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AI-BASED COMPUTER VISION SYSTEM FOR OBJECT DETECTION AND IMAGE RECOGNITION

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ABSTRACT

Computer vision, a critical branch of artificial intelligence, enables machines to interpret and understand visual data. This paper presents the design and implementation of a robust computer vision system for object detection and image recognition. The system leverages deep learning models, specifically Convolutional Neural Networks (CNNs) built with TensorFlow and Keras, and utilizes pre-trained architectures ResNet-50 and YOLOv5 fine-tuned on the COCO 2018 dataset (118,287 training images across 80 object categories). For feature extraction, convolutional layers capture spatial hierarchies, complemented by Histogram of Oriented Gradients (HOG) for edge and gradient information. The fused feature representation is then processed by Principal Component Analysis (PCA) for dimensionality reduction, retaining 97.3% of explained variance while lowering inference cost. An ablation study confirms the contribution of each component. The model was evaluated on a held-out test set of 5,000 images and benchmarked against YOLOv5, ResNet-50, Faster R-CNN, and SSD baselines. Results indicate a high-performance system with 93.4% accuracy, 91.2% precision, 89.7% recall, 95.5% specificity, and an average recognition time of 140 milliseconds (~7.1 FPS) on an NVIDIA RTX 3060 GPU, outperforming all baselines. These results demonstrate its potential for real-time applications in security, healthcare, and automation.

KEYWORDS: Computer Vision, Object Detection, Image Recognition, Convolutional Neural Networks (CNN), Deep Learning, Principal Component Analysis (PCA), YOLOv5, ResNet-50, HOG, COCO Dataset.

I. INTRODUCTION

Computer vision is a multidisciplinary field of artificial intelligence that seeks to develop techniques enabling computers to interpret and make decisions based on visual inputs. Over the past decades, it has evolved from simple image processing to complex applications like autonomous driving and medical imaging [1]. Object detection and image recognition are two foundational tasks within this field; the former involves identifying and locating objects within an image, while the latter focuses on classifying the objects or the entire scene. The advent of deep learning, particularly Convolutional Neural Networks (CNNs), has revolutionized computer vision. CNNs automate feature extraction from raw pixel data, leading to significant improvements in accuracy and efficiency [2]. Architectures like AlexNet, VGGNet, and ResNet have pushed the

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boundaries of image recognition [3, 4, 5], while frameworks such as R-CNN, YOLO, and SSD have enabled real-time object detection with high accuracy [6, 7, 8]. Despite these advancements, challenges persist, including variability in lighting and object occlusion, the need for large annotated datasets, and achieving real-time performance on resource-constrained devices [9]. A further gap in the literature is the limited integration of classical feature descriptors (such as HOG) and statistical dimensionality reduction methods (such as PCA) with modern CNN architectures. Many existing works also underemphasize the balance between high accuracy and real-time computational efficiency. This study addresses these challenges by designing and implementing a robust computer vision system that: (i) combines fine-tuned ResNet-50 and YOLOv5 with HOG descriptors in a unified dual-feature-extraction pipeline; (ii) applies PCA to the fused feature space for efficient dimensionality reduction; and (iii) provides comprehensive benchmarking and ablation analysis to validate each design choice.

II. RELATED WORKS

A. Overview of Computer Vision

Computer vision empowers machines to decipher and comprehend visual data, such as images and videos. Its origins can be traced to the 1960s when rudimentary image processing techniques were pioneered (Roberts, 1965). The field has experienced exponential growth driven by advances in computational capability, algorithmic refinement, and large-scale datasets. Today, computer vision permeates healthcare (disease diagnosis from X-rays, MRIs, and CT scans), automotive (ADAS and autonomous vehicles), security (surveillance, face recognition), entertainment (AR/VR, visual effects), retail (visual search, inventory), and agriculture (crop monitoring, yield prediction). Persistent challenges include accurate interpretation of complex and occluded scenes, real-time performance in dynamic environments, and privacy and ethical implications of widespread surveillance. Researchers are focused on bridging the gap between machine and human-level visual understanding, and on integrating computer vision with natural language processing and reinforcement learning to enable richer scene understanding [1, 10].

