International Journal of Combinatorial Optimization Problems and Informatics, 16(3), May-Aug 2025, 323-333. ISSN: 2007-1558.
https://doi.org/10.61467/2007.1558.2025.v16i3.715

www.editada.org

AI-Based Decision Support for Helmet Detection and Safety Monitoring in Construction Sites

Salem Jassim[1], Khaled Mirfaei[2], Affan Alkim[2], Hamad Al-Nuaimi[1], Ali Bin Khalifa[1], Latifa Bint Ahmed[1]
[1] Computer Engineering Department, Qatar University, Qatar
[2] Department of Information Technology, Lusail University, Qatar
E-mails: alkim@lu.edu.qa

Abstract. This paper explores the application of advanced deep learning models, particularly YOLOv7, for helmet detection in construction sites to enhance workplace safety. The study evaluates YOLOv7's performance using key metrics such as precision, recall, mean Average Precision (mAP), and F1 score, ensuring a comprehensive assessment of its detection accuracy and efficiency. A comparative analysis with YOLOv8 highlights YOLOv7's superior performance in detection accuracy and computational efficiency, making it a practical choice for resource-constrained environments. Despite challenges such as adapting to dynamic and complex construction site conditions, YOLOv7 proves to be a reliable and efficient tool in real-time safety monitoring. YOLOv7 achieved a precision of 0.659 and a recall of 0.641, demonstrating strong detection capabilities while maintaining lower computational requirements compared to YOLOv8, which achieved a precision of 0.783 and a recall of 0.756. The findings suggest that YOLOv7-based helmet detection systems can significantly reduce human error, improve worker safety, and contribute to lowering incident rates. Thus, the results emphasize the potential of deep learning in transforming safety protocols, ensuring regulatory compliance, and fostering a culture of accountability in construction.

Keywords: Construction Site Safety, Computer Vision, Safety Monitoring, Real-Time Detection

Article Info
Received January 28, 2025
Accepted April 15, 2025

1 Introduction

Occupational health and safety are critical concerns in industries such as construction, manufacturing, and mining, where workers are frequently exposed to hazardous conditions. Among the various safety measures, wearing a helmet is one of the most fundamental protections against head injuries [1]. Helmets play a vital role in reducing the impact of falling objects, collisions, and accidental slips, significantly lowering the risk of traumatic brain injuries [2, 3]. According to the Occupational Safety and Health Administration (OSHA), head injuries account for a considerable percentage of workplace fatalities and severe injuries [4]. Ensuring helmet compliance in such environments is essential for worker safety and regulatory adherence, making helmet detection an important aspect of occupational safety management. Effective helmet detection is crucial for ensuring worker safety, reducing workplace injuries, and complying with safety regulations. Manual monitoring methods are prone to human error and inefficiency, especially in large-scale construction sites where constant supervision is challenging. Automated helmet detection systems can address these limitations by providing real-time monitoring and compliance enforcement. By leveraging advanced image processing and artificial intelligence (AI) techniques, such systems can detect non-compliance cases instantly and alert safety personnel, reducing the likelihood of accidents and enhancing overall workplace safety [5-8]. Additionally, automated helmet detection can aid in regulatory compliance, as many labor laws mandate strict adherence to personal protective equipment (PPE) protocols.

Deep learning has revolutionized the field of computer vision, particularly in object detection tasks [9-15]. Traditional computer vision techniques often struggle with varying lighting conditions, occlusions, and diverse object appearances, limiting their effectiveness in real-world applications [16, 17]. However, deep learning-based object detection models, especially convolutional neural networks (CNNs), have demonstrated superior accuracy and robustness [18-20]. These models automatically learn hierarchical features from images, enabling them to detect objects with high precision. State-of-the-art object detection architectures, such as Faster R-CNN, SSD, and YOLO (You Only Look Once), have significantly improved detection accuracy and speed [21-24]. Among these, YOLO-based models have gained widespread adoption due to their real-time processing capabilities, making them suitable for safety monitoring applications [25-29]. The YOLO family of models has undergone several iterations, each introducing enhancements in accuracy, speed, and computational efficiency [30, 31]. YOLOv7, the latest in this series, offers significant improvements in object detection through innovative architectural modifications, including extended efficient layer aggregation networks (E-ELAN) and model scaling techniques. Unlike its predecessors, YOLOv7 achieves a better balance between detection accuracy and computational efficiency [21, 32], making it particularly suitable for real-time deployment in UAV-based safety systems, as confirmed in our computational tests. Evaluating YOLOv7's effectiveness in helmet detection is crucial, particularly in resource-constrained environments where computational efficiency is a determining factor for deployment feasibility.

