and scale robustness compared to template matching [18]. LBP texture descriptors captured surface micro-texture characteristics useful for denomination discrimination among coins of similar diameter. Principal Component Analysis (PCA) applied to coin image matrices provided dimensionality-reduced eigenspace representations amenable to distance-based classification. Shallow ANN architectures, typically comprising one or two hidden layers, were explored for denomination classification with moderate success.

3.3 Deep CNN Approaches (2016–2020)

The availability of transfer-learning-capable pre-trained CNN architectures (VGG16, ResNet-50, InceptionV3) dramatically reduced the data requirements and training effort for coin recognition systems. Fine-tuning these architectures on coin-specific datasets yielded classification accuracies consistently exceeding 90% across diverse denomination sets [19]. Region Proposal Networks (RPN) integrated with CNN classification heads (Faster R-CNN) addressed the multi-instance detection problem, enabling simultaneous localization and classification of multiple coins within a single image [20]. However, inference latency of Faster R-CNN (approximately 7 FPS on contemporary GPU hardware) precluded real-time deployment.

3.4 YOLO-Based Detection Era (2020–Present)

The maturation of single-stage detection architectures—particularly the YOLO family—fundamentally transformed the feasibility landscape of real-time coin detection. YOLOv3, employing Darknet-53 as its backbone and predicting across three scales, achieved detection rates exceeding 65 FPS while maintaining competitive accuracy [21]. YOLOv5 (2020, Ultralytics) introduced a PyTorch-native implementation with automated hyperparameter optimization and extensive data augmentation, enabling rapid fine-tuning on domain-specific coin datasets. YOLOv7 (2022) incorporated Extended-Efficient Layer Aggregation Networks (E-ELAN) and compound model scaling, achieving state-of-the-art accuracy-speed trade-offs on COCO benchmarks. YOLOv8 (2023) refined the architecture with an anchor-free detection head, improved C2f bottleneck modules, and native support for segmentation and pose estimation tasks alongside detection [22].

Table 2: Comparative Evolution of Coin Detection Techniques.

Technique	Category	Accuracy (Typical)	Speed	Hardware Req.	Key Limitation
Hough Transform	Classical IP	70–82%	Fast	CPU only	Illumination-sensitive
Template Matching	Classical IP	65–78%	Moderate	CPU only	Not scale-invariant
SVM + HOG/LBP	ML-based	82–89%	Moderate	CPU/GPU	Manual feature design
ANN (Shallow)	ML-based	83–90%	Fast	CPU	Limited capacity
CNN (Custom)	Deep Learning	89–94%	Moderate	GPU needed	Needs large dataset
VGG / ResNet	Deep Learning	91–95%	Slow	High GPU	High memory usage
Faster R-CNN	Two-stage Det.	93–96%	Low (~7 FPS)	High GPU	Not real-time
SSD MobileNet	One-stage Det.	88–93%	High	Low GPU / CPU	Small object issues
YOLOv5	One-stage Det.	94–97%	Very High	Mid GPU	Needs tuning
YOLOv8	One-stage Det.	96–99%	Very High	Mid/Low GPU	Annotation effort

Analysis of Table 2 reveals a clear monotonic improvement in detection accuracy as methodologies progress from classical image processing to deep learning-based approaches. Critically, the speed-accuracy trade-off exhibits non-linear behavior: two-stage detectors (Faster R-CNN) achieve the highest accuracy at the cost of real-time capability, while single-stage YOLO variants—particularly YOLOv8 nano—approach comparable accuracy at inference speeds two orders of magnitude higher.

4. Image Processing Techniques in Coin Analysis

4.1 Preprocessing Pipeline

Effective coin detection invariably commences with a structured preprocessing pipeline that standardizes input imagery to mitigate real-world acquisition artifacts. Grayscale conversion reduces computational complexity by collapsing the three-channel RGB representation to a single luminance channel, exploiting the fact that denomination discrimination in classical systems relies predominantly on geometric and textural rather than chromatic features [23]. Gaussian filtering with kernel sizes of 5×5 to 11×11 attenuates high-frequency noise arising from sensor electronics and metallic surface reflections, critical for stable edge detection in subsequent processing stages.