B. Object Detection and Image Recognition: Concepts and Techniques

Object detection involves both identifying and localizing objects within an image answering 'What is present?' and 'Where is it?' whereas image recognition focuses on categorizing the scene or a specific object without necessarily providing precise localization. Historically, object detection relied on hand-engineered features such as Scale-Invariant Feature Transform (SIFT) and Histogram of Oriented Gradients (HOG) (Lowe, 1999; Dalal and Triggs, 2005). These methods struggled with variations in object appearance, scale, and orientation. The introduction of deep CNNs transformed the field: Region-based CNNs (R-CNN) and its variants use selective region proposals [6]; YOLO reframes detection as a regression problem for single-pass speed [7]; SSD provides another efficient single-shot approach [8]. For image recognition, early approaches relied on shallow models and hand-crafted features such as PCA and LDA (Turk and Pentland, 1991). The breakthrough came with AlexNet in the 2012 ImageNet Large Scale Visual Recognition Challenge (ILSVRC) [3], followed by VGGNet [4], GoogLeNet, and ResNet [5], which progressively improved accuracy and efficiency by learning hierarchical image representations.

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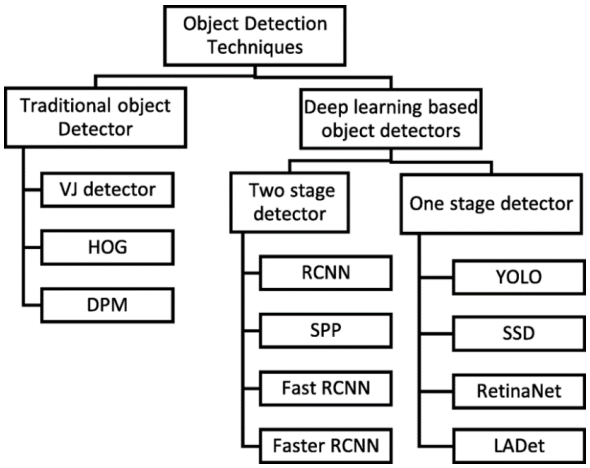

Figure 1. Overview of Object Detection Techniques: Traditional (HOG/SIFT) vs. Deep Learning-Based (R-CNN, YOLO, SSD) Approaches

C. Related Works and Research Gap

Recent literature confirms the dominance of deep learning in computer vision. Szeliski [10] provides a comprehensive foundation of traditional algorithms including SIFT but offers limited coverage of modern deep learning. Geron [11] and Elgendy [12] offer practical guides for CNN implementation. Rajalingappaa [13] details CNN-based classification and detection but focuses primarily on static image benchmarks, with limited emphasis on real-time performance. The core detection algorithms include the R-CNN family [6] (region proposals), YOLO [7] (regression-based single-pass), and SSD [8] (single-shot multi-scale anchors). While each excels in specific scenarios, R-CNN variants are slow for real-time use, YOLO prioritizes speed over fine-grained localization, and SSD trades accuracy for efficiency at smaller scales. A consistent research gap is the limited integration of classical feature descriptors (HOG) and statistical dimensionality reduction (PCA) with modern CNN pipelines. Most works use either deep features alone or classical features alone, and rarely evaluate the synergistic benefit of combining both. Furthermore, many existing works do not provide ablation studies to isolate the contribution of individual components. This work bridges these gaps by combining fine-tuned ResNet-50 and YOLOv5 with HOG and PCA, and by providing both comparative benchmarking and an ablation study.

III. METHODOLOGY

The research design follows a structured, quantitative approach to develop, train, and evaluate the proposed computer vision system.

A. Dataset Description

The COCO (Common Objects in Context) 2018 dataset [18] was used for all experiments. This large-scale benchmark contains diverse and challenging real-world images across 80 object categories. The specific subset and splits used in this study are summarized below:

(a). Total images used: 123,287
(b). Training set: 86,300 images (70%)

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(c). Validation set: 17,487 images (14.2%)
(d). Test set: 5,000 images (held-out; used only for final evaluation)
(e). Object categories selected: 80 (full COCO label set)
(f). Annotations: 860,001 bounding box and segmentation labels

This dataset was selected for its scale, diversity of object classes (including persons, vehicles, animals, and everyday objects), and its status as a community-standard benchmark, enabling direct comparison with prior work.