Unmanned Aerial Vehicles (UAVs) have emerged as powerful tools for safety monitoring, surveillance, and inspection in hazardous environments [33]. UAVs offer the advantage of mobility, allowing for efficient monitoring of large-scale construction sites without the need for constant human supervision [34]. Equipped with high-resolution cameras and AI-based object detection models, UAVs can be deployed to inspect construction sites, detect non-compliance with safety regulations, and enhance overall workplace safety [35-37]. The integration of UAVs with automated helmet detection systems presents an opportunity to improve safety enforcement while minimizing the need for manual intervention. Integrating object detection models with UAVs requires the consideration of various factors, including camera resolution, real-time processing capabilities, and system compatibility with embedded computing platforms. UAVs must be equipped with onboard computing systems capable of running deep learning models efficiently while maintaining real-time processing speeds. Edge computing devices, such as NVIDIA Jetson boards, offer a practical solution by enabling AI-powered object detection directly on UAVs [38]. This integration allows for real-time helmet detection, instant alerts, and data logging, facilitating proactive safety management in dynamic construction environments.

In this study, we explore the application of YOLOv7 for helmet detection in construction sites using UAV-based monitoring. By leveraging the high-speed detection capabilities of YOLOv7, our approach aims to provide an efficient and scalable solution for workplace safety enforcement. The UAV-mounted system captures real-time video footage of construction sites, processes the images using YOLOv7, and identifies instances of non-compliance with helmet-wearing regulations. The results are analyzed to assess the accuracy, efficiency, and feasibility of deploying such a system in real-world conditions. Our study also compares YOLOv7's performance with previous YOLO versions to evaluate its advantages and limitations in helmet detection tasks. Conclusively, this paper presents a structured evaluation of UAV-based helmet detection using YOLOv7, addressing the need for efficient safety monitoring solutions in construction environments. The study examines the integration of deep learning-based object detection with UAVs, evaluates the computational efficiency of YOLOv7, and provides insights into the feasibility of deploying such a system for real-time safety compliance monitoring. The findings contribute to the ongoing development of AI-driven safety solutions, offering practical implications for improving occupational health and safety enforcement in high-risk industries.

2 Experimental Procedures

2.1 YOLOv7 Detection Algorithm

This study utilizes YOLOv7, a single-shot detection algorithm widely recognized for its modular and innovative architecture as well as its high accuracy and efficiency in real-time object detection. As a single-stage object detection model, YOLOv7 analyzes an input image just once to perform both classification and localization tasks simultaneously [39]. Thanks to its enhanced network architecture and optimizations compared to earlier YOLO models, YOLOv7 delivers superior performance with high accuracy, speed, and efficiency. It excels in real-time applications with minimal hardware requirements. Its ability to detect both small and large objects simultaneously makes it a versatile algorithm, distinguishing it from others. Innovative features like the Extended Efficient Layer Aggregation Network (E-ELAN) [40] allow the model to learn deeper and more complex features, while scaling methods enable precise adjustments to depth and width.

As illustrated in Figure 1, the YOLOv7 architecture comprises three primary components: Backbone, Neck, and Head [41]. The Backbone component is responsible for extracting meaningful features from the input image, generating valuable data fragments from raw, low-resolution pixel information. This process is achieved using a CNN architecture [42]. The Backbone processes the low-level pixel data to derive higher-level features, enabling accurate object differentiation. YOLOv7's Backbone is reinforced with components like CBS (Convolution – BatchNorm – SiLU) and E-ELAN. E-ELAN enhances the network's learning capacity and optimizes gradient paths, facilitating the learning of deeper and more complex features. The CBS module streamlines feature extraction and learning processes, increasing the model's stability while ensuring efficient performance. It is an integral component of modern learning networks, contributing to their effectiveness and reliability. The ELAN structure strengthens information flow across layers in the YOLOv7 architecture, increasing both the width and depth of the network for more detailed feature extraction. By optimizing and aggregating information from multiple layers, ELAN enhances the model's ability to recognize and detect complex objects at varying resolutions. The Backbone's MaxPooling1 block reduces the spatial resolution of the input while retaining critical features, filtering out noise, and reducing computational load for improved efficiency.

