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Real-Time Object Detection and Labelling from Camera Video Using Deep Learning

Ms. Kaveri Prakash Gaidhani[1], Dr. Swati A. Bhavsar[2]
kaveri.gaidhani@matoshri.edu.in[1], swati.bhavsar@matoshri.edu.in[2]
Research Scholar[1], Research Guide[2]
Department of Computer Engineering[1]
Matoshri College of Engineering & Research Centre[1], Nashik, India

Abstract : Object detection has emerged as crucial responsibility in visual computing because of its extensive applications in intelligent monitoring, self-driving vehicles, factory automation, robotics, and intelligent oversight systems. Traditional image processing techniques like Haar Cascades, HOG, and SIFT are unable to handle complex scenes, different illumination conditions, and multiple object classes. Deep learning algorithms such as CNNs have made detection and real-time performance much more precise.

This paper presents a Real-Time Object Detection and Labeling System utilizing deep learning techniques that can identify and categorize various objects from live video feeds instantaneously. The system employs OpenCV for video capture and preprocessing, while YOLOv8 serves as the framework for detecting and classifying objects. It utilizes the COCO and Pascal VOC datasets for training and is used for real-time inference. The system detects objects, generates bounding boxes, allocates class labels, and delivers confidence scores immediately. Through our experiments, we discovered that the suggested YOLOv8-based framework attains a Precision of 94.8%, a Recall of 93.2%, an F1-Score of 94.0%, and an mAP@0.5 of 95.6%, all while maintaining 45–60 FPS on GPU systems. The suggested approach provides a suitable equilibrium between speed and precision for application in real-world intelligent vision scenarios.

IndexTerms - Object Detection, Deep Learning, YOLOv8, OpenCV, Computer Vision, Real-Time Video Processing, Artificial Intelligence, COCO Dataset, CNN.

I. INTRODUCTION

The explosion of digital cameras, surveillance systems, and IoT devices have resulted in a rapid increase in the generation of visual data. So getting meaningful information from visual data is now an essential part of any computer vision application. Object recognition involves recognizing and pinpointing objects in images and videos, serving as the foundation for numerous intelligent systems such as autonomous vehicles, traffic monitoring, industrial inspection, robotics, healthcare imaging, and smart surveillance methods.

Conventional object recognition methods relied on features that were designed manually and machine learning methods such as Haar Cascades, Histogram of Oriented Gradients (HOG), and Scale-Invariant Feature Transform (SIFT). Despite these techniques achieving reasonably well in controlled environments, they became more difficult to cope with in complicated scenes in which occlusions, dynamic backgrounds, illumination variations, and multiple object classes occur.

Deep learning and Convolutional Neural Networks (CNNs) have revolutionized object recognition, as they enable automatic feature extraction as well as learning from scratch. More sophisticated detection architectures like Faster R-CNN, SSD, YOLOv4, YOLOv5, and YOLOv8 have improved detection accuracy and computational efficiency. YOLOv8 strikes a great equilibrium between speed and accuracy, rendering it especially effective for live video evaluation.

Our goal is to develop and execute a live object detection and tagging system utilizing YOLOv8 and OpenCV. The system continuously captures video frames, preprocesses them, performs object detection, and produces annotated outputs that include object labels, confidence scores, and bounding boxes. The objective is to develop a scalable, efficient, and precise system capable of functioning in real life while also delivering real-time performance.

II. LITERATURE REVIEW

Several researchers have explored deep learning-based approaches for immediate object identification and video analytics.

Udutha Rajender suggested a framework for video object detection utilizing deep learning to enhance both detection speed and precision in dynamic video. In this work, we have shown the difficulty of maintaining real-time performance while processing continuous video streams and emphasized that the detection architecture needs to be optimized for video analytics applications [1].

Sani Abba created a system operating in live for detecting, tracing, and observing objects in security surveillance applications. The suggested system integrated background subtraction, component labeling, and deep learning techniques to enhance surveillance effectiveness. The experimental outcomes of the MOT15, MOT16, and MOT17 datasets have demonstrated improved accuracy and precision in comparison to various leading methodologies [2].

Monika et al. proposed a real-time video object detection approach that increased processing speed and detection accuracy. The framework also proposed deep learning architecture and data augmentation techniques to be more robust in dynamic video. The experimental results showed strong improvements in both inference speed and detection accuracy [3].