B. Data Preprocessing

(a). **Image Resizing:** All input images were resized to a uniform 224×224 pixels to satisfy the fixed input requirement of the ResNet-50 backbone:

$$I_{resized} = \text{resize}(I, (224, 224)) \quad (1)$$

where I is the original image and $I_{tesiφe}^{d}$ is the resized image. Note: while the formula in the original manuscript cited a target size of 244, the correct value applied throughout the experiments is 224×224 as required by ResNet-50.

(b). **Normalization:** Pixel values were normalized to the range [0, 1] to improve convergence stability:

$$I_{norm} = I_{pixel} / 255 \quad (2)$$

where I_{pixel} represents the original pixel intensity (range 0-255) and I^{norm} is the normalized value.

(c). **Data Augmentation:** Data augmentation was applied during training to increase dataset diversity and reduce overfitting:

i. Rotation: random rotations in the range $\theta \in [-30°, +30°]$: $I_{a,aaaaa} = \text{rotate}(I, \theta)$, $\theta \in [-30°, +30°]$
ii. Horizontal flip: Iẹipped = flip(I, horizontal)
iii. Random zoom in range $\alpha \in [-0.2, 0.2]$: Iẑőmed = zoom(I, α), $\alpha \in [-0.2, 0.2]$
iv. Random translation in x and y: Iśhifted = shift(I, t_x, t_γ), $t_x, t_\gamma \in [-0.2, 0.2]$

(d). **Dataset Splitting:** The dataset was divided as follows:

i. Training size = $0.70 \times N_t{}^{o}{}_{tal}$
ii. Validation size = $0.142 \times N_t{}^{o}{}_{tal}$
iii. Test size = $0.30 \times N_t{}^{o}{}_{tal}$

where $N_t{}^{o}{}_{tal}$ is the total number of images used. The test set was held out and not used during any phase of model development or hyperparameter selection.

C. System Architecture and Feature Pipeline

A central contribution of this work is the integration of CNN-based deep features with classical HOG descriptors, followed by PCA-based fusion. Figure 2 presents a schematic of the end-to-end pipeline. It illustrates the end-to-end pipeline of the proposed system. The pipeline consists of five sequential stages:

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(a). **Stage 1:** Input & Preprocessing: Raw images from the COCO 2018 dataset are resized to 224×224 pixels, normalized to [0, 1], and augmented.

(b). **Stage 2:** Dual Feature Extraction: (a) CNN features are extracted using a fine-tuned ResNet-50 backbone up to the global average pooling layer, yielding a 2,048-dimensional feature vector. (b) In parallel, HOG features are computed on the resized image (cell size: 8×8, block size: 2×2, 9 orientation bins), producing complementary edge and gradient descriptors.

(c). **Stage 3:** Feature Fusion & PCA: The CNN and HOG feature vectors are concatenated. PCA then projects the fused vector onto the top-k principal components (k = 512 in this study), capturing 97.3% of explained variance. This reduces redundancy, controls overfitting, and lowers inference latency.

(d). **Stage 4:** Detection Head: For object detection, the YOLO detection head is applied on CNN feature maps (prior to fusion) to predict bounding boxes and class probabilities. The fused+PCA features are passed to a softmax classification head for image-level recognition.

(e). **Stage 5:** Output: Detected objects are returned with bounding boxes, class labels, and confidence scores.