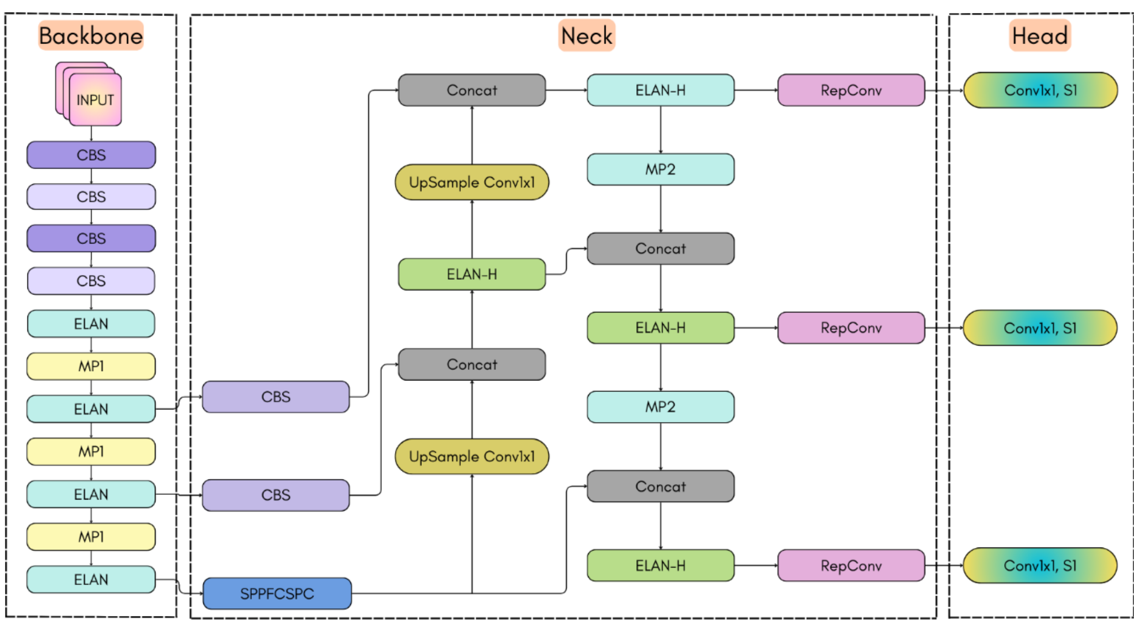

Figure 1. The overall architecture and key components of YOLOv7.

The Neck component utilizes the features extracted by the Backbone to create feature pyramids, enabling the detection of objects at different scales within the image [43]. By combining feature maps from various layers at different resolutions, YOLOv7 ensures effective detection of objects regardless of their size. This integration of features from different resolutions facilitates the simultaneous detection of small, medium, and large objects. Advanced operations such as linking and rearranging further enhance the algorithm's learning capacity. Moreover, the High-Level Efficient Layer Aggregation Network (ELAN-H) used in the Neck delivers exceptional performance in multi-scale object detection tasks, optimizing information flow. With its multi-input and multi-output structure, ELAN-H efficiently resizes low-resolution data features, providing a significant advantage for detecting smaller objects. The SPPFCSPC block, a powerful module within YOLOv7's Backbone, combines Spatial Pyramid Pooling Fast (SPPF) and Cross Stage Partial Network (CSPNet) structures [44]. SPPF applies pooling operations of varying sizes (e.g., 1x1, 5x5, 9x9) to aggregate spatial information at different scales, enabling better detection of large and small objects while minimizing spatial information loss.

UpSample modules scale low-resolution feature maps to higher resolutions for detailed and high-resolution analysis, enabling multi-scale predictions for improved detection of smaller objects. MaxPooling2 (MP2) resizes resolution to merge feature maps from different scales, summarizing information from deeper layers and enhancing the model's multi-scale detection capability. By emphasizing distinct data features, MP2 facilitates better focus and learning for YOLOv7, minimizing information loss by selecting the maximum value from specific regions of the feature map. The RepConv module introduces a significant update to YOLOv7's architecture, distinguishing it from previous YOLO family members. RepConv enhances model speed by reorganizing and merging parameters from multiple layers in earlier convolutional networks. It uses 1x1 convolution to enable stronger feature extraction, accommodating the complex structure of convolutional layers.

The Head component of YOLOv7 generates the final detection results, leveraging features extracted by the Backbone and Neck to classify objects and position bounding boxes. At this stage, the model predicts object classes and locations, completing the inference process. Innovative modules like Conv1x1 play a critical role in YOLOv7's Head, offering efficient and rapid predictions without altering resolution. Each grid cell processes only its pixel channel data independently of neighboring pixels, making it vital for outputting results for each grid cell in the image. YOLOv7's Conv1x1 module extracts both bounding box coordinates and class predictions for each grid cell. Despite maintaining resolution, 1x1 convolutions significantly increase information density, contributing to YOLOv7's speed and efficiency. Additionally, for a more comprehensive comparison, Table 1 summarizes the key differences between YOLOv7 and YOLOv8. The table focuses on several important factors, such as the architecture, detection accuracy, inference speed, and computational efficiency of each model.

Table 1. Key difference between YOLOv7 and YOLOv8.