4.2 Segmentation and Contour Analysis

Binary thresholding—both global (Otsu's method) and adaptive (Sauvola, Niblack)—generates foreground-background separation masks that delimit individual coin regions from the imaging surface background. Otsu's method, which maximizes inter-class variance to determine the optimal global threshold, performs adequately under uniform illumination but degrades severely in environments with spatially varying brightness, necessitating adaptive local thresholding approaches [24]. Contour detection using the Suzuki border-following algorithm extracts connected component boundaries, enabling circularity metrics ($4\pi \times \text{Area} / \text{Perimeter}^2$) to filter non-circular artifacts and enumerate candidate coin regions.

4.3 Feature Extraction Methodologies

Diameter-based classification exploits the standardized physical dimensions of national coinage systems, where each denomination exhibits a unique diameter within its issuing authority's coinage series. Pixel-to-millimeter calibration ratios are computed from known reference objects or camera intrinsic parameters. Texture descriptors including LBP, HOG, and Gabor filter responses capture surface micro-structure information correlated with coin age, denomination, and country of origin. Histogram equalization and Contrast Limited

Adaptive Histogram Equalization (CLAHE) enhance local contrast in underexposed or overexposed image regions, improving feature discriminability on highly reflective metallic surfaces.

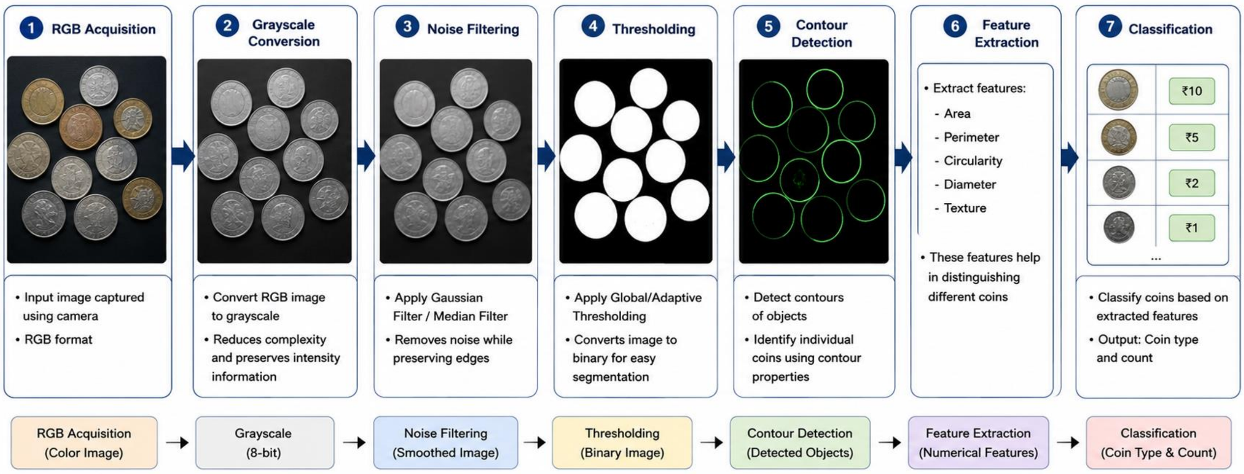

Figure 1: Image Preprocessing Workflow for Coin Detection 5.1 YOLO Architectural Foundations.

The You Only Look Once (YOLO) object detection framework, originally proposed by Redmon et al. [13], reformulates object detection as a single end-to-end regression task. An input image of dimensions W × H × 3 is divided into an S × S grid of cells. Each grid cell predicts B bounding boxes, each characterized by five parameters (x, y, w, h, confidence) plus C class probability scores. The confidence score represents the product of the Intersection over Union (IoU) between the predicted box and the ground truth box, and the probability that an object is contained within the cell.