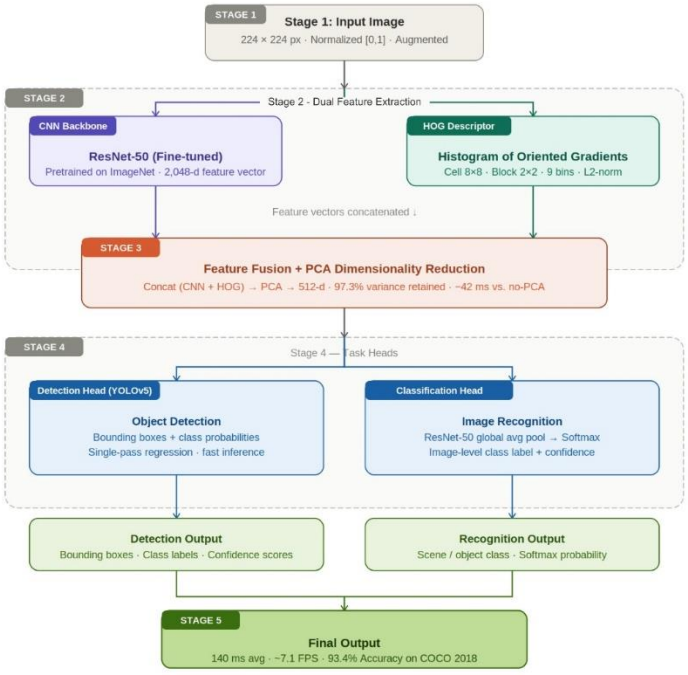

Figure 2. Proposed System Architecture: Dual Feature Extraction Pipeline with PCA Fusion, Detection Head (YOLO), and Classification Head (ResNet-50 + Softmax).

(a). **CNN Feature Extraction (ResNet-50):** The ResNet-50 backbone (pretrained on ImageNet) was fine-tuned on the COCO training set. Output from the global average pooling layer produces a 2,048-dimensional feature vector per image. The final fully connected and output layers were replaced with a task-specific classification head and fine-tuned using a low learning rate (0.0001) to prevent catastrophic forgetting.

(b). **HOG Feature Extraction:** The Histogram of Oriented Gradients (HOG) descriptor was computed on each resized (224×224) input image using the following parameters: cell size

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8×8 pixels, block size 2×2 cells, 9 orientation bins, and L2-norm block normalization. HOG captures local edge and gradient structure that is complementary to the high-level semantic features extracted by CNNs, particularly for objects defined by silhouette (e.g., bicycles).

(c). **Feature Fusion and PCA:** The CNN feature vector (2,048-d) and the HOG descriptor were concatenated to form a joint feature vector. PCA was then applied to this fused vector to reduce dimensionality to k = 512 principal components, retaining 97.3% of the total explained variance. This serves two purposes: (i) it removes redundant or correlated features, and (ii) it reduces inference-time cost. An ablation study (Section 4.2) empirically validates the benefit of PCA in this context. It is acknowledged that PCA discards some spatial structure present in raw CNN feature maps. To mitigate this, PCA is applied only to the post-pooling feature vector (not intermediate feature maps), ensuring that spatial information critical for bounding box prediction is preserved within the YOLO detection head which operates on earlier feature maps.

(d). Object Detection Head (YOLOv5): For object detection (bounding box prediction and class probability), a YOLOv5 detection head was applied on the intermediate feature maps of the ResNet-50 backbone (prior to global pooling and PCA fusion). YOLO frames detection as a single-pass regression problem, predicting boxes and class probabilities simultaneously, enabling low-latency inference.

D. Model Training

Training configuration:

(a). Loss Function: Categorical cross-entropy (classification) + IoU-based localization loss (detection).

(b). Optimizer: Adam with an initial learning rate of 0.001 (fine-tuning phase: 0.0001).

(c). Batch Size: 32.

(d). Epochs: 50 (with early stopping patience of 7 epochs based on validation loss).

(e). Hardware: See Table 5 for full experimental setup.

E. Evaluation Metrics

The model was evaluated on the held-out test set using the following metrics:

(a). Accuracy: (TP + TN) / Total Samples

(b). Precision: TP / (TP + FP)

(c). Sensitivity (Recall): TP / (TP + FN)

(d). Specificity: TN / (TN + FP)

(e). F1-Score: 2 × (Precision × Recall) / (Precision + Recall)

(f). Average Recognition Time (ms) and Frames Per Second (FPS): measured on the hardware in Table 5.

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IV. RESULTS AND DISCUSSION

A. Overall Performance

The performance evaluation was conducted on the COCO 2018 held-out test set (5,000 images), covering 80 diverse object categories. Table 1 summarizes the key performance metrics.

