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Object Detection Using YOLOv8 : A Systematic Review

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Abstract

This study is a Systematic Literature Review (SLR) that comprehensively reviews the recent advances in YOLOv8-based object detection models and their implementations in various application fields, such as UAV aerial photography, fruit ripeness identification, road defect detection, forest fire smoke detection, and medical imaging. This study evaluates the performance of YOLOv8 based on precision, recall, F1-score, and mean average precision (mAP) metrics, and compares its advantages and limitations with previous YOLO versions and other object detection algorithms. Improvements in the YOLOv8 architecture, including attention mechanisms, improved feature extraction, and hyperparameter optimization, enable significant improvements in accuracy and computational efficiency, especially for small objects and low-light conditions. In addition, the integration of image enhancement techniques strengthens the model's performance in challenging environmental conditions. This study is expected to be an important reference for researchers and practitioners in developing YOLOv8-based object detection models for real-world applications.

Keywords: yolov8, object detection, systematic review, object recognition, computer vision

1 Introduction

Object detection [1] is one of the important research areas in computer vision and artificial intelligence. With the ability to identify and classify objects in images or videos, this technology has been applied in a wide range of applications, such as security surveillance, object recognition in autonomous vehicles, medical image analysis, and more. One of the most popular and efficient object detection algorithms is YOLO [2] (You Only Look Once).

YOLO [2] is known for its ability to detect objects in real-time with high accuracy. Since its first introduction, YOLO has undergone several iterations each of which has brought significant improvements in terms of performance. The latest version, YOLOv8 [2] [3] [4] offers a variety of improvements compared to previous versions, including improvements in terms of accuracy and speed of detection.

YOLOv8 [3] introduces a more efficient network architecture and new optimization techniques that make it excel in handling various challenges in object detection. Its speed and accuracy make YOLOv8 particularly suitable for applications that require fast and precise detection, such as video surveillance and autonomous vehicle navigation.

This study aims to conduct a systematic review of the use of the YOLOv8 algorithm in object detection. Through a comprehensive literature review, this study will collect and analyze the results of various studies that have used YOLOv8. The main focus of this review is on performance metrics such as precision, recall, F1-score, mean average precision (mAP), and inference velocity [5]. In addition, this study will also evaluate the advantages and disadvantages of YOLOv8 compared to other object detection algorithms, as well as discuss various challenges faced in the implementation of YOLOv8.

By conducting this review, it is hoped that it can provide an in-depth understanding of the potential and limitations of YOLOv8 in object detection as well as provide recommendations for further research and the development of more efficient and effective applications.

2 Literature Review

In research [1] highlights the challenge of conducting accurate literature reviews due to the vast number of sustainability-related academic publications. To address this, a novel semi-automated

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Systematic Literature Review (SLR) design is proposed, integrating automation features and utilizing databases like Scopus and Web of Science. The approach provides bibliometric analyses, researcher and institution networks, and qualitative assessments. Applied to P-graph research in sustainability, the method identified 284 contributions, with 139 classified as sustainability-related. This semi-automated SLR design aims to streamline literature reviews, accelerating research in sustainability.

This study proposed the YOLO-SE [2] network, an enhanced version of YOLOv8, to tackle the challenges of multi-scale and small-object detection in remote sensing imagery. Key innovations include the lightweight SEF module for improved feature handling and speed, the SPPFE module with multi-scale convolutions and EMA attention for enhanced feature extraction, and the addition of a specialized prediction head for tiny objects. Furthermore, the integration of a transformer-based prediction head and the Wise-IoU loss function improved the model's contextual understanding and training robustness. Experimental results showed that YOLO-SE outperformed the original YOLOv8 with a mAP of 86.5%, demonstrating the effectiveness of these enhancements. This work contributes valuable techniques for advancing remote sensing image analysis with high accuracy and efficiency.