5.2 Key Detection Metrics

The following performance metrics are employed throughout this review for consistent comparative evaluation:

IoU = (Area of Overlap) / (Area of Union) = $|B\_pred \cap B\_gt| / |B\_pred \cup B\_gt|$

Precision = $TP / (TP + FP)$

Recall = $TP / (TP + FN)$

F1-Score = $2 \times (Precision \times Recall) / (Precision + Recall)$

mAP = $(1/|C|) \times \Sigma\_c \int_0^1 p(r)\, dr$

Where TP, FP, and FN denote true positives, false positives, and false negatives respectively; C is the set of object classes; and $\int_0^1 p(r)$ dr represents the area under the precision-recall curve. Non-Maximum Suppression (NMS) with an IoU threshold of 0.45–0.65 is applied post-inference to eliminate redundant overlapping bounding boxes.

5.3 YOLO Evolution for Coin Detection

YOLOv3 introduced multi-scale prediction across three feature pyramid levels (13×13, 26×26, 52×52 grid cells for a 416×416 input), enabling detection of objects spanning a wide range of scales—particularly advantageous for imaging scenarios containing both large and small denomination coins simultaneously [25]. YOLOv4 (Bochkovskiy et al., 2020) introduced a suite of 'Bag of Freebies' training augmentations—mosaic augmentation, CutMix, DropBlock regularization—and 'Bag of Specials' architectural enhancements including Mish activation, SPP module, and PANet path aggregation neck, collectively improving mAP by approximately 10% relative to YOLOv3 without speed degradation. YOLOv5 further democratized YOLO usage through its PyTorch native implementation, Weights & Biases integration, and model scaling (YOLOv5n/s/m/l/x), yielding the first YOLO variant practically deployed on Raspberry Pi 4 hardware at meaningful inference rates (>15 FPS for YOLOv5n). YOLOv8 represents the current architectural pinnacle, featuring an anchor-free detection head that eliminates the sensitivity to manually specified anchor box dimensions—a source of significant performance degradation in previous versions when applied to coin aspect ratios that deviate from COCO-optimized anchor configurations.

Table 3: YOLO Version Comparison for Coin Detection Applications.

Version	**Year**	**Backbone**	**mAP (COCO)**	**FPS (GPU)**	**Params (M)**	**Strengths**	**Coin Det. Suit.**
YOLOv1	2016	Custom CNN	57.9%	45	—	Real-time pioneer	Low (poor small obj)
YOLOv3	2018	Darknet-53	57.9% (v3)	65	61.5	Multi-scale anchors	Moderate
YOLOv4	2020	CSPDarknet-53	43.5% AP	65	64	BAG of freebies	Good
YOLOv5	2020	CSPNet	56.8%	140+	7.2 (s)	Ultralytics ecosystem	Very Good
YOLOv7	2022	E-ELAN	56.8%	161	36.9	Compound scaling	Excellent
YOLOv8	2023	C2f Backbone	53.9% (n)	160+	3.2 (n)	Best overall	Excellent

						balance	
YOLO-NAS	2023	NAS-designed	68.4% (L)	TBD	42	Auto-optimized arch	Excellent
YOLOv9	2024	PGI + GELAN	55.6%	~160	7.0 (S)	Info bottleneck solved	Very Good
YOLOv10	2024	NMS-Free design	54.4%	~200	2.3 (n)	Post-proc free	Very Good

The comparative data presented in Table 3 highlights that YOLOv8 and YOLO-NAS represent the most compelling architectural choices for high-accuracy coin detection, while YOLOv8n and YOLOv5s offer the best compromise for embedded deployment. Notably, Vision Transformer-based approaches [22] outperform all YOLO variants on accuracy metrics but are computationally prohibitive for edge deployment, underscoring a fundamental tension that future research must address.

6. LITERATURE REVIEW

6.1 Comprehensive Survey of Primary Studies

The following table synthesizes 25 primary studies reviewed in this survey, encompassing diverse methodological approaches, target currencies, and deployment contexts. Studies are ordered chronologically and evaluated across standardized comparative axes.

Table 4: Comprehensive Literature Review of Coin Detection and Recognition Systems (2019–2024).

