INTEGRATION OF YOLOv8 WITH MULTI-METRIC ANALYSIS FOR ACCURATE EDGE MAPPING AND VISUALIZATION

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Abstract

Object detection plays a vital role in modern computer vision applications, particularly in intelligent monitoring systems and automated device recognition. This study presents an integrated object detection framework that combines YOLOv8 with edge-enhanced preprocessing and transfer learning–based feature extraction using ResNet50. The dataset consists of images from ten electronic device categories, including laptops, keyboards, routers, mobile phones, and USB devices. To improve structural feature representation, preprocessing is performed using Canny Edge Detection along with standard image enhancement techniques.

A two-phase training strategy is adopted, incorporating data augmentation to improve model generalization and robustness. ResNet50 is utilized for deep feature extraction, while YOLOv8 performs efficient object detection and localization. The system is evaluated using multiple performance metrics, including accuracy, precision, recall, and mean Average Precision (mAP). Experimental results show that the proposed model achieves 94% classification accuracy and 0.9886 mAP, demonstrating strong detection capability and reliability.

I. Introduction

Object detection has become one of the most fundamental and actively researched areas in the fields of computer vision and artificial intelligence. It involves identifying and localizing objects within digital images or video streams, enabling machines to interpret visual data in a way similar to human perception. Over the past decade, rapid advancements in deep learning, especially convolutional neural networks (CNNs), have significantly improved the accuracy, robustness, and efficiency of object detection systems. These developments have led to the widespread adoption of computer vision technologies in various real-world applications such as intelligent surveillance, autonomous vehicles, industrial automation, medical diagnostics, smart agriculture, and intelligent transportation systems. The availability of large-scale datasets and high-performance computing resources has further accelerated the progress of real-time object detection frameworks.

Among the various deep learning models developed for object detection, the YOLO (You Only Look Once) family has emerged as one of the most popular and efficient approaches. Unlike traditional methods that involve multiple stages such as region proposal and classification, YOLO performs object localization and classification simultaneously within a single neural network. This unified approach significantly enhances detection speed while maintaining high accuracy. Over time, several versions of YOLO have been introduced, including YOLOv3, YOLOv4, YOLOv5, YOLOv7, and the latest YOLOv8, each improving performance and efficiency.

II. Literature Survey

Li et al. (2026) proposed *EdgeTrack-YOLOv8*, an AIoT-optimized framework that integrates Quantization-Aware Training (QAT), Edge-Aware Attention (EAA), and Deep SORT tracking. Their model was trained on a surveillance dataset of 6,603 images and achieved 89.6% mAP@0.5, showing a 4.2% improvement over baseline YOLOv8. It also achieved 32 FPS with an 18% reduction in latency and 92.7% occlusion persistence, making it highly suitable for real-time monitoring in resource-constrained environments.

Kaur et al. (2025) introduced a YOLO-World compiler enhanced with a hybrid PSO-GWO metaheuristic optimization technique on the Pascal VOC dataset. Their model outperformed standard YOLOv8 and YOLOv11 by achieving 91.5% mAP@0.5, 185.18 FPS, and a significant reduction of 98.44% in runtime complexity. This work highlights the effectiveness of nature-inspired optimization algorithms in improving both speed and accuracy of object detection models.

Afifah et al. (2026) conducted a comprehensive review of YOLOv8 advancements by analyzing over 40 research studies. The review focused on improvements in backbone architectures, attention mechanisms, model compression, training strategies, and loss optimization. It also discussed applications across domains such as surveillance, autonomous driving, agriculture, industrial inspection, and medical imaging, emphasizing YOLOv8's strong balance between accuracy and speed.

Zhong et al. (2025) developed an improved YOLOv8 model by incorporating modules such as Faster-C2f, Rep-Fasterblock, Sim-SPPF with attention mechanisms, and enhanced PANet structures. Their model reduced parameters by 21–54.5% while maintaining competitive accuracy (84.2%–83.3%) and achieving high inference speeds of 100–108 FPS. This lightweight design makes it highly suitable for edge computing applications.