Feature	YOLOv7	YOLOv8
Model Architecture	Utilizes a slightly older backbone with traditional convolutional layers and network design.	Features an improved backbone with more efficient convolutional operations and optimized layers.
Detection Accuracy	Good accuracy, but can struggle with smaller or occluded objects in certain settings.	Enhanced accuracy, especially for small or occluded objects, due to improvements in feature extraction and loss functions.
Inference Speed	Faster inference compared to previous YOLO versions, but slightly slower than YOLOv8.	Faster inference, thanks to optimizations in both the backbone and detection head, enabling more efficient real-time applications.
Computational Efficiency	More resource-intensive, requiring higher computational resources for optimal performance.	More optimized for low-resource environments (e.g., UAVs), offering better computational efficiency.
Model Size	Larger model size with more parameters, making it more computationally demanding.	Smaller, more compact model size that allows for better performance on embedded systems with limited resources.
Loss Function and Training	Standard loss function, with some limitations in handling large datasets.	Improved loss functions that provide better stability during training and improved convergence for large datasets.

2.2 Dataset and Experimental Platform

A comprehensive dataset was created for helmet detection using YOLOv7, especially considering the construction industry's need for minimal error tolerance. The dataset was expanded using images obtained from UAV flights and web-based resources. Particular attention was given to capturing images from various heights and angles. Additionally, images taken at different times of the day ensured the algorithm's robustness under variable lighting conditions. Figure 2 presents sample images from the dataset used in this study, which includes aerial imagery captured by UAVs under various environmental conditions. The dataset was collected under diverse environmental conditions, including varying lighting scenarios, different times of the day, and multiple weather conditions such as cloudy, sunny, and partially shaded environments. The UAVs were flown at different altitudes and angles to capture a range of perspectives, ensuring robustness in detection performance. These variations allow for a comprehensive evaluation of the model's ability to generalize across real-world construction site conditions. These images serve as the foundation for training the YOLO-based detection models. To further improve detection accuracy, several data enhancement techniques were applied to the dataset, as illustrated in Figure 3. These enhancements include adjustments to brightness and contrast, as well as the application of filtering techniques to improve image clarity and robustness under diverse lighting conditions. In the figure, the first image is the original image, while the others are new images obtained through various filtering and enhancement techniques. The images on the top row are those obtained with sharpness and contrast adjustments, while the ones on the bottom row are the new images produced through filtering. By incorporating such augmentations, the dataset becomes more representative of real-world scenarios, thereby enhancing the generalization ability of the detection models.

Figure 2. Sample images from the UAV-captured dataset used for helmet detection. (a) Clear daylight image from a high altitude. (b) Early morning image with low-light conditions. (c) Image under partial shadow and cloudy weather. (d) Mid-day image with glare and high contrast. (e) Close-range image with complex object occlusion.

The UAVs utilized in this study are modified commercial-grade rotary-wing UAVs, equipped with high-resolution cameras, advanced gimbals for image stabilization, high-precision GPS modules, extended-capacity batteries, and large-capacity data storage units. These UAVs are designed for urban environments, offering the flexibility to adjust flight parameters such as altitude and speed. Additionally, they are outfitted with Jetson Xavier NX hardware, which facilitates real-time processing and efficient object detection during aerial flights. This combination of modifications ensures optimal performance in capturing high-quality images suitable for vehicle detection and enhances the overall robustness of the system in dynamic urban settings. However, deploying UAV-based helmet detection systems in real-world environments presents several challenges, particularly due to variations in lighting and weather conditions. Low-light scenarios, such as early morning or nighttime operations, can reduce image clarity, while direct sunlight can cause glare and overexposed regions, leading to false detections. Additionally, adverse weather conditions, including fog, rain, and dust, can obscure objects and degrade image quality, affecting detection accuracy. To mitigate these challenges, the dataset used for training incorporates data augmentation techniques such as brightness normalization, contrast enhancement, and synthetic shadowing to improve model robustness. Furthermore, adaptive exposure correction is applied during image preprocessing to optimize visibility under different lighting conditions.

Figure 3. Examples of data enhancement. The first image is the original image, while the others are new images obtained through various filtering and enhancement techniques. The images on the top row are those obtained with sharpness and contrast adjustments, while the ones on the bottom row are the new images produced through filtering.

3 Test Results

The computational tests were conducted on a dataset of 3505 high-resolution construction site images captured from a UAV during multiple flight sessions across different times of the day. The images composing the dataset were collected under varying lighting conditions, including bright daylight, overcast skies, and low-light environments, to simulate real-world monitoring scenarios. The dataset also included images taken in different weather conditions and with minor obstructions, ensuring that the models were evaluated under diverse environmental factors. The data was split into a 65% training set, a 15% validation set, and a 20% testing set, allowing for an assessment of the models' performance and robustness in a variety of conditions. This comprehensive testing environment reflects the real-world challenges of deploying object detection algorithms in aerial monitoring applications.