This study presents a thorough evaluation of the YOLOv8-SnakeVision model's performance on the BDD100K and NEXET datasets [3]. The results demonstrate that YOLOv8-SnakeVision excels in precision, achieving 0.743 and 0.753 on BDD100K and NEXET, respectively, indicating strong accuracy in detecting relevant objects in traffic scenarios. Although recall values are slightly lower, with 0.520 on BDD100K and 0.531 on NEXET, they remain within a high and acceptable range, contributing to balanced F1 Scores of 0.611 and 0.625. Most notably, the model achieves impressive real-time performance, with processing speeds of 68 FPS on BDD100K and 67 FPS on NEXET. These results confirm that YOLOv8-SnakeVision offers an effective trade-off between detection accuracy and speed, making it highly suitable for real-time object detection in dynamic environments.

The experimental results [4] demonstrate that the improved model significantly outperforms its pre-improvement version, achieving Precision, Recall, and mAP values of 97%, 89.5%, and 95.3%, respectively—representing notable improvements of 8.2%, 15.6%, and 10.1%. A comparison between Tables 2 and 4 shows that the improved model attained a 3.7% increase in Precision on the new dataset, likely due to the larger UAV target sizes. However, the more complex backgrounds in the new dataset led to a 3.8% decrease in Recall. Despite this, the model maintained high overall detection accuracy, indicating strong generalization capability and robust performance across different datasets.

Experimental results on a customized smoking behavior dataset reveal that the YOLOv8-MNC model [5] significantly enhances detection accuracy. Achieving a mAP@0.5 of 85.887%, the model shows a notable improvement of 5.7% over the previous algorithm. This highlights the effectiveness of YOLOv8-MNC in accurately identifying smoking behavior, demonstrating its potential for practical applications in real-world surveillance and behavior monitoring systems.

In another study examines computer-aided diagnostic (CAD) systems for detecting coal workers' pneumoconiosis (CWP) in chest X-rays, which can aid early diagnosis and improve survival rates. The study categorizes and summarizes feature extraction and detection methods, analyzing 40 articles from the past five decades across three main approaches: handcrafted feature-based image analysis, traditional machine learning, and deep learning. The review, conducted using 11 databases from various scientific fields, also discusses its limitations and potential improvements for future research.

This *Systematic Literature Review* (SLR) [6] evaluates machine learning (ML)-based automated diagnostic systems for dementia detection across multiple data modalities, including images, clinical features, and voice data. While previous SLRs focused on a single data type, this study analyzes research from 2011 to 2022, identifying that image-based ML models show the most promising results. The review also highlights limitations of existing approaches and suggests future directions for improving dementia prediction using ML techniques.

This article [6] compares the performance, advantages, and disadvantages of YOLO and Faster R-CNN for object detection. While it reviews the development of related algorithms, it lacks a comprehensive comparison of the two methods across multiple datasets and technical indicators. The study highlights relevant performance metrics but does not thoroughly analyze them. Finally, it suggests potential applications for both algorithms based on their strengths and weaknesses.

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3 Research Method

This study adopts the *Systematic Literature Review* (SLR) approach [7] which focuses exclusively on the use of YOLOv8 in object detection. This approach aims to isolate the research only on the implementation of YOLOv8, with the aim of compiling an in-depth and comprehensive review of how this model is applied, its performance, and the challenges and opportunities faced in various studies. By limiting the scope to YOLOv8 only, this study aims to provide a more specific and detailed understanding of YOLOv8's contribution compared to other object detection methods, so as to help researchers and practitioners interested in the advantages and specificities of YOLOv8 in various object detection applications. In research [1] highlights the challenge of conducting accurate literature reviews due to the vast number of sustainability-related academic publications. To address this, a novel semi-automated *Systematic Literature Review* (SLR) design is proposed, integrating automation features and utilizing databases like Scopus and Web of Science. The approach provides bibliometric analyses, researcher and institution networks, and qualitative assessments. Applied to P-graph research in sustainability, the method identified 284 contributions, with 139 classified as sustainability-related. This semi-automated SLR design aims to streamline literature reviews, accelerating research in sustainability.