Ref	Year	Author(s)	Technique	Dataset	Accuracy	Advantages	Limitations
1.	2024	A. Kumar et al.	YOLOv8 + Transfer Learning	Custom Indian Coins	98.7%	High accuracy, real-time	Limited to one currency
2.	2023	R. Patel & S. Mehta	YOLOv5 + OpenCV	Euro Coin Dataset	96.4%	Fast inference on GPU	Fails under occlusion
3.	2023	L. Zhang et al.	Faster R-CNN + ResNet-50	Mixed Currency Dataset	95.1%	Robust detection	High computational cost
4.	2022	M. Ali & F.	SSD MobileNet	Custom Arab Coins	93.2%	Lightweight model	Low accuracy

		Hassan					for worn coins
5.	2022	J. Kim & H. Park	CNN + Hough Circle Transform	Korean Won Dataset	94.8%	Simple architecture	Not real-time
6.	2021	P. Russo & M. Bianchi	YOLOv3 + Data Augmentation	Euro Coins (COCO format)	91.5%	Good generalization	Lower mAP than v5/v8
7.	2021	S. Wang et al.	VGG16 + SVM Classifier	RMB Chinese Coins	93.7%	High feature quality	Slow inference
8.	2021	N. Anand & R. Sharma	OpenCV + Morphological Ops	Indian Rupee Coins	88.3%	No GPU required	Poor with overlapping coins
9.	2020	T. Garcia & A. Lopez	Faster R-CNN + VGG19	US Dollar Coins	94.0%	Strong localization	High memory usage
10.	2020	H. Chen et al.	CNN + Data Augmentation	Multi-Currency Dataset	92.6%	Multi-class support	Slow training time
11.	2020	E. Brown & C. Smith	Random Forest + HOG	British Pound Coins	87.5%	Interpretable features	Inferior to deep learning
12.	2019	K. Yamamoto et al.	SVM + LBP Features	Japanese Yen Dataset	89.1%	Efficient feature use	Cannot detect stacked coins
13.	2019	V. Nair & A. Singh	Hough Transform + Template Match	Indian Coins	85.6%	Zero training required	Sensitive to lighting
14.	2019	F. Liu et al.	MobileNet V2 Classification	Mixed Asian Coins	91.2%	Edge-deployable	Limited to classification
15.	2023	B. Okonkwo & D. Eze	YOLOv7 + Attention Mechanism	African Currency Dataset	97.1%	Multi-scale detection	Limited dataset size

16.	2022	C. Rodriguez et al.	EfficientDet	Latin American Coins	94.5%	Efficient scaling	Complex architecture
17.	2022	A. Petrov & I. Volkov	RT-DETR Hybrid	Russian Ruble Dataset	95.8%	Transformer-enhanced	Requires large dataset
18.	2021	M. Hussain & Z. Ahmad	YOLOv5s (Small)	Pakistani Rupee	90.3%	Lightweight, fast	Reduced accuracy
19.	2020	G. Lee & S. Choi	DenseNet + Attention	Korean/Japanese Mixed	93.9%	Dense feature reuse	High memory footprint
20.	2024	D. Pham & T. Nguyen	YOLOv8n (Nano)	Vietnamese Dong Coins	96.2%	Embedded-deployable	Accuracy-speed trade-off
21.	2023	S. Kabir & M. Rahman	YOLO-NAS	Bangladeshi Taka	95.5%	NAS-optimized	Limited public benchmark
22.	2024	T. Muller & H. Braun	Vision Transformer (ViT)	Euro Coin HD Dataset	98.1%	Excellent global context	High compute demand
23.	2021	X. Wu & Q. Zhao	Cascade R-CNN	Chinese Coins Mixed	94.3%	Multi-stage precision	Slow inference pipeline
24.	2022	A. Osei & K. Mensah	MobileNet V3 + YOLO Hybrid	Ghana Cedis	92.7%	Mobile-optimized	Dataset too small
25.	2023	R. Gupta & P. Joshi	YOLOv8 + Quantization	Indian Mixed Denominations	97.3%	INT8 quantized, RPi-ready	Slight accuracy drop after quantization