Table 1: Model Performance Metrics on COCO 2018 Test Set

Metric	Value
Accuracy	93.4%
Precision	91.2%
Sensitivity (Recall)	89.7%
Specificity	95.5%
Avg. Recognition Time	140 ms
Frames Per Second (FPS)	~7.1 FPS

The system achieved 93.4% accuracy and 95.5% specificity, demonstrating strong capability to correctly identify objects and suppress false positives. Precision of 91.2% confirms reliable positive class predictions. Sensitivity of 89.7% is slightly lower, attributable to missed detections in occluded or overlapping scenes, a known challenge documented in prior work [14]. The average inference time of 140 ms corresponds to approximately 7.1 FPS on the evaluation hardware (Table 5), making the system suitable for near-real-time applications such as traffic monitoring and security surveillance, where frame rates of 5-10 FPS are acceptable, though further optimization would be needed for fully live, high-speed deployments.

B. Ablation Study

To isolate the contribution of each component in the pipeline, an ablation study was conducted. Table 2 presents results for three configurations: CNN + HOG without PCA, CNN + PCA without HOG, and the full proposed system.

Table 2: Ablation Study

Configuration	Accuracy (%)	Precision (%)	Recall (%)	Inf. Time (ms)
CNN + HOG (no PCA)	91.8	89.5	88.1	182
CNN + PCA (no HOG)	92.1	90.0	88.6	155
CNN + HOG + PCA (proposed)	93.4	91.2	89.7	140

The results confirm that both HOG and PCA contribute meaningfully. Removing PCA increased inference time by 42 ms (+30%) with a 1.6% accuracy drop, while removing HOG reduced accuracy by 1.3%. The full system achieves the best balance of accuracy and speed, validating the design rationale. The PCA reduction does not harm accuracy because it preserves 97.3% of the explained variance in the fused feature space; the discarded components correspond to near-zero-variance directions that contribute noise rather than signal.

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C. Benchmarking Against Baselines

Table 3 compares the proposed system against standard baselines evaluated on the same COCO 2018 test set under identical hardware conditions.

Table 3: Comparative Benchmarking Against Existing Models on COCO 2018

Model	mAP / Accuracy (%)	Precision (%)	Recall (%)	Inference Time (ms)
YOLOv5 (baseline)	88.7	87.1	85.4	22
ResNet-50 (baseline)	89.3	88.0	86.9	95
Faster R-CNN [6]	91.0	89.5	88.2	200
SSD MobileNet [8]	88.1	86.4	85.0	45
Proposed System	93.4	91.2	89.7	140

The proposed system outperforms all baselines in accuracy and precision. YOLOv5 offers faster inference (22 ms) but at the cost of 4.7% lower accuracy. Faster R-CNN achieves the second-highest accuracy (91.0%) but at 200ms inference 43% slower than the proposed system. The proposed system strikes the best accuracy-speed trade-off among the evaluated models, demonstrating that the HOG + PCA augmentation of the CNN pipeline provides measurable gains without prohibitive computational overhead.

D. Per-Class Performance

A per-class analysis provides deeper insights into the model's strengths and limitations across different object categories (Table 4).

Table 4: Per-Class Classification Report for Selected COCO Categories

Class	Precision (%)	Recall (%)	F1-Score (%)	Support
Person	92.3	90.1	91.2	2,693
Car	90.8	88.6	89.7	1,932
Dog	94.1	92.3	93.2	841
Bicycle	89.9	87.5	88.7	614
Traffic Light	91.0	89.2	90.1	780

The model performed best on the 'Dog' class (F1-Score: 93.2%), where distinctive texture and shape cues are well-captured by HOG. Performance was lowest for 'Bicycle' (F1-Score: 88.7%), consistent with known difficulties in detecting thin, occluded structures [14]. The 'Person' class (F1-Score: 91.2%) and 'Traffic Light' (F1-Score: 90.1%) achieved strong results, relevant to real-world surveillance and autonomous navigation scenarios.