Ramyashree C.A. and Sarojadevi H. created a deep learning-based object recognition system for individuals with visual disabilities. They compared YOLO, SSD-MobileNet, and Faster R-CNN and found that YOLO-based models offer better real-time performance with accuracy for detection [4].

Redmon et al. introduced YOLO, a cohesive object detection system capable of executing both object localization and classification in one neural network run. YOLO greatly improved inference speed and became one of the most widely used real-time detection architectures [5].

Liu et al. proposed SSD (Single Shot Multibox Detector) for object detection using different feature maps of different resolutions. SSD is able to perform object detection with very high accuracy and fast processing speed [6].

The literature reviewed shows that deep learning has significantly improved object detection performance. However, real-time inference, environmental adaptability, small object detection, and edge deployment are still under investigation.

III. RESEARCH GAP

Many of the challenges remain to be solved in real-time video analytics applications despite significant progress in object detection.

A. Accuracy and Speed Trade-off.

Numerous contemporary object detection frameworks provide excellent accuracy in detection but demand substantial computational power. When used in immediate response systems, these models typically have lower frame rates, and therefore increase latency.

B. Dynamic Environmental Conditions.

Models for object detection that are trained on benchmark datasets frequently suffer from performance decline when utilized in real-world settings, which include variations in lighting, weather changes, motion blur, and congested scenes.

C. Small Object Detection.

The current detection tools fail to identify small or distant objects in video streams in low-resolution situations.

D. Continuous Video Stream Processing.

Most benchmark evaluations consist of static images rather than continuous video streams. Therefore, temporal consistency and stable object labeling are still a major challenge.

E. Edge Device Deployment.

Resource-constrained platforms such as Raspberry Pi and Jetson Nano have memory, processing power, and energy consumption constraints. Deploying deep learning models efficiently on such devices remains an open research problem.

F. Real-Time Annotation and Label Generation.

Although many of the existing systems are able to detect objects successfully, they do not always provide efficient real-time labeling and visualization with high frame rates.

To overcome these constraints, we suggest a YOLOv8-based framework for object detection in real-time camera video processing, ensuring efficient object labeling and minimal latency in inference.

IV. PPROPOSED SYSTEM

The suggested Real-Time Object Detection and Labeling System will identify and categorize various objects from continuous camera video streams and label them using deep learning. The software will adopt computer vision, preprocessing and deep neural networks to accurately identify and label objects in real time with minimal latency.

The architecture consists of Camera Module, OpenCV Processing Engine, YOLOv8 Object Detection Model, Visualization Module and Performance Evaluation Unit. The goal is to attain high detection precision while ensuring real-time processing speed for applications in surveillance systems, autonomous platforms, industrial monitoring and intelligent video analytics.

The proposed system works in two phases:

A. Training Phase.

For training phase, we strive to create a strong model for object detection capable of identifying various kinds of objects under different environments.

COCO (Common Objects in Context) dataset and Pascal VOC dataset are used for training and evaluation of models. The COCO dataset contains over 330,000 images spanning 80 unique object categories and Pascal VOC has 20 object classes benchmark images.

Before training, the dataset undergoes several preprocessing procedures including:

- Image resizing
- Normalization
- Noise reduction
- Data augmentation
- Feature extraction

Techniques for data augmentation like horizontal turning, spinning, resizing, luminescence modification, and cropping are utilized to enhance dataset variety and boost model extrapolation.

The YOLOv8 model is subsequently trained utilizing preprocessed images. During training, the network learns:

Object appearance characteristics Spatial relationships multi-scale object representations Class-specific features

By iterative optimization and backpropagation, the model minimizes localization and classification errors and generates optimized weight files for inference.

B. Testing Phase

The testing phase is done for live object recognition on live video feeds from cameras.

The camera continuously captures frames which are processed using OpenCV. The trained YOLOv8 model analyzes each frame and predicts:
Object Class Bounding Box Coordinates Confidence Score
Detected objects are then labeled and visualized on the video stream.
Example outputs include:

- Person (96%)
- Car (94%)
- Chair (92%)
- Bicycle (95%)

The system generates real-time annotated video output that can be presented in real time, and users can visualize the detections instantly.