To evaluate the performance of YOLOv7 in helmet detection, a comprehensive comparison was conducted using four key metrics: Precision, Recall, mAP (mean Average Precision), and F1 Score [5]. These metrics provide insights into the accuracy, consistency, and overall effectiveness of the models, shedding light on which one delivers superior performance. To offer a relative perspective on YOLOv7's performance, the same detection tests were also conducted using YOLOv8 [21]. Compared to YOLOv7, YOLOv8 strikes a better balance between accuracy and real-time speed, making it particularly well-suited for deployment on UAVs and other resource-constrained platforms, as demonstrated in this study's aerial monitoring applications. Some visual examples of helmet detection using YOLOv7 are provided in Figure 4.

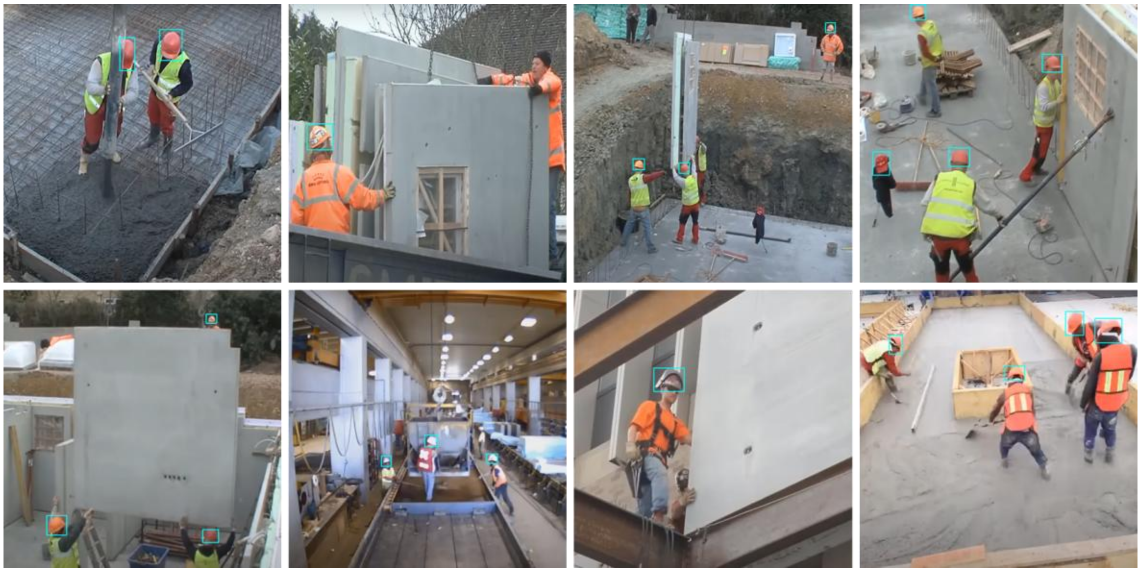

Figure 4. Some visual examples of helmet detection performed with YOLOv7. The examples are specifically chosen from situations where the algorithm achieved successful detection.

The performance results obtained from both algorithms are summarized in Table 2. Precision measures the model's ability to produce correct results in helmet detection. In other words, it evaluates how often the model's "helmet detected" predictions are accurate [5]. In the construction sector, precision is a critical metric because false positives can lead to significant issues. For example, if the model mistakenly identifies a worker without a helmet as wearing one, it might trigger unnecessary safety alerts. Mathematically, precision is calculated by dividing the number of true positives by the sum of true positives and false positives. According to test results, YOLOv7 achieved a precision score of 0.659, while YOLOv8 achieved 0.783. YOLOv8's higher precision indicates fewer false positives, which is vital for minimizing unnecessary warnings in construction environments. High precision ensures that safety managers can focus on accurate detections, improving the reliability of safety measures.

Table 2. Comparison of the performance of both algorithms in helmet detection.

Model	Performance Metrics			
	Precision	Recall	mAP	F1-Score
YOLOv7	0.659	0.641	0.650	0.650
YOLOv8	0.783	0.756	0.748	0.769

Recall evaluates the model's ability to correctly identify all helmeted workers. Essentially, it measures the success of the model in detecting helmeted workers without missing any [5]. In hazardous environments like construction sites, low recall (indicating a high false-negative rate) poses serious safety risks. If the model fails to detect a worker wearing a helmet (false negative), that worker might remain outside the scope of safety measures, increasing accident risks. Recall is calculated by dividing the number of true positives by the sum of true positives and false negatives. YOLOv7 achieved a recall score of 0.641, while YOLOv8 scored 0.756. YOLOv8's higher recall demonstrates its superior ability to identify helmeted workers effectively, reducing the likelihood of safety gaps and preventing potential accidents.

mAP (mean Average Precision) is a summary metric that combines precision and recall to evaluate the model's overall detection performance across all classes (in this case, helmets and other objects) [5]. A high mAP value indicates that the model consistently produces accurate results across all object classes. Mathematically, mAP is expressed as $1/N \sum_{i=1}^{N} AP_i$, where AP (Average Precision) is the precision for each class, and N is the total number of classes. YOLOv7 achieved a mAP of 0.650, while YOLOv8 scored 0.748. YOLOv8's superior mAP underscores its enhanced overall detection accuracy and consistency, making it more reliable for safety-critical tasks like helmet detection. A high mAP ensures that the model contributes significantly to improving construction site safety.