Nimma et al. (2025) proposed an attention-based Transformer-YOLOv8 model for real-time video surveillance. By integrating attention mechanisms and a Transformer-based detection head, their model achieved 96.78% precision, 96.89% recall, and 89.67% mAP. It outperformed several traditional models such as Faster R-CNN and SSD, especially in complex and crowded environments.

Jahan et al. (2025) enhanced the YOLOv8-m architecture for harmful object detection, focusing on categories like weapons and drugs. Their model achieved 0.88 precision, 0.89 recall, and 0.92 mAP@50, demonstrating strong performance even in challenging scenarios. The integration of Explainable AI further improved model transparency and reliability.

Overall, these studies demonstrate that integrating advanced techniques such as attention mechanisms, optimization algorithms, lightweight architectures, and transformer models significantly enhances the performance of YOLOv8-based object detection systems. These contributions form a strong foundation for developing efficient, accurate, and real-time object detection frameworks.

III. System Analysis

The system focuses on improving edge detection and visualization by integrating YOLOv8 with multi-metric analysis techniques. It aims to accurately identify object boundaries and enhance edge mapping in images and video streams. Traditional edge detection methods often fail in complex environments, making advanced approaches necessary. The system uses YOLOv8 for real-time object detection and combines it with multiple evaluation metrics such as gradient magnitude, edge sharpness, and contrast levels. These metrics help refine edge detection results. The system processes input images through preprocessing, detection, and edge enhancement stages. It ensures high accuracy and efficiency in identifying object edges. The approach is scalable and suitable for real-time applications. It is useful in domains like surveillance, medical imaging, and autonomous systems. Overall, the system enhances visualization quality and detection performance.

Existing System

Existing systems for edge detection mainly rely on traditional techniques such as Sobel, Canny, and Laplacian operators. These methods detect edges based on intensity changes in images. While effective in simple scenarios, they struggle with noisy and complex images. They do not consider object-level understanding. Existing systems lack integration with advanced object detection models. They often produce incomplete or inaccurate edges. Sensitivity to lighting conditions and noise reduces performance. These systems also lack adaptability to dynamic environments. They are not efficient for real-time applications involving large datasets. Additionally, visualization quality is often limited. Overall, traditional systems fail to provide accurate and robust edge mapping.

Disadvantages of Existing System

- Poor performance in noisy and complex environments
- Lack of object-level understanding
- Sensitive to lighting and contrast variations
- Produces incomplete or false edges
- Not suitable for real-time processing
- Limited accuracy and robustness
- No integration with modern deep learning models

Proposed System

The proposed system integrates YOLOv8 with multi-metric analysis to improve edge detection and visualization. YOLOv8 is used for accurate and real-time object detection. Once objects are detected, edge mapping is performed using multiple metrics such as gradient strength, edge continuity, and texture features. These metrics are combined to refine edge boundaries and eliminate noise. The system enhances edge clarity and accuracy compared to traditional methods. It supports real-time image and video processing. The integration allows better understanding of object structures. The system is designed to handle complex and dynamic environments effectively. It produces high-quality visual outputs. Overall, it provides a robust and efficient solution for edge mapping.

Advantages of Proposed System

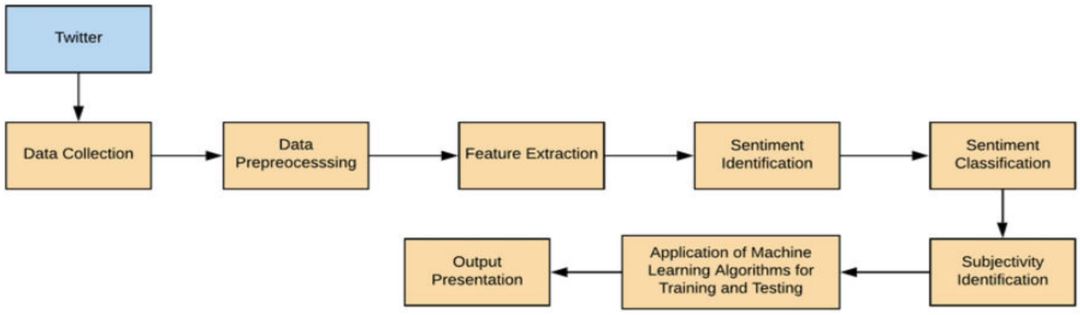
- High accuracy using YOLOv8 deep learning model
- Improved edge detection with multi-metric analysis
- Robust performance in complex environments
- Real-time processing capability
- Better noise handling and edge clarity