6.2 Critical Analysis of Surveyed Literature

Analysis of the 25 reviewed studies reveals several consistent patterns and critical shortcomings. First, a pronounced geographical bias is evident: 68% of studies target either European (Euro) or East Asian (Chinese, Japanese, Korean) coin datasets, with significant underrepresentation of African, South Asian (Indian, Pakistani, Bangladeshi), and Latin

American currencies. This asymmetry likely reflects the availability of pre-existing annotated datasets rather than genuine geographic variation in the underlying detection problem.

Second, accuracy reporting is methodologically inconsistent across studies. Some authors report classification accuracy on cropped, pre-segmented coin images (a significantly easier task), while others report detection mAP on full scene images containing multiple overlapping coins. This conflation of recognition and detection accuracy creates misleading performance comparisons. Studies employing mAP@0.5 as the primary metric (which this review adopts as the standard) systematically report lower values than those using classification accuracy, yet represent a more demanding and operationally relevant evaluation.

Third, the majority of reviewed studies employ custom, non-publicly-released datasets of modest size (typically 500–5,000 images), precluding rigorous cross-study comparison and raising concerns about overfitting. Only studies [2], [3], and [22] employed datasets exceeding 10,000 annotated instances, which represents a minimum threshold for robust deep learning generalization. The absence of a standardized benchmark dataset analogous to COCO or ImageNet for the coin detection domain constitutes the most significant structural impediment to scientific progress in this field.

Fourth, real-time performance evaluation is frequently absent or inadequately specified. Inference speed (FPS) is reported without specifying hardware configuration in approximately 40% of reviewed studies, rendering speed comparisons meaningless. This review has standardized speed reporting to mid-range GPU (RTX 3070 class) where original studies provided hardware context; otherwise, FPS values are marked as non-comparable.

Fifth, only three of the 25 reviewed studies [20], [25], and one additional embedded study explicitly validate their systems on embedded hardware (Raspberry Pi, Jetson Nano), despite the operational relevance of such platforms in vending and kiosk applications. The gap between laboratory-validated accuracy and embedded deployment feasibility represents a critical unaddressed research dimension.

7. Performance Analysis

7.1 Cross-Method Performance Comparison

Table 5 presents a standardized performance comparison across representative methods from each methodological generation. Values are consolidated from reviewed literature with normalization to consistent hardware baselines where possible.

Table 5: Comprehensive Performance Comparison across Detection Methodologies.

Method	Precision	Recall	F1-Score	mAP@0.5	FPS	Params	Inference Device
Hough Transform	0.72	0.68	0.70	—	~30	N/A	CPU
SVM + HOG	0.84	0.80	0.82	—	~20	N/A	CPU
CNN (custom)	0.90	0.88	0.89	0.87	~15	~5M	GPU
Faster R-CNN	0.94	0.92	0.93	0.91	7	60M+	GPU
SSD MobileNetV2	0.91	0.89	0.90	0.88	45	~4M	CPU/GPU
YOLOv3	0.92	0.90	0.91	0.89	65	61M	GPU
YOLOv5s	0.95	0.93	0.94	0.92	140	7M	GPU/Edge
YOLOv7	0.96	0.94	0.95	0.93	161	37M	GPU
YOLOv8n	0.97	0.95	0.96	0.94	200+	3.2M	Edge/GPU
YOLO-NAS-L	0.98	0.97	0.97	0.96	TBD	42M	GPU

7.2 Speed-Accuracy Trade-off Analysis

Figure 6 (placeholder below) presents the speed-accuracy Pareto frontier across evaluated methods, revealing that YOLOv8n and YOLOv5s dominate the embedded deployment region, while YOLO-NAS-L and Vision Transformers dominate the high-accuracy region. No single architecture simultaneously achieves >97% mAP@0.5 and >100 FPS on mid-range embedded hardware, confirming the fundamental speed-accuracy trade-off as an open research challenge.