F1 Score balances precision and recall, offering a comprehensive measure of the model's performance [5]. In the construction industry, both false positives and false negatives are undesirable. The F1 score evaluates the model's ability to achieve a balance between accurate detections and avoiding missed detections. Mathematically, Mathematically, F1 Score is obtained by dividing twice the product of precision and recall values by the sum of precision and recall values. YOLOv7 achieved an F1 score of 0.650, while YOLOv8 achieved 0.769. YOLOv8's higher F1 score demonstrates its balanced performance, making it more effective and reliable for ensuring safety in construction environments. A high F1 score indicates that the model minimizes safety gaps while maintaining accurate detection.

To support the claim that YOLOv7 may be more suitable for resource-constrained environments, we conducted a comparative analysis of the computational performance of YOLOv7 and YOLOv8. This includes inference time per frame and GPU memory consumption using an NVIDIA Jetson Xavier NX. As shown in Table 3, YOLOv7 demonstrated a slightly faster inference time and lower memory consumption than YOLOv8. While the difference in speed is marginal, the reduced memory usage could be critical in real-time UAV applications with limited hardware resources. These findings validate the assertion that YOLOv7, despite having marginally lower detection accuracy, remains a suitable choice for deployment in computationally constrained environments.

Table 3. Computational efficiency comparison between YOLOv7 and YOLOv8.

Model	Inference Time (ms/frame)	Peak GPU Memory Usage (MB)
YOLOv7	38.6	1290
YOLOv8	42.1	1510

Conclusively, the test results show that YOLOv8 outperforms YOLOv7, providing more reliable and accurate results for helmet detection tasks. Its higher precision and recall values indicate fewer false alarms and more accurate detection of helmeted workers, critical for improving workplace safety. The improvement in mAP highlights YOLOv8's consistent performance across various detection scenarios, while the higher F1 score reflects its ability to maintain a balance between accuracy and sensitivity. Overall, YOLOv8 emerges as a more dependable and effective solution, particularly for the construction sector, where high accuracy and reliability are essential for safety-critical tasks.

Both YOLOv7 and YOLOv8 perform well in various object detection tasks, but they have limitations when it comes to helmet detection. The challenges include the small size and scale variability of helmets, which may make them difficult to detect, especially when individuals are distant or partially obscured. Additionally, helmets can be occluded by other objects in the scene, reducing detection accuracy in crowded or complex environments. Lighting conditions, shadows, and glare may further hinder detection, and the class imbalance between helmets and larger objects in real-world images can lead to reduced detection reliability. To address these issues, a more specialized training dataset focusing on helmets, including diverse poses and occlusion scenarios, would be needed for more robust detection performance.

4 Conclusion

This study evaluated the performance of YOLOv7 in helmet detection tasks using high-resolution UAV-captured construction site images under diverse environmental conditions. To provide a comparative analysis, YOLOv8 was also tested on the same dataset, and its performance was assessed against YOLOv7 using four key evaluation metrics: Precision, Recall, mAP, and F1 Score. The results indicate that YOLOv8 consistently outperformed YOLOv7 across all metrics, demonstrating higher detection accuracy, improved recall, and better overall reliability in safety-critical applications. Despite these findings, YOLOv7 remains a strong and viable option for helmet detection. While it exhibited slightly lower performance metrics compared to YOLOv8, it still achieved competitive results, proving its capability in real-world monitoring scenarios. Notably, YOLOv7's precision and F1 score values suggest that it can still effectively contribute to helmet detection tasks, particularly in applications where computational efficiency and model interpretability are important considerations. Given that YOLOv7 has a relatively streamlined architecture compared to YOLOv8, it may still be advantageous in scenarios requiring rapid processing with limited computational resources, such as real-time monitoring on UAVs with hardware constraints.

Furthermore, both models faced challenges related to small object detection, occlusions, lighting variations, and class imbalances within the dataset. Moreover, in real construction environments, YOLOv7 faces several challenges that can impact its detection performance. These challenges include the cluttered and dynamic nature of construction sites, where numerous objects, such as machinery, vehicles, and workers, are often in close proximity and may overlap or occlude each other. Additionally, fluctuating lighting conditions and environmental variability, such as shadows or sudden brightness changes, can hinder YOLOv7's ability to detect objects accurately. Small object detection also becomes a challenge in construction sites, where tools and debris may be difficult to detect, especially when they are partially visible or at a distance. These challenges highlight the need for specific optimizations and enhancements to improve YOLOv7's performance in such complex environments.