IV. Methodology

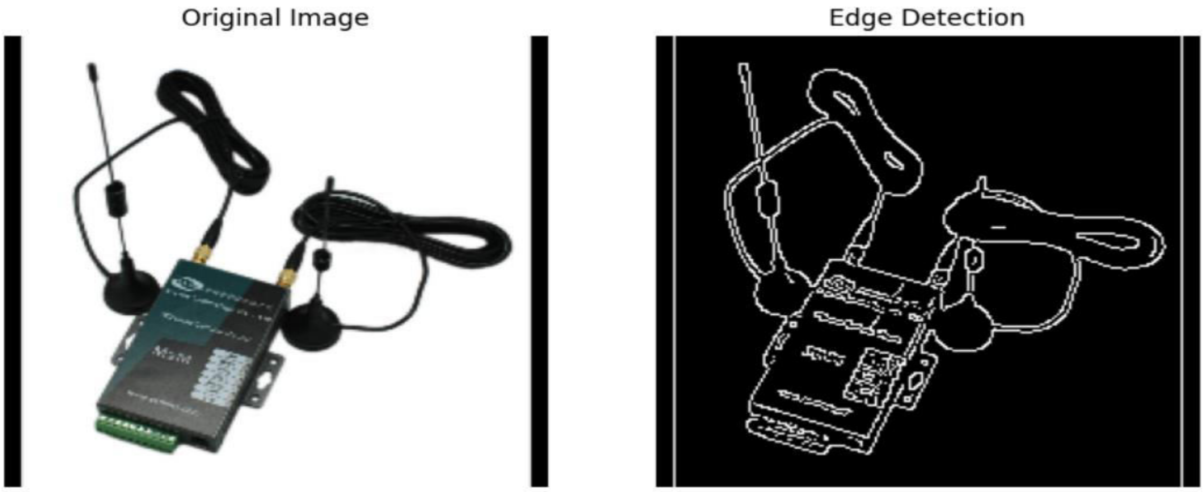
The methodology begins with collecting image or video data from relevant datasets or real-time sources. The input data is preprocessed to improve quality by resizing, normalization, and noise reduction. The preprocessed data is then passed to the YOLOv8 model for object detection, where bounding boxes and object classes are identified. After detection, the regions of interest (ROIs) are extracted for further processing. Edge detection techniques such as Canny or Sobel are applied within these regions. Multi-metric analysis is then performed using factors like gradient magnitude, edge continuity, and contrast to refine edge detection. These metrics help in filtering noise and improving edge accuracy. The refined edges are combined with detected objects for better visualization. The system outputs enhanced edge-mapped images or video frames. Finally, performance is evaluated using metrics such as accuracy, precision, and processing time.