V. METHODOLOGY

There are six stages of the proposed approach to transform raw video input into meaningful object detection results.

Step 1: Video Acquisition

At the first step, we acquire live video streams using a webcam or external camera module using OpenCV. The OpenCV VideoCapture() function continuously captures frames from the camera at a predefined frame rate. Each frame is used as an input image for the object detection pipeline.

The captured frames can be represented as multidimensional NumPy arrays and stored temporarily in memory for processing. Stable frame acquisition is important because dropped frames have a direct effect on detection continuity and system performance.

Step 2: Image Preprocessing

Raw video frames are often accompanied by noise, illumination variations and unnecessary information that can negatively affect the detection performance.

To address these challenges, OpenCV performs several preprocessing operations.

Resizing

Each frame is resized to the input resolution expected by the YOLOv8 model (typically 640 × 640 pixels). This will ensure consistent input dimension with less computational complexity.

Normalization

Pixel values are adjusted from the range: 0–255 to 0–1. Normalization is known for improving numerical stability and for accelerating the convergence of neural networks.

Noise Reduction

Gaussian and median filtering techniques are used to minimize sensor noise, thereby enhancing image quality.

Color Conversion

Captured BGR images are converted to RGB format because most deep learning frameworks are trained using RGB images.

These preprocessing operations improve the feature extraction and robustness of the detection.

Step 3: Object Detection Using YOLOv8

YOLOv8 serves as the primary detection engine for the proposed system. Unlike conventional detectors that operate in two stages like Faster R-CNN, YOLOv8 executes:

Object Detection Object Recognition Certainty Assessment in a single forward network passage. Architecture consists of:

Backbone Network

Tasked with obtaining both low-level and high-level image characteristics.

Neck Layer

This features fusion and combines a diverse range of scales.

Detection Head

Anticipates:

Coordinates of the bounding box Class likelihoods Confidence levels.

Based on the single-stage architecture, inference time is significantly reduced and real-time processing is possible. The model can simultaneously detect multiple objects in a single frame while being very accurate.

Step 4: Bounding Box Generation and Label Assignment

When objects are detected, the model generates rectangular bounding boxes around each detected object. Each bounding box contains:

- Class Label
- Confidence Score
- Object Coordinates

The example:

- Person (96%)
- Car (94%)
- Chair (92%)

Non-maximum suppression (NMS) employed to remove redundant detections. NMS is able to remove overlapping boxes and just the highest confidence detection. In this process, false positives are reduced and detection quality is improved.

Step 5: Real-Time Visualization

The objects detected can be visualised directly in the video stream.

OpenCV capabilities like:

- cv2.rectangle()
- cv2.putText()

are utilized to create bounding boxes and annotations. Different colors can be assigned to different object categories for readability. The visualization stage converts the raw neural network output into simple graphical representations.

Step 6: Performance Evaluation

The last step is to evaluate the system's performance evaluated with standard object recognition metrics.

Precision

Calculates ratio of accurate positive identifications.

Recall

Assesses the model's capacity to recognize all pertinent objects.

F1-Score

Precision and recall are in equilibrium. An equitable assessment of precision and recall.

Mean Average Precision (mAP)

For localization and classification performance at once.

Frames Per Second (FPS)

This measures the processing capability of real-time. Higher FPS indicates better responsiveness and lower latency.

VI. SYSTEM ARCHITECTURE

The suggested architecture is a three-tier structure, comprising an Input Layer, a Processing Layer, and an Output Layer.