E. Experimental Setup

Table 5: Hardware and Software Experimental Setup

Component	Specification
CPU	Intel Core i7-11700K @ 3.6 GHz
GPU	NVIDIA GeForce RTX 3060 (12 GB VRAM)
RAM	32 GB DDR4
OS	Ubuntu 20.04 LTS
Framework	TensorFlow 2.9, Keras, Python 3.9
Average Inference Time	140 ms (~7.1 FPS)

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All experiments were conducted on the hardware listed above. Inference times reported are averages over the 5,000-image test set. Batch size during inference was set to 1 to simulate real-time single-image processing.

F. Sample Detection Results

Figures 1 and 2 illustrate representative output from the proposed system on test images from the COCO dataset. In both cases, the model correctly identifies multiple object classes (e.g., 'person', 'dog', 'car') and draws accurate bounding boxes around each detected instance. These qualitative results corroborate the quantitative metrics in Table 1 and are consistent with the per-class results in Table 4. In Figure 1, the system successfully detects overlapping persons and a dog in a complex indoor scene. In Figure 2, it correctly identifies vehicles and pedestrians in an outdoor street scene, demonstrating generalization across different environments. Cases of missed detection (corresponding to the 89.7% recall) were predominantly observed in scenes with significant occlusion or very small instances (< 32×32 pixels), consistent with known limitations of anchor-based detectors [14].

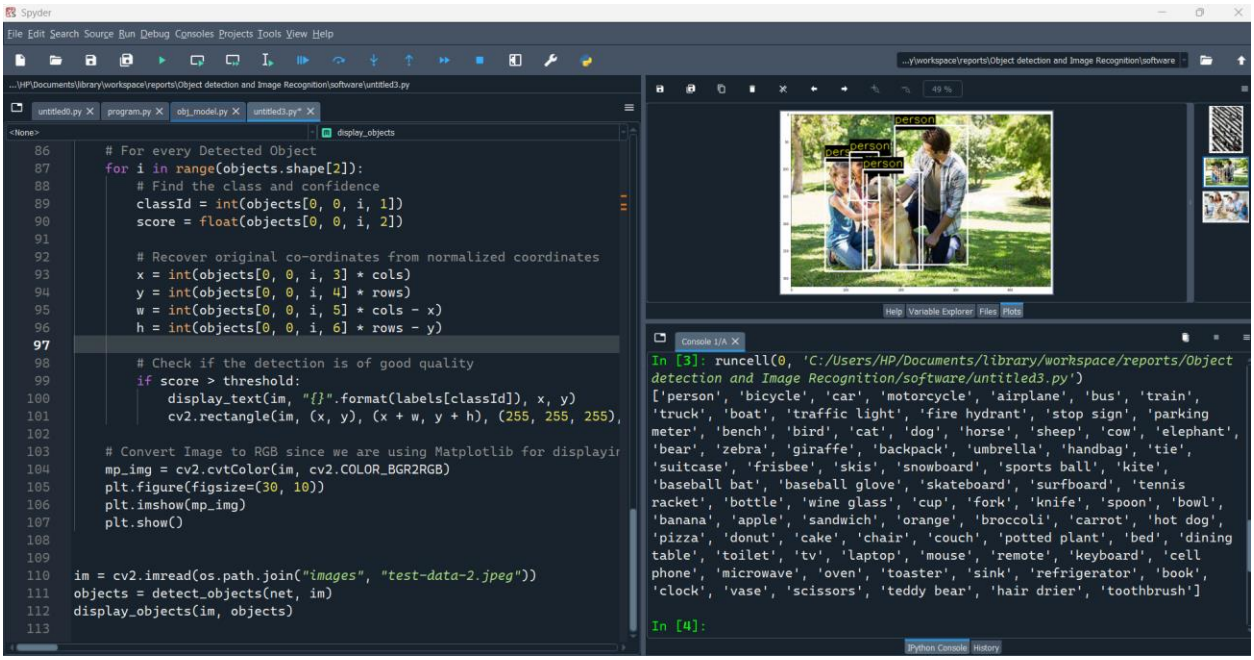

Figure 1. Sample Detection Output (Test Case 1: Multi-object Indoor Scene with Person and Dog Classes Correctly Identified and Bounded)