These limitations highlight the need for further research into optimizing deep learning-based object detection algorithms for helmet detection in complex environments. Future improvements could include augmenting training datasets with a broader range of helmet appearances, utilizing advanced data augmentation techniques, and integrating hybrid detection approaches to enhance robustness under challenging conditions. Conclusively, while YOLOv8 proves to be the superior model in terms of accuracy and detection reliability, YOLOv7 remains a practical and effective alternative. Its demonstrated performance affirms its suitability for UAV-based helmet detection applications, particularly where computational efficiency is a priority. Future research should explore enhancements tailored specifically to helmet detection, ensuring even greater reliability in workplace safety monitoring.

References

1. Almaskati, D., Kermanshachi, S., Pamidimukkala, A., Loganathan, K., Yin, Z. (2024). A Review on Construction Safety: Hazards, Mitigation Strategies, and Impacted Sectors. *Buildings*, *14*(526). https://doi.org/10.3390/buildings14020526
2. Rajkumar, S., Poddar, H., Sree Harsha, S., Garg, Y., Shuraj, R., Vinodhini, M. (2024). Transforming Workplace Safety: The Intelligent Helmet Approach for Instantaneous Monitoring with Warning System. In *2024 3rd International Conference on Artificial Intelligence For Internet of Things* (pp. 1-6). IEEE Press. https://doi.org/10.1109/AIIoT58432.2024.10574606
3. Alves, D.N.A., Barboza, E.D.A., Vieira, T.F. (2024). TinyPPE: Ensuring Workplace Safety Helmet Compliance with Tiny Machine Learning. In *2024 XIV Brazilian Symposium on Computing Systems Engineering* (pp. 1-6). IEEE Press. https://doi.org/10.1109/SBESC65055.2024.10771910
4. Hope, M., Tiesman, S.K., Jennifer, L.B. (2011). The epidemiology of fatal occupational traumatic brain injury in the U.S.. *American Journal of Preventive Medicine*, *41*(1), 61-67. https://doi.org/10.1016/j.amepre.2011.03.007
5. Bakirci, M. (2024). Utilizing YOLOv8 for enhanced traffic monitoring in intelligent transportation systems (ITS) applications, *Digital Signal Processing*, *152*, 104594. https://doi.org/10.1016/j.dsp.2024.104594
6. Nex, F., Remondino, F. (2014). UAV for 3D mapping applications: a review. *Appl Geomat*, *6*, 1–15. https://doi.org/10.1007/s12518-013-0120-x
7. Bakirci, M. (2023). A novel swarm unmanned aerial vehicle system: Incorporating autonomous flight, real-time object detection, and coordinated intelligence for enhanced performance. *Traitement du Signal, 40*(5), 2063-2078. https://doi.org/10.18280/ts.400524
8. Tsouros, D.C., Bibi, S., Sarigiannidis, P.G. (2019). A Review on UAV-Based Applications for Precision Agriculture. *Information*, *10*, 349. https://doi.org/10.3390/info10110349
9. Adade, R., Aibinu, A.M., Ekumah, B. et al. (2021). Unmanned Aerial Vehicle (UAV) applications in coastal zone management—a review. *Environ Monit Assess*, *193*, 154. https://doi.org/10.1007/s10661-021-08949-8
10. Bakirci, M. (2024). Efficient air pollution mapping in extensive regions with fully autonomous unmanned aerial vehicles: A numerical perspective. *Science of The Total Environment*, *909*, 168606. https://doi.org/10.1016/j.scitotenv.2023.168606