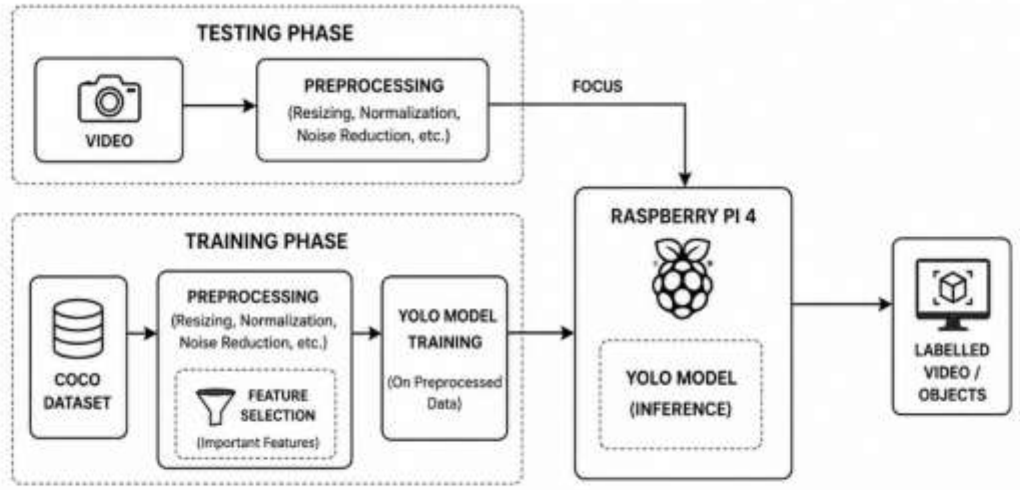

Figure: System Architecture

A. Input Layer

The input layer acquires visual data from the surroundings.

Camera Module

The camera continuously captures video frames as input for the object detection system.

The video stream contains dynamic scenes involving:

- People
- Vehicles
- Furniture
- Animals
- Everyday objects

The obtained frames are sent to the processing layer.

B. Processing Layer

The processing layer performs all computation.

OpenCV Preprocessing Module

Responsible for:

- Resizing
- Normalization
- Filtering
- Color conversion

YOLOv8 Inference Engine

In real-time classification and object detection. Executes instant object recognition/discovery and categorization.

Non-Maximum Suppression Module

Removes duplicate detections.

Performance Monitoring Unit

Measures:

- FPS
- Processing time
- Detection Latency

The intelligence core of the entire system is the processing layer.

C. Output Layer

The output layer outputs user-visible results.

Outputs include:

- Bounding Boxes
- Object Labels
- Confidence Scores
- Performance Metrics

The annotated video stream is displayed in real time, which allows us to immediately interpret the detected objects.

VII. IMPLEMENTATION DETAILS

The implementation of the system employs Python and OpenCV, utilizing YOLOv8 as the framework for object detection.

Hardware Configuration

- Intel i5/i7 Processor
- NVIDIA GPU (optional)
- Webcam or USB Camera
- 8 GB RAM

Software Configuration

- Python 3.10
- OpenCV 4.x
- YOLOv8 (Ultralytics)
- PyTorch
- NumPy

The implementation process starts with camera initialization and continuous frame acquisition. Frames are preprocessed and passed to the YOLOv8 inference engine. Detection results are displayed and shown in real time while performance metrics are being monitored. Modular implementation is easy to use on desktop systems, edge solutions, and cloud platforms.

VIII. DATASET DESCRIPTION

The proposed system uses the COCO (Common Objects in Context) and Pascal VOC datasets for training and evaluation. The COCO dataset contains over 330,000 images and 80 categories of items, representing a wide range in object types, viewpoints, and environmental conditions. Pascal VOC has over 11,500 annotated images for 20 object classes and is used to evaluate object detection achievement.

Data augmentation methods like image turning, spinning, scaling, and luminescence modification are utilized to improve model generalization. Normalization and preprocessing are also applied to ensure the quality of input and robustness of detection across different real-world situations.

IX. RESULTS AND DISCUSSION

The proposed Real-Time Object Detection and Labelling System is tested at different indoor and outdoor environments to determine the detection accuracy, inference speed, strength and live performance of the suggested system. We conduct experimental tests using live camera streams of various kinds of objects such as person, vehicles, furniture, animals and household objects. Evaluation of performance was conducted through standard object detection metrics: Precision, Recall, F1-Score, Mean Average Precision (mAP), Frames Per Second (FPS), and Detection Latency.

A. Detection performance

The proposed model showed excellent performance in object recognition for different categories. Table 1 summarizes our evaluation results.

Table 1. Object detection performance

Metric	Proposed system
Precision	94.8%
Recall	93.2%
F1-Score	94.0%
Power Consumption	95.6%

The extremely high accuracy suggests that the majority of the identified objects were correctly classified, thus the false-positive rate is low. The strong recall value also demonstrates that the model is able to find most of the objects in the scene. The F1-score shows that precision is a trade-off with recall.