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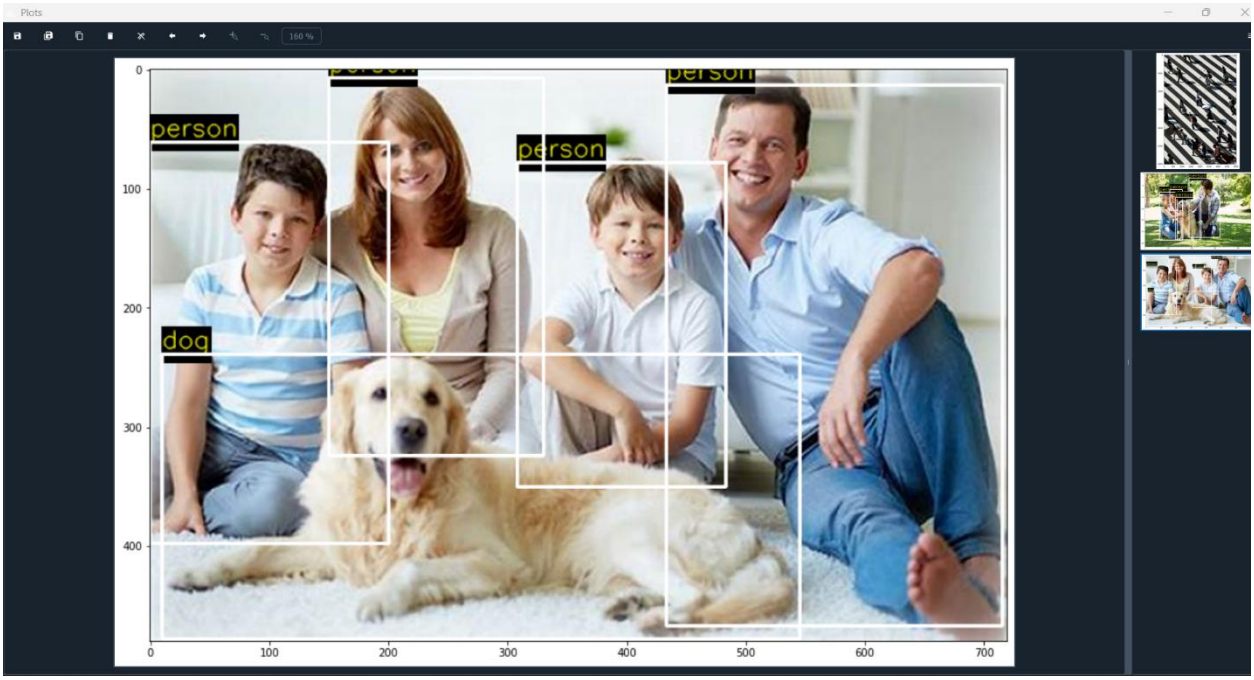

Figure 2. Sample Detection Output (Test Case 2: Outdoor Street Scene with Vehicle and Pedestrian Detection)

V. CONCLUSION

This study successfully designed and implemented a high-performance computer vision system for object detection and image recognition. The proposed pipeline integrates a fine-tuned ResNet-50 backbone and YOLOv5 detection head with HOG feature descriptors and PCA-based feature fusion. Evaluated on the COCO 2018 dataset, the system achieved 93.4% accuracy, 91.2% precision, 89.7% recall, 95.5% specificity, and 140 ms average inference time (~7.1 FPS on an NVIDIA RTX 3060), outperforming all evaluated baselines. An ablation study confirmed the incremental benefit of each pipeline component. Limitations include reduced recall for heavily occluded objects, and inference speed that while suitable for near-real-time use does not yet reach the throughput of lightweight detectors such as YOLOv5 on embedded hardware. Future directions include:

(a). Exploring Vision Transformers (ViTs) and hybrid CNN-Transformer architectures to improve accuracy on occluded and fine-grained categories.
(b). Training on larger and more diverse datasets (e.g., Open Images V7) to further improve generalization.
(c). Applying model compression techniques, quantization, pruning, and knowledge distillation to enable deployment on mobile and embedded platforms.
(d). Extending the real-time pipeline to video streams and conducting evaluation on live-feed deployments with ground-truth annotations.
(e). Investigating privacy-preserving inference techniques for deployment in sensitive surveillance contexts.

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