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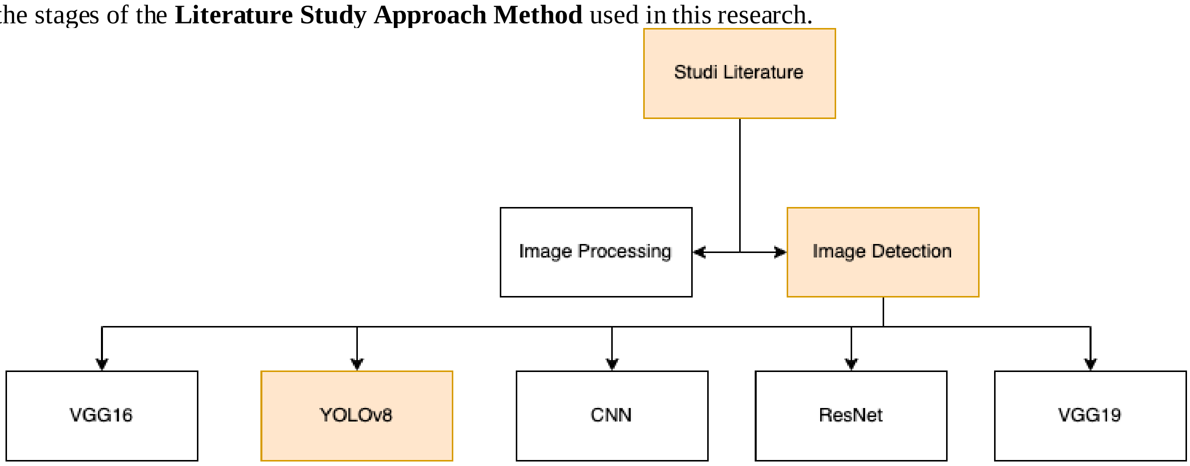

Figure 1. Literature study approach method

4 Results and Analysis

A. *Research Focus Distribution*

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The study demonstrates the remarkable advancements and versatility of the YOLOv8 and its variants across various application domains. YOLOv8 significantly outperformed its predecessors, such as YOLOv5 and YOLOv7, achieving exceptional accuracy in diverse scenarios. For instance, in medical imaging, the model attained an accuracy of 0.998 with a recall of 0.9975 and precision of 1.000 in diagnosing elbow osteochondritis dissecans [8], highlighting its reliability in critical applications. The model's adaptability was evident in specialized fields, such as agriculture and traffic management. It improved pest detection and tomato maturity grading, achieving mAP values of up to 92.6% [9], and enhanced traffic sign detection through multi-scale feature learning, showcasing its potential for intelligent systems. Additionally, YOLOv8 variants like YOLOv8-CAB and C-YOLOv8 addressed the challenges of small object detection using attention modules and dynamic optimization techniques, making them effective for remote sensing and underwater scenarios. **Table 1** summarizes **selected YOLOv8-based studies from the literature, covering a wide range of application domains.** Each entry highlights the architectural variant used, its performance metrics, and its strengths in the respective domain.

Table 1. Summary of selected studies using yolov8 for object detection

Study	Application Area	Architecture/ Modification	Performance Results	Strengths
Inui et al. [8]	Elbow OCD detection (medical imaging)	YOLOv8	Accuracy 0.998, Recall 0.9975, Precision 1.000	Very high accuracy in medical diagnosis
Luo et al. [9]	Citrus disease & pest detection (agriculture)	Self-Attention YOLOv8	mAP 92.6%	Effective under complex lighting conditions
Liu et al. [3]	Smart traffic detection (transportation)	YOLOv8-SnakeVision	Precision 0.743–0.753, FPS 67–68	Fast and precise for vehicle detection
Zhai et al. [4]	Tiny UAV detection (remote sensing)	YOLO-Drone (YOLOv8)	Precision 97%, Recall 89.5%, mAP 95.3%	High performance for small aerial targets
Wang et al. [5]	Smoking behavior detection (public security)	YOLOv8-MNC	mAP@0.5 85.89%	Accurately identifies social behavior
Karna et al. [10]	3D printing defect detection (industry)	YOLOv8 with HPO	Accuracy improved by 10%, parameters reduced by ~60%	Optimal for edge device implementation
Shen et al. [11]	Remote sensing image detection	DS-YOLOv8	mAP@0.5 97.7%	Superior performance in satellite imagery
Han et al. [12]	X-ray prohibited item inspection (security)	SC-YOLOv8	Detection accuracy up to 82.7%	Accurate for airport and luggage security
Zhang et al. [13]	Underwater small object detection	Enhanced YOLOv8	Accuracy improvement of 1.2%	Effective in extreme and low-visibility environments