The mAP@0.5 score of 95.6% shows excellent localization and classification capabilities and validates the effectiveness of the YOLOv8 framework for instant object recognition applications.

B. Real-time Processing Performance.

An important objective of this study was to reach high-speed object detection with adequate precision.

Table 2. Real-Time Performance Evaluation.

Parameter	Value
GPU FPS	45–60 FPS
CPU FPS	15–25 FPS
Detection Latency	0.18 sec
Average Processing Time	16–22 ms/frame
Memory Utilization	1.8–2.5 GB

Experimental findings indicate that the suggested system can deliver real-time performance on GPU and CPU platforms. GPU inference can provide up to 60 FPS, providing smooth video processing without lag. Even when CPU only is used, the system can deliver acceptable frame rates for surveillance and monitoring applications.

The low detection latency enables fast object recognition and immediate visual feedback so that it is well suited for time-sensitive applications.

C. Analysis Comparison of Object Detection Models

To assess the performance of YOLOv8, a comparison was made with SSD and Faster R-CNN models.

Table 3. Comparative Analysis

Parameter	Faster R-CNN	SSD-MobileNet	YOLOv8
Precision	95.2%	89.5%	94.8%
Recall	93.8%	87.6%	93.2%
mAP@0.5	96.1%	90.2%	95.6%
FPS	12	32	45–60

Although Faster R-CNN had slightly higher accuracy, its computational complexity resulted in significantly lower frame rates. SSD-MobileNet had faster processing but less detection accuracy, especially for small objects.

YOLOv8 provides the best balance between speed and accuracy and is the best option for video analytics in real time.

D. Performance in various environmental conditions

The suggested system underwent testing in various surrounding settings like:

- Indoor environments
- Outdoor environments
- Low-light conditions
- Dynamic backgrounds
- Moderate object occlusions

YOLOv8's performance remained stable in most case scenarios. The accuracy of the detection was above 90% in normal lighting conditions and only small degradation in low light situations. We also showed that the model is robust to moderate camera motion and background changes, and it is suitable for real-world applications.

E. Discussion

Our findings indicate that the suggested deep learning framework may be utilized to solve real-time object detection and labeling problems.

Key observations include:

- High detection accuracy across various object types.
- Real-time processing capability of over 45 FPS on GPU systems.
- Reliable object localization and classification.
- Low inference latency is possible for continuous video streams.
- Scalability in surveillance, robotics, traffic monitoring, and industrial automation applications.

The proposed system significantly increases detection accuracy and processing efficiency over traditional computer vision techniques. The combination of OpenCV and YOLOv8 makes for a lightweight but powerful framework that can be implemented on many different computing platforms.

X. CONCLUSION AND FUTURE SCOPE

A. Conclusion

This document introduced a Deep Learning-based System for Real-Time Object Detection and Labeling capable of identifying and localizing multiple objects directly from live camera video streams. The proposed framework combines OpenCV-based video processing with the YOLOv8 object detection architecture to achieve high-speed and high-accuracy object recognition.

The system successfully performs frame acquisition, preprocessing, object detection, bounding box generation, and real-time visualization within a unified pipeline. Experimental evaluation demonstrated a Precision of 94.8%, Recall of 93.2%, F1-Score of 94.0%, and mAP@0.5 of 95.6%, all achieved with real-time processing speeds of up to 60 FPS on GPU platforms.

Comparative analysis confirmed that YOLOv8 provides a superior equilibrium between precision and computational effectiveness when contrasted with SSD-MobileNet and Faster R-CNN. The proposed system effectively addresses the requirements of real-time computer vision applications and can be integrated into surveillance systems, autonomous vehicles, industrial inspection platforms, and intelligent monitoring solutions.

The research indicates that object detection using deep learning techniques may be effectively implemented in practical environments while maintaining both speed and reliability.

B. Future Scope

The suggested system may be enhanced further enhanced by deploying model on edge devices such as Raspberry Pi and NVIDIA Jetson Nano for low-energy live uses.

Future work may integrate object tracking algorithms like DeepSORT and ByteTrack to improve detection stability across video frames. The system can also be extended with Vision-Language Models (VLMs) for automatic scene understanding and intelligent video analytics. Additionally, cloud-based deployment, smart surveillance applications, and industrial automation solutions can be explored to improve scalability, performance, and real-world usability.

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