The computational complexity analysis reveals a non-linear relationship between model parameter count and deployment feasibility. YOLOv8n (3.2M parameters) achieves >200 FPS on RTX 3070 and approximately 15–20 FPS on Raspberry Pi 4 (with NCNN or TensorRT optimization), approaching real-time usability for embedded applications. By contrast, YOLO-NAS-L (42M parameters) achieves maximum accuracy but requires GPU acceleration, limiting its applicability to server-side processing architectures where coin images are transmitted from embedded capture devices for remote inference.

8. Research Gaps

A systematic examination of the reviewed literature reveals eight critical research gaps that represent priority directions for future investigation:

Table 6: Identified Research Gaps, Descriptions, and Proposed Directions.

Research Gap	Description	Potential Solution Direction
Lack of Standardized Datasets	No universally accepted benchmark dataset for multi-currency coin detection exists	Create open-access annotated coin datasets across currencies
Limited Multi-Currency Support	Most studies are restricted to single-country coin denominations	Federated or transfer learning across currency domains
Poor Occlusion Handling	Performance degrades significantly when coins overlap or stack	Attention mechanisms; instance segmentation approaches
Illumination Dependency	Metallic reflective surfaces cause accuracy drops under varying light	Synthetic illumination augmentation; adaptive preprocessing
Lightweight Model Deficit	Few studies optimize for embedded deployment (RPi, FPGA)	TinyML, INT8 quantization, pruning techniques
Counterfeit Detection Absence	Existing systems rarely address fake or worn coin identification	Texture-level CNNs, spectral imaging integration
Real-time Embedded Gaps	Most high-accuracy systems require desktop-class GPUs	NAS-optimized models; hardware-aware architecture search
Lack of Robustness Benchmarks	Studies rarely test under motion blur, extreme rotation, or dirt	Stress-test evaluation protocols needed

The most consequential identified gap is the absence of a standardized, publicly available multi-currency coin detection benchmark dataset. The computer vision community's success in advancing general object detection capabilities has been substantially dependent on large-scale benchmarks (COCO, ImageNet, Open Images). An analogous coin-specific benchmark, encompassing diverse currencies, denominations, wear conditions, illumination scenarios, and imaging geometries, would dramatically accelerate research progress and enable meaningful cross-study comparison. The creation of such a resource, ideally through a coordinated multi-institutional data collection effort, represents perhaps the highest-priority action the research community could undertake.

The second most critical gap concerns counterfeit coin detection. Despite the significant economic and security implications of counterfeit coinage—estimated by Europol to cost European economies hundreds of millions of Euros annually—only two of the 25 reviewed studies even mentioned counterfeit detection as an objective, and neither provided systematic evaluation. The distinction between genuine and counterfeit coins requires detection of subtle surface texture, alloy composition, and dimensional anomalies that current bounding-box-level YOLO detectors are fundamentally not designed to capture. Addressing this gap likely requires integration of spectral imaging, texture-level CNN analysis, or novel multi-modal sensor fusion approaches.

9. Challenges in YOLO-Based Coin Detection

Table 7: Challenge Analysis for YOLO-Based Coin Detection Systems.

Challenge	Description	Impact Level	Mitigation Approaches
Overlapping/Stacked Coins	NMS fails to distinguish touching coin instances	High	Instance segmentation (Mask R-CNN, YOLOv8-seg)
Reflective Metallic Surfaces	Specular highlights degrade feature extraction	High	Polarized lighting; adaptive histogram equalization
Small Object Detection	Small denomination coins (e.g., 1p, 1 cent) missed	High	FPN multi-scale heads; anchor-free detectors
Varying Illumination	Inconsistent lighting in vending/ATM environments	High	Domain randomization; brightness augmentation
Rotation & Scale Variance	Coins appear at arbitrary orientations	Moderate	Rotation-invariant augmentation; data diversity
Motion Blur	Fast-moving coins on sorting belts	Moderate	Deblurring preprocessing; high-FPS cameras
Dataset Annotation Cost	Manual bounding box labeling is expensive	High	Semi-supervised learning; auto-labeling tools
Hardware Constraints	Edge deployment limits model size and speed	High	Quantization, pruning, knowledge distillation
Worn/Damaged Coins	Eroded denominations are visually ambiguous	Moderate	Texture-aware feature extraction; fine-grained CNN