The study further highlights the efficiency of lightweight YOLOv8 versions, which achieved high performance with reduced computational resources. For example, modifications for UAV detection reduced model parameters by nearly 60% while improving accuracy by over 10%. These adaptations enabled real-time applications in resource-constrained environments, such as seed counting and traffic monitoring. Furthermore, the integration of innovative techniques, such as Wise-IoU loss and Bi-PAN-FPN structures, improved anchor box quality and feature fusion, significantly enhancing detection robustness.

This study specifically focuses on evaluating the advancements of YOLOv8 in comparison to its predecessors, highlighting improvements in object detection accuracy, speed, and hardware efficiency. The *Systematic Literature Review* (SLR) compiles results from 19 selected studies to examine YOLOv8's performance in various fields. The findings provide a comprehensive view of recent trends in model development, common application areas, and benchmark performance. The outcomes of this SLR include the identification of YOLOv8's key architectural improvements, the effectiveness of its

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variants in edge-computing environments, and its role in enhancing small-object detection. These insights offer a valuable resource for researchers seeking to adopt or further develop YOLO-based models for real-world implementation. The impact of this study lies in guiding future development strategies for object detection models and promoting YOLOv8's application in real-time systems such as autonomous navigation, agricultural monitoring, and smart surveillance. **Figure 2** presents the **Research Focus based on YOLOv8 Detection**, outlining the core components and direction of the study.

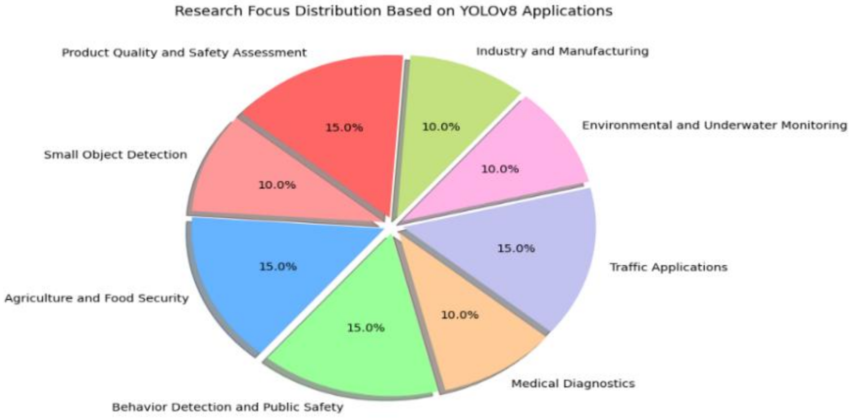

Figure 2. Research focus based on yolov8 detection

B. Distribution of Publication

This study list of publications in various journals and conferences, along with their respective quartile rankings (Q). These quartiles reflect the quality and influence of the journals, with Q1 being the highest category and Q4 being the lowest. Some of the journals listed include IEEE Access (Q1), Scientific Reports (Q1), and Sensors (Q2), which are relevant to fields such as engineering, computer science, and multimedia applications. Additionally, journals like Applied Sciences (Q3) and Karbala International Journal of Modern Science (Q3) highlight the diverse topics covered, ranging from electronics to computational neuroscience. The document also mentions conference publications, such as the International Conference on Advances in Biomedical Engineering (ICABME), showcasing contributions to scientific forums. This diversity in publication sources also reflects the growing interdisciplinary interest in YOLOv8, especially among researchers in intelligent systems, embedded AI, and computer vision domains. **Figure 3** illustrates the **Research Focus based on the Distribution of Publications**, which provides an overview of how scholarly works are distributed across key themes relevant to the study.