11. Cheng, N., Wu, S., Wang, X., Yin, Z., Li, C. et al. (2023). AI for UAV-Assisted IoT Applications: A Comprehensive Review. *IEEE Internet of Things Journal*, *10*(16), 14438-14461. https://doi.org/10.1109/JIOT.2023.3268316
12. Mozaffari, M., Saad, W., Bennis, M., Nam, Y.H., Debbah, M. (2019). A Tutorial on UAVs for Wireless Networks: Applications, Challenges, and Open Problems. *IEEE Communications Surveys & Tutorials*, *21*(3), 2334-2360. https://doi.org/10.1109/COMST.2019.2902862
13. Bakirci, M. (2024). Enhancing vehicle detection in intelligent transportation systems via autonomous UAV platform and YOLOv8 integration. *Applied Soft Computing*, *164*, 112015. https://doi.org/10.1016/j.asoc.2024.112015
14. Motlagh, N.H., Bagaa, M., Taleb, T. (2017). UAV-Based IoT Platform: A Crowd Surveillance Use Case. *IEEE Communications Magazine*, *55*(2), 128-134. https://doi.org/10.1109/MCOM.2017.1600587CM
15. Bakirci, M. (2024). A drone-based approach to enhance spatial insight into surrounding air pollutant distributions for healthier indoor environments. *Journal of Building Engineering*, *87*, 109023. https://doi.org/10.1016/j.jobe.2024.109023
16. Thammawichai, M., Baliyarasimhuni, S.P., Kerrigan, E.C., Sousa, J.B. (2018). Optimizing Communication and Computation for Multi-UAV Information Gathering Applications. *IEEE Transactions on Aerospace and Electronic Systems*, *54*(2), 601-615.
17. Adil, M., Jan, M.A., Liu, Y., Abulkasim, H., Farouk, A., Song, H. (2023). A Systematic Survey: Security Threats to UAV-Aided IoT Applications, Taxonomy, Current Challenges and Requirements With Future Research Directions. *IEEE Transactions on Intelligent Transportation Systems*, *24*(2), 1437-1455.
18. Montambault, S., Beaudry, J., Toussaint, K., Pouliot, N. (2010). On the application of VTOL UAVs to the inspection of power utility assets. In *2010 1st International Conference on Applied Robotics for the Power Industry* (pp. 1-7). IEEE Press.
19. Bakirci, M. (2024). Real-time vehicle detection using YOLOv8-nano for intelligent transportation systems. *Traitement du Signal*, *41*(4), 1727-1740. https://doi.org/10.18280/ts.410407
20. Ryan, A., Zennaro, M., Howell, A., Sengupta, R., Hedrick, J.K. (2004). An overview of emerging results in cooperative UAV control. In *2004 43rd IEEE Conference on Decision and Control* (pp. 602-607). IEEE Press.
21. Samad, A.M., Kamarulzaman, N., Hamdani, M.A., Mastor, T.A., Hashim, K.A. (2013). The potential of Unmanned Aerial Vehicle (UAV) for civilian and mapping application. In *2013 IEEE 3rd International Conference on System Engineering and Technology* (pp. 313-318). IEEE Press.
22. Fotouhi, A., Qiang, H., Ding, M., Hassan, M., Giordano, L.G. et al. (2019). Survey on UAV Cellular Communications: Practical Aspects, Standardization Advancements, Regulation, and Security Challenges. *IEEE Communications Surveys & Tutorials*, *21*(4), 3417-3442.
23. Gupta, L., Jain, R., Vaszkun, G. (2016). Survey of Important Issues in UAV Communication Networks. *IEEE Communications Surveys & Tutorials*, *18*(2), 1123-1152.
24. Ju, C., Son, H.I. (2018). Multiple UAV Systems for Agricultural Applications: Control, Implementation, and Evaluation. *Electronics*, *7*, 162. https://doi.org/10.3390/electronics7090162
25. Cao, L., Zheng, X., Fang, L. (2023). The Semantic Segmentation of Standing Tree Images Based on the Yolo V7 Deep Learning Algorithm. *Electronics*, *12*, 929. https://doi.org/10.3390/electronics12040929
26. Bakirci, M. (2025). Advanced ship detection and ocean monitoring with satellite imagery and deep learning for marine science applications. *Regional Studies in Marine Science*, *81*, 103975. https://doi.org/10.1016/j.rsma.2024.103975
27. Wang, G., Chen, Y., An, P., Hong, H., Hu, J., Huang, T. (2023). UAV-YOLOv8: A Small-Object-Detection Model Based on Improved YOLOv8 for UAV Aerial Photography Scenarios. *Sensors*, *23*, 7190. https://doi.org/10.3390/s23167190
28. Lou, H., Duan, X., Guo, J., Liu, H., Gu, J., Bi, L., Chen, H. (2023). DC-YOLOv8: Small-Size Object Detection Algorithm Based on Camera Sensor. *Electronics*, *12*, 2323. https://doi.org/10.3390/electronics12102323
29. Bakirci, M. (2025). Advanced aerial monitoring and vehicle classification for intelligent transportation systems with YOLOv8 variants. *Journal of Network and Computer Applications*, *237*, 104134. https://doi.org/10.1016/j.jnca.2025.104134
30. Bakirci, M., Bayraktar, I. (2024). Assessment of YOLO11 for ship detection in SAR imagery under open ocean and coastal challenges. In *2024 21st International Conference on Electrical Engineering, Computing Science and Automatic Control (CCE)* (pp. 1-6). IEEE Press. https://doi.org/10.1109/CCE62852.2024.10770926
31. Elgamily, K.M., Mohamed, M.A., Abou-Taleb, A.M. et al. (2025). Enhanced object detection in remote sensing images by applying metaheuristic and hybrid metaheuristic optimizers to YOLOv7 and YOLOv8. *