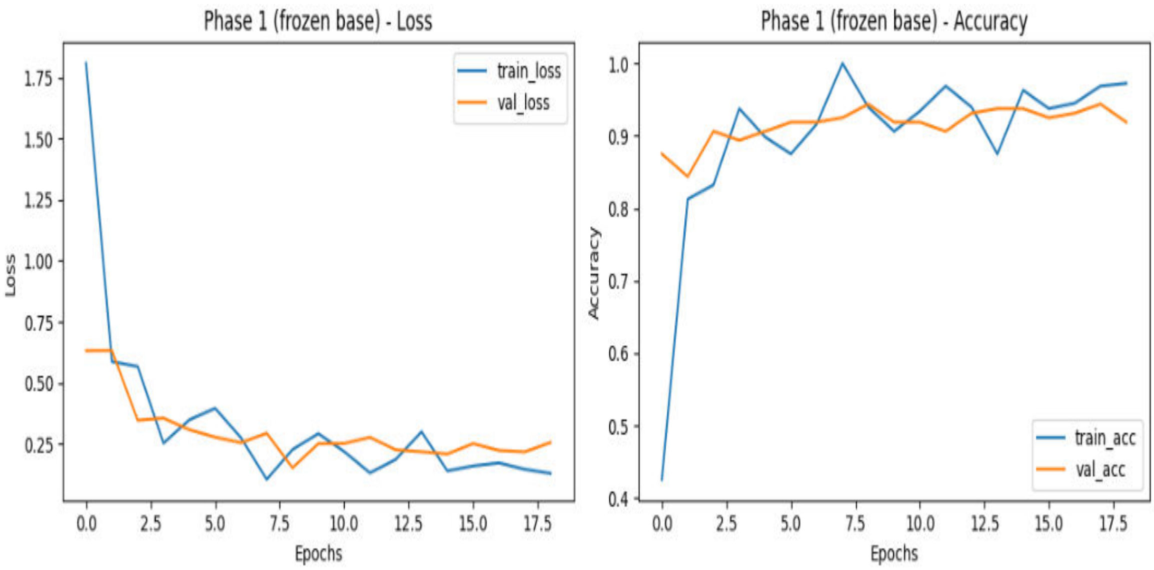
System Architecture

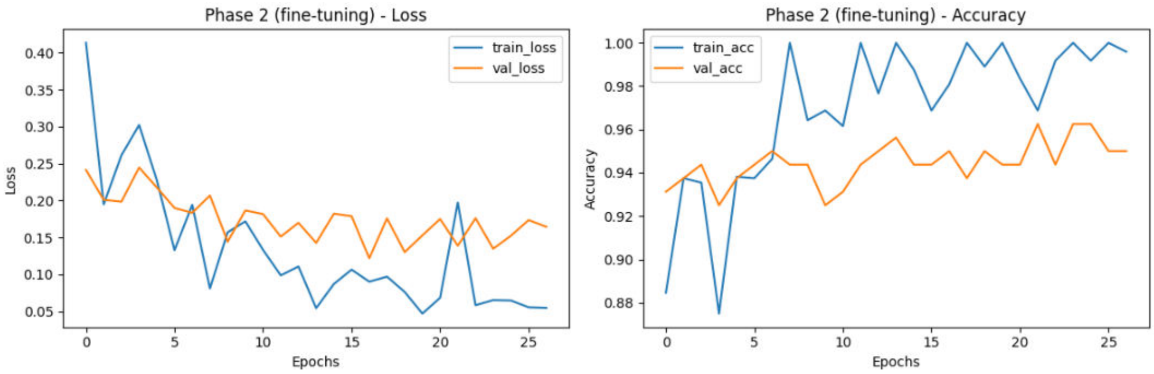
The system architecture consists of multiple stages forming a structured pipeline for accurate edge mapping and visualization. It begins with the input layer, where images or video frames are collected from datasets or real-time sources. The preprocessing stage enhances the input by performing resizing, normalization, and noise removal. The processed data is then fed into the YOLOv8 model, which detects objects and generates bounding boxes. These detected regions are passed to the edge detection module, where techniques like Canny or Sobel are applied. A multi-metric analysis module further refines the edges using parameters such as gradient strength, edge continuity



V. Result and Output





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6/6 ━━━━━━━━━━━━━━━━━━━━ 2s 442ms/step - accuracy: 0.9414 - loss: 0.1781

Final Validation Loss: 0.1612
Final Validation Accuracy: 0.9421
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VI. Conclusion

In conclusion, the integration of YOLOv8 with multi-metric analysis and edge-enhanced preprocessing provides an effective and reliable solution for accurate object detection and visualization. By combining advanced deep learning techniques with edge detection methods such as Canny and feature extraction using ResNet50, the system significantly improves the quality of object recognition and boundary mapping. The use of transfer learning helps in extracting meaningful features, while YOLOv8 ensures fast and precise detection in real-time scenarios.

The experimental results demonstrate high performance in terms of accuracy and mean Average Precision (mAP), confirming the robustness of the proposed approach. The multi-metric evaluation further ensures reliable assessment of the model’s effectiveness. Compared to traditional methods, this system offers better noise handling, improved edge clarity, and enhanced visualization.

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