IDENTIFICATION/DETECTION OF NON-OBJECT AREAS FOR DATA MINING IN IMAGES USING YOLOV8

A Project Based Learning Report Submitted in partial fulfilment of the requirements for the award of the degree

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Submitted by

2310080022: JAGGAVARAPU AKHIL SAI REDDY

2310080007: MOHAMMED SHOAIB HANNAN

Under the guidance of

Dr. Gangamohan Paidi

Department of Electronics and Communication Engineering

Koneru Lakshmaiah Education Foundation, Aziz Nagar

Aziz Nagar – 500075

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Introduction

Traditionally, the majority of research in image processing and computer vision has been centered around object detection, where algorithms are trained to identify and classify visible entities such as humans, vehicles, animals, or specific items of interest. However, in many real-world scenarios, the non-object areas or background regions of an image hold equally significant value. Similarly, in manufacturing, the detection of irregular patterns in non-object surfaces may indicate defects.

With the advancement of deep learning, particularly convolutional neural networks (CNNs), new opportunities have emerged to utilize background information. Among the state-of-the-art models, YOLOv8 (You Only Look Once, version 8) stands out as a powerful and versatile detection framework. Unlike its predecessors, YOLOv8 offers enhanced speed, accuracy, and adaptability across tasks such as object detection, image segmentation, and classification.

These non-object areas can be segmented out once the objects are detected, thereby isolating the background for further data mining. By doing this, the project addresses a research gap: most existing detection systems overlook the hidden information in non-object areas, leading to incomplete understanding of the scene. Our approach, therefore, expands the traditional scope of object detection toward holistic image analysis, where both object and non-object features are studied.

This work has multiple practical applications. In remote sensing, background details such as vegetation patterns, deforestation, or water spread can be mined for environmental monitoring. In medical imaging, non-object regions may represent tissues, textures, or anomalies that require closer examination. In industrial inspection, the background surfaces of products may reveal flaws, cracks, or irregularities invisible to the naked eye. Furthermore, in autonomous systems, understanding non-object areas such as road boundaries, empty paths, or unsafe terrain is critical for navigation.

Thus, this project aims to develop a framework that integrates YOLOv8 with data mining techniques to systematically analyze non-object areas in images. The broader goal is to contribute toward knowledge discovery from images beyond object-centric approaches, unlocking valuable patterns and contextual information that have so far remained underutilized. By bridging object detection with non-object analysis, this project not only enhances the scope of computer vision but also provides a new dimension to data-driven decision-making in diverse application domains.

LITERATURE REVIEW

Fast R-CNN is used for object detection in images and videos, with applications in autonomous driving, surveillance, and medical imaging. It achieves 66.9% mAP on VOC 2007, 66.1% on VOC 2010, and 65.7% on VOC 2012, improving to 68.4% with extra data. While faster than older models, it is not real-time due to slow region proposals. Training is expensive, requiring powerful GPUs and long hours. The RoI pooling layer loses details, affecting small object detection and accuracy. Too many object proposals can confuse the model instead of improving detection. Multi-scale training is costly, requiring high memory and processing power. [8,11].

Despite these challenges, it remains one of the best choices for object detection due to its balance between speed and accuracy [10]. the use of Convolutional Neural Networks (CNNs) and YOLO for object detection in images and videos. Applications include autonomous vehicles, surveillance, medical imaging, and industrial automation, where fast and accurate detection is essential. The accuracy of Faster R-CNN reaches a mean Average Precision (mAP) of 76.4, but it is slower, while YOLO achieves an mAP of 78.6 with a speed of 155 FPS, making it much faster. However, YOLO struggles with detecting small objects and unusual aspect ratios and requires high computational resources [8,11]. YOLO-based object detection, which is widely used in autonomous driving, surveillance, medical imaging, agriculture, and industrial automation due to its fast inference speed. The model achieves a mean Average Precision (mAP) of 63.4% for YOLO and 70% for Fast R-CNN, but YOLO is about 300 times faster, making it preferable for real-time applications. However, YOLO struggles with detecting small objects, handling overlapping objects, and is sensitive to environmental variations [9].

DAMO-YOLO, a real-time object detection model with applications in autonomous driving, surveillance, healthcare, and industrial automation. It achieves mAP scores of 43.6% to 51.9% on COCO for different model scales while maintaining low latency on T4 GPUs. The lightweight versions for edge devices achieve 32.3% to 40.5% mAP with efficient processing on x86-CPU. However, A novel object detection algorithm used in autonomous driving, surveillance, medical imaging, robotics, and industrial automation. It improves upon previous YOLO versions by incorporating EfficientNet-B4 as a backbone and NAS-FPN for better feature fusion. The model achieves an APAS (Average Precision Across Scales) score of 52.7 on the COCO dataset, outperforming YOLOv7's 50.3. YOLOv8 struggles with small object detection, occlusions, and computational demands, making it less suitable for low-power devices [1]. The ViT-YOLO model is designed for object detection in drone-captured images, making it useful for aerial surveillance, agriculture, delivery systems, and autonomous navigation. It improves upon previous YOLO versions by integrating multi-head self-attention (MHSA) and BiFPN, allowing for better small object detection and feature fusion.

The proposed AFC-enhanced YOLO maintains high accuracy while optimizing frame control, ensuring real-time processing for network camera inputs. The model achieves consistent object detection without frame delays, improving real-time performance compared to standard YOLO. However, it still faces hardware dependency issues, high computational demands, and struggles with complex environments [3]. Image-Adaptive YOLO (IA-YOLO) for object detection in adverse weather conditions, with applications in autonomous driving, surveillance, and low-light environments. IA-YOLO enhances detection by using a differentiable image processing (DIP) module, improving accuracy in foggy and low-light conditions. The model achieves an mAP of 72.03% on VOC_Foggy and 37.08% on RTTS, outperforming traditional YOLOv3.It requires high computational power and struggles with extreme weather variations. IA-YOLO significantly enhances detection in challenging environments [2].

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