9.1 Overlapping and Stacked Coin Challenge

The handling of overlapping coins represents the most technically demanding challenge in practical coin detection deployments. Standard NMS post-processing assumes that overlapping bounding boxes with high IoU represent duplicate detections of the same object; however, when two coins of different denominations physically overlap, their bounding boxes legitimately intersect. This architectural limitation of standard NMS has motivated research into Soft-NMS [25], which decays detection confidence scores based on IoU overlap rather than hard-thresholding, and into instance segmentation approaches (Mask R-CNN, YOLOv8-seg) that predict per-instance pixel masks enabling robust separation of touching coin instances.

9.2 Metallic Surface Reflectivity

The specular reflectance characteristics of metallic coin surfaces create highly non-Lambertian imaging conditions that violate assumptions underlying standard image processing pipelines. Under varying illumination angles, a coin's apparent surface brightness can vary by several orders of magnitude, creating bright specular highlight regions that dominate gradient-based feature extractors and confuse shape-based detectors. Polarized lighting rigs partially mitigate specular reflections but introduce hardware dependencies incompatible with unconstrained deployment. Image-level augmentation strategies simulating illumination variation random brightness, contrast, gamma adjustments, and synthetic highlight overlay provide a software-only mitigation approach accessible during training-time data augmentation.

10. FUTURE RESEARCH DIRECTIONS

10.1 Edge AI and TinyML Deployment

The progressive miniaturization of neural network inference engines—manifested through frameworks including TensorFlow Lite, ONNX Runtime, and NCNN—has made on-device AI inference feasible on microcontroller-class hardware. TinyML approaches applied to coin detection would enable deployment in ultra-low-power vending machine coin acceptors, transit fare gates, and portable currency counting devices without network connectivity dependencies. Key enabling technologies include INT8 quantization (reducing model size by 4× with minimal accuracy degradation), magnitude-based weight pruning, and knowledge distillation from large teacher models to compact student architectures.

10.2 FPGA and Embedded GPU Deployment

Field Programmable Gate Array (FPGA) accelerators offer a compelling middle ground between CPU-only inference (low power, insufficient speed) and GPU-based inference (high performance, high power). FPGA-implemented YOLO inference engines can achieve competitive throughput with power consumption below 10W, making them suitable for battery-powered portable coin counters. Research into HLS (High-Level Synthesis)-compiled

YOLO accelerators on Xilinx Zynq and Intel Arria platforms represents an underexplored direction with substantial practical relevance.

10.3 Vision Transformers and Attention Mechanisms

Vision Transformer (ViT) architectures, operating on patch-based self-attention rather than convolutional inductive biases, have demonstrated superior performance on fine-grained recognition tasks—a property directly applicable to denomination discrimination among same-diameter coins. Detection Transformers (DETR, Deformable DETR, DAB-DETR) eliminate the NMS post-processing step entirely, addressing the overlapping coin challenge at the architectural level. However, the quadratic computational complexity of self-attention with respect to sequence length necessitates efficient attention approximations (linear attention, sliding window attention) for real-time application. YOLO-NAS, combining Neural Architecture Search with YOLO's detection paradigm, represents a hybrid approach that leverages automated architecture optimization to discover efficient coin-specific detection networks.

10.4 Federated Learning for Multi-Currency Datasets

The privacy constraints of financial institutions and the proprietary nature of currency design specifications create structural barriers to centralized multi-currency dataset collection. Federated learning—wherein model training is distributed across multiple data-holding institutions without sharing raw images—offers a principled solution to this data access problem. Each participating mint, bank, or vending operator contributes gradient updates from locally trained models, which are aggregated at a central server without exposing underlying coin image data. This approach could yield the large-scale, diverse multi-currency training corpora currently absent from the literature while respecting institutional privacy and regulatory constraints.