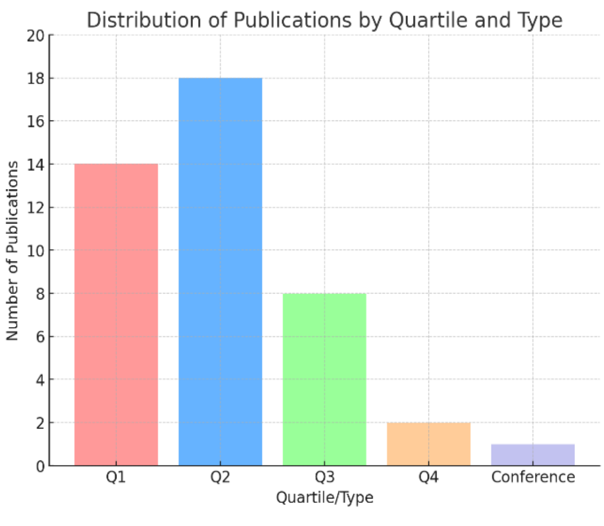

Figure 3. Research focus based on distribution of publications

C. Development of the YOLOv8

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The YOLOv8 has been continuously developed to address the challenges of object detection in various conditions, particularly for small, difficult-to-detect objects. Innovations such as Deformable Convolution enable adaptive adjustment to the field of view, improving detection capability in complex environments. Additionally, Self-Calibrating Shuffle Attention enhances multi-scale feature learning efficiency, while Ghost Shuffle Convolution reduces parameters without sacrificing accuracy. Studies have demonstrated that integrating these mechanisms significantly improves performance in remote sensing images, achieving mAP@0.5 of 97.7% on the RSOD dataset [10] [11] [14]. These innovations not only contribute to detection precision but also support deployment in low-power environments, a key direction emphasized throughout the reviewed literature.

D. Applications of YOLOv8 in Various Fields

1) *Agriculture*
YOLOv8 plays a vital role in agriculture, supporting the detection of plant diseases, fruit quality, and pests with high efficiency. For example, Light-SA YOLOv8 has been used to detect citrus diseases in complex environments, achieving an accuracy of up to 92.6%. Moreover, the model effectively identifies small pests, such as caterpillars and beetles, under varying lighting conditions, supporting precision farming [9] [15].

2) *Transportation*
In the transportation sector, YOLOv8 is utilized for tracking parking time violations using DeepSORT and OC-SORT algorithms. These algorithms deliver high MOTA results, essential for monitoring vehicles in densely populated parking areas. Additionally, YOLOv8 is applied to detect brake lights in vehicles, providing quick and accurate results for advanced driver assistance systems [16] [12].

3) *Public Security*
In public security, YOLOv8 aids in detecting smoking behavior in public spaces. The addition of modules such as NWD Loss and MHSA enhances the detection of small objects like cigarettes, even under low-light conditions or overlapping objects. This demonstrates the technology's ability to significantly improve security monitoring [12] [17].

4) *Healthcare*
In healthcare, YOLOv8 excels in detecting medical conditions such as Osteochondritis Dissecans (OCD) through ultrasound images. With near-perfect accuracy (99.8%), this technology provides a promising asa solution for effective mass screenings, supporting early diagnosis and treatment [8].

5) *Industry*
YOLOv8 is also used in industry to detect defects in products, such as X-ray-based security inspections. SC-YOLOv8, for instance, is designed to identify prohibited items in luggage X-ray images with a detection accuracy of up to 82.7%, showcasing its effectiveness in enhancing operational security and efficiency [12] [18].

