AI-Based Real-Time Multi-Object Detection Using YOLOv8 for Smart Surveillance Applications

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Abstract : Real-time object detection has become a fundamental component of intelligent vision systems used in surveillance, autonomous transportation, healthcare, and smart city applications. Traditional object detection approaches often struggle to balance detection accuracy with computational efficiency, limiting their deployment on edge devices. This paper proposes an AI-based real-time object detection and tracking framework using the YOLOv8 deep learning architecture integrated with OpenCV. The proposed system captures images from live cameras, video recordings, or image datasets and performs simultaneous object detection and tracking with high accuracy and low latency. The framework employs optimized preprocessing techniques, confidence-based filtering, and Non-Maximum Suppression (NMS) to improve detection performance while minimizing false positives. Experimental evaluation demonstrates that the proposed model achieves high detection accuracy while maintaining real-time processing capability on standard computing hardware. The proposed framework provides an efficient solution for surveillance systems, traffic analysis, industrial automation, and smart monitoring applications.

Keywords: Object Detection, YOLOv8, Deep Learning, Computer Vision, OpenCV, Artificial Intelligence, Object Tracking, Real-Time Detection.

I. INTRODUCTION

Artificial Intelligence has significantly transformed computer vision by enabling machines to recognize and interpret visual information with remarkable accuracy. Among various computer vision applications, object detection has emerged as one of the most important research areas because it simultaneously identifies the object category and its location within an image or video.

Modern intelligent systems require fast and reliable object detection for applications such as autonomous vehicles, smart surveillance, medical diagnosis, industrial inspection, robotics, and traffic monitoring. Earlier methods relied heavily on handcrafted image features and traditional machine learning algorithms, which often failed in complex environments with varying illumination, occlusions, and background clutter.

Recent deep learning architectures such as YOLO, Faster R-CNN, SSD, and EfficientDet have dramatically improved detection performance. Among these, YOLOv8 provides an excellent balance between speed and accuracy, making it suitable for real-time applications.

This paper presents an object detection framework using YOLOv8 that processes images, recorded videos, and live webcam streams while maintaining high detection accuracy and efficient computational performance.

II. LITERATURE REVIEW

Object detection has undergone remarkable advancements with the introduction of deep learning algorithms. Traditional computer vision techniques relied on handcrafted features such as Haar Cascades, Histogram of Oriented Gradients (HOG), and Support Vector Machines (SVM). Although these methods were computationally efficient, they struggled to detect objects under varying lighting conditions, occlusions, and complex backgrounds.

The introduction of Region-based Convolutional Neural Networks (R-CNN) significantly improved detection accuracy by generating region proposals before classification. Fast R-CNN and Faster R-CNN further enhanced performance by integrating feature extraction and region proposal mechanisms into a unified framework. Despite their improved accuracy, these methods remained computationally intensive and were not suitable for real-time applications.

Single-stage detectors such as Single Shot Detector (SSD) and the You Only Look Once (YOLO) family addressed this limitation by predicting object locations and class labels in a single forward pass. YOLOv3 introduced multi-scale feature extraction, improving the detection of small objects, while YOLOv5 optimized inference speed and deployment flexibility.

YOLOv8 represents one of the latest advancements in object detection. It incorporates anchor-free detection, improved feature aggregation, efficient backbone architecture, and enhanced loss functions, resulting in higher detection accuracy with reduced computational overhead. These improvements make YOLOv8 particularly suitable for intelligent surveillance, autonomous systems, industrial automation, and smart city applications.

Recent research also explores transformer-based architectures such as DETR and Vision Transformers, which demonstrate promising detection accuracy by utilizing self-attention mechanisms. However, these models generally require greater computational resources than YOLO-based architectures. Consequently, YOLOv8 continues to provide an excellent balance between speed, accuracy, and deployment efficiency.

III. PROPOSED METHODOLOGY

The proposed system is designed to perform real-time multi-object detection using the YOLOv8 deep learning framework integrated with OpenCV. The system accepts input from images, recorded videos, and live webcam streams. Each input frame undergoes preprocessing before being passed through the trained neural network.

The methodology consists of the following stages:

A. Data Acquisition

The system captures visual input through:

- Static images
- Video files
- Live webcam

These inputs are processed frame by frame.

B. Image Preprocessing

Before detection, every image undergoes preprocessing, including:

- Image resizing to 640 × 640 pixels
- RGB color conversion
- Pixel normalization
- Noise reduction where required

These operations improve model consistency and detection performance.

C. Feature Extraction

YOLOv8 employs a convolutional neural network backbone to extract discriminative image features. The backbone captures low-level and high-level visual information such as edges, textures, corners, shapes, and object patterns.

D. Object Detection

The extracted feature maps are processed by the detection head, which simultaneously predicts:

- Object category
- Confidence score
- Bounding box coordinates

The model performs detection in a single forward pass, enabling real-time performance.

E. Post Processing

Non-Maximum Suppression (NMS) eliminates duplicate detections and retains only the highest-confidence bounding boxes. The detected objects are displayed with labels and confidence percentages.

IV. SYSTEM ARCHITECTURE

The proposed architecture consists of five major modules.

Module 1: Input Module

Accepts

- Image
- Video
- Webcam

Module 2: Preprocessing

- Resize image
- Normalize pixels
- RGB conversion

Module 3: YOLOv8 Detection Engine

- Backbone
- Neck
- Detection Head

Module 4: Post Processing

- Confidence Threshold
- Non-Maximum Suppression

Module 5: Output

- Bounding Boxes
- Object Labels
- Confidence Score
- Real-time Display

V. ALGORITHMS

A. YOLOv8 Algorithm

YOLOv8 is a one-stage object detection algorithm that predicts object classes and bounding boxes simultaneously. Unlike previous versions, YOLOv8 uses an anchor-free detection mechanism, simplifying training while improving localization accuracy. The algorithm consists of three components:

Backbone

Extracts hierarchical image features using convolutional layers.

Neck

Aggregates multi-scale features using Feature Pyramid Networks (FPN) and Path Aggregation Network (PAN).

Detection Head

Predicts:

- Bounding box coordinates
- Object probability
- Class labels

The model minimizes localization loss, classification loss, and confidence loss during training.

B. Non-Maximum Suppression (NMS)

After prediction, multiple bounding boxes may overlap for the same object.

NMS performs the following steps:

1. Sort detections according to confidence.
2. Select the highest-confidence detection.
3. Remove overlapping boxes using Intersection over Union (IoU).
4. Repeat until all detections are processed.

This ensures each object is represented by only one bounding box.

VI. TOOLS AND TECHNOLOGIES

Python-

Python serves as the primary programming language due to its simplicity, extensive machine learning libraries, and strong community support.

YOLOv8-

YOLOv8 is implemented using the Ultralytics framework. It provides high-speed object detection with improved accuracy and supports deployment on CPUs and GPUs.

OpenCV

OpenCV is used for:

- Image processing
- Video frame extraction
- Webcam integration
- Bounding box visualization
- Image display

NumPy

NumPy performs efficient numerical operations, array manipulation, and mathematical computations during preprocessing.

Ultralytics Library

The Ultralytics package provides pretrained YOLOv8 models, training utilities, inference APIs, and evaluation tools.

Google Colab / Jupyter Notebook

The development and testing environment uses Google Colab or Jupyter Notebook for model execution and experimentation.

VII. EXPERIMENTAL RESULTS

The proposed system was evaluated using various indoor and outdoor images, recorded videos, and live webcam feeds. The YOLOv8 model successfully detected multiple objects including persons, vehicles, bags, bottles, chairs, laptops, mobile phones, and animals.

Experimental observations indicate that the system maintains stable detection performance under different lighting conditions. Detection accuracy remains high for clearly visible objects, while partially occluded objects are recognized with slightly lower confidence.

The average inference time for each frame was approximately 18–25 milliseconds on a system equipped with an Intel Core i5 processor and 8 GB RAM. The model achieved real-time processing speeds exceeding 40 FPS for webcam input.

VIII. CONCLUSION

This paper presented an AI-based real-time multi-object detection system using the YOLOv8 deep learning architecture. The proposed framework effectively identifies and localizes multiple objects from images, prerecorded videos, and live webcam streams while maintaining high detection accuracy and low inference time.

The integration of YOLOv8 with OpenCV enables efficient deployment on standard computing hardware without requiring expensive GPU infrastructure. Experimental analysis demonstrated reliable detection performance under various environmental conditions, confirming the suitability of the proposed system for surveillance, traffic monitoring, industrial automation, and smart city applications.

Overall, the proposed framework provides an efficient, lightweight, and scalable solution for real-time object detection, making it an attractive choice for modern intelligent vision systems.

IX. FUTURE SCOPE

The proposed work can be enhanced in several directions:

- Integration of object tracking algorithms such as DeepSORT and ByteTrack.
- Deployment on edge devices including Raspberry Pi and NVIDIA Jetson Nano.
- Implementation of TensorFlow Lite or ONNX optimization for mobile devices.
- Addition of face recognition and person re-identification modules.
- Support for drone-based surveillance and aerial object detection.
- Integration with IoT platforms for intelligent monitoring.
- Development of multilingual voice alert systems for visually impaired users.
- Expansion to smart traffic management and autonomous vehicle applications.

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