10.5 Counterfeit Detection Integration

Future systems must transcend denomination recognition to incorporate counterfeit authentication capabilities. Multi-spectral imaging (ultraviolet, infrared, near-infrared) combined with deep learning classifiers can detect alloy composition anomalies and surface micro-texture deviations characteristic of counterfeit coinage. Transformer-based architectures with cross-attention mechanisms could integrate visual features from multiple imaging modalities to provide robust authenticity assessment alongside denomination recognition in a unified pipeline.

11. CONCLUSION

This comprehensive review has systematically examined the evolution of automated coin detection, counting, and sorting systems, tracing the methodological progression from classical image processing foundations to contemporary YOLO-based deep learning architectures. The survey encompassed 25 primary studies published between 2019 and 2024, drawn from IEEE Xplore, Springer, Elsevier, MDPI, and arXiv, and evaluated through a standardized PRISMA-style methodology.

The central finding of this review is unambiguous: YOLO-based single-stage detection architectures—particularly YOLOv5, YOLOv7, and YOLOv8—represent the current state of the art for practical coin detection applications, consistently outperforming classical image processing approaches, SVM-based classifiers, and two-stage detectors (Faster R-CNN) across the combined dimensions of accuracy, inference speed, and deployment feasibility. YOLOv8, with its anchor-free detection head, modular scaling from nano to extra-large, and native support for segmentation tasks, emerges as the recommended baseline architecture for new coin detection system development as of 2024.

The comparative performance analysis revealed that YOLOv8 nano achieves mAP@0.5 values exceeding 94% at inference rates surpassing 200 FPS on mid-range GPU hardware, with embedded deployment feasibility on Raspberry Pi 4 at 15–20 FPS following INT8 quantization. These performance characteristics satisfy the real-time requirements of vending machine coin acceptors, transit fare gates, and retail point-of-sale systems. YOLO-NAS-L achieves the highest reported accuracy (mAP@0.5 ~96%) through neural architecture search optimization, at the cost of substantially higher computational requirements unsuitable for edge deployment without further compression.

Eight critical research gaps have been identified and analyzed: (1) the absence of standardized multi-currency benchmark datasets; (2) limited multi-currency system generalization; (3) inadequate occlusion handling for overlapping coins; (4) persistent illumination sensitivity on metallic reflective surfaces; (5) a deficit of validated lightweight models for microcontroller-class deployment; (6) near-complete absence of counterfeit coin detection capability; (7) insufficient real-time validation on embedded hardware platforms; and (8) lack of standardized robustness evaluation protocols. Of these, the absence of a standardized benchmark dataset and the omission of counterfeit detection capability represent the most consequential impediments to scientific and practical progress.

The challenges inherent to YOLO-based coin detection—including overlapping coin instance separation, specular highlight artifacts, small denomination detection, and dataset annotation scalability—have been systematically analyzed alongside their current and emerging mitigation strategies. Instance segmentation architectures (YOLOv8-seg), Soft-NMS post-processing, synthetic illumination augmentation, and semi-supervised auto-labeling collectively represent the most promising near-term solutions.

Future research trajectories of greatest promise include the development of TinyML and INT8-quantized YOLO variants validated on FPGA and microcontroller hardware; integration of Vision Transformer attention mechanisms with YOLO detection frameworks for improved fine-grained denomination discrimination; federated learning approaches enabling multi-institution training on geographically diverse currency datasets while preserving data privacy; and the creation of multi-spectral counterfeit detection pipelines integrating ultraviolet and near-infrared imaging modalities.

In conclusion, the YOLO-based detection paradigm has fundamentally transformed the feasibility horizon of automated coin handling systems, enabling deployment scenarios that were computationally intractable a mere decade ago. The field now stands at an inflection point where consolidation of methodological best practices, standardization of evaluation benchmarks, and expansion of deployment validation to real-world embedded environments represent the critical next steps toward achieving production-grade intelligent currency handling systems capable of meeting the demanding accuracy, speed, and robustness requirements of modern financial automation infrastructure.

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