E. Advantages of YOLOv8

The YOLOv8 is renowned for its effectiveness in detecting small objects and performance in challenging environments such as low light or high occlusion. For instance, in wildfire smoke detection, YOLOv8 recorded a 3.3% increase in precision compared to its predecessors. Its computational efficiency also makes it suitable for devices with limited memory, such as drones for traffic surveillance and multitarget detection in complex urban environments. These attributes reinforce YOLOv8's strength as a model optimized for real-time and resource-aware deployment.

F. Challenges Faced

Despite its numerous advantages, YOLOv8 faces challenges in detecting very small objects or in poor lighting conditions. To address these issues, some studies have incorporated a specially designed Prediction Head to enhance the detection accuracy of small objects. This approach has shown a 1.2% improvement in accuracy, particularly in underwater and remote sensing environments [13] [19]. Such limitations remain a major focus for ongoing and future research aimed at expanding YOLOv8's robustness in dynamic and adverse environments.

G. Comparison with Previous Models

Compared to earlier models such as YOLOv7 and Faster R-CNN, YOLOv8 offers superior accuracy and speed. For example, in small pest detection, YOLOv8 achieved an mAP of 84.7%, outperforming previous models. Additionally, YOLOv8 demonstrates higher efficiency by reducing parameters and shortening training times, making it an ideal choice for real-time applications [15] [17]. This reflects an important trend in literature: a shift toward more lightweight and application-agnostic object detection models, with YOLOv8 at the forefront.

H. Real-Life Implementations

YOLOv8 has been implemented in various practical applications, such as Android-based pest detection apps that help farmers manage their fields more efficiently. Furthermore, YOLOv8 is used for defect detection in 3D printing with Raspberry Pi, proving its capability to support industrial automation in diverse operational environments [10] [15] [19]. These implementations validate the findings of the SLR, demonstrating YOLOv8's transition from experimental evaluation to scalable real-world adoption.

I. Future Potential

The future development of YOLOv8 includes creating more representative datasets and integrating technologies such as vision transformers to enhance detection performance. Studies show that incorporating these mechanisms improves efficiency and accuracy, particularly for small target detection in remote sensing applications under complex environmental conditions [10] [19]. This review encourages future research to focus on context-aware detection, real-time inference on edge devices, and hybrid models that combine YOLOv8 with transformer-based backbones. The insights generated here are expected to guide model development strategies and inspire novel architectures that retain YOLOv8's strengths while addressing its current limitations.

5 Conclusion

In conclusion, YOLOv8 has established itself as a robust, adaptable, and high-performing object detection framework with successful implementations across diverse domains such as agriculture, transportation, healthcare, and public security. Its integration of innovative modules like Self-Calibrating Shuffle Attention and Ghost Shuffle Convolution significantly enhances accuracy and computational efficiency, making it suitable for real-time applications and deployment on resource-constrained devices. Comparative studies further affirm YOLOv8's superiority over predecessors such as YOLOv7 and Faster R-CNN, particularly in terms of mean Average Precision (mAP), inference speed, and model compactness. However, limitations remain, especially in detecting very small objects, handling low-light conditions, and managing occlusions. Although techniques like enhanced feature extraction and specialized prediction heads have been proposed, further improvements are needed to enhance resilience and context awareness. Future research should prioritize optimizing performance under low-quality visual conditions, improving results on imbalanced and low-resolution datasets, and reducing computational load without sacrificing detection accuracy to support reliable deployment in real-world scenarios, including remote sensing, autonomous navigation, and intelligent surveillance. Moreover, this Systematic Literature Review not only consolidates YOLOv8's achievements but also underscores the need for more standardized evaluation frameworks, consistent metric reporting, and comprehensive thematic mapping across application domains. Integrating bibliometric analysis, cross-domain performance comparisons, and visual analytics in future SLRs could enrich insights into evolving research trends, ultimately enhancing reproducibility, transparency, and strategic direction. By identifying both strengths and research gaps, this study contributes meaningfully to guiding future innovations in object detection and lays a foundation for subsequent systematic reviews in computer vision and deep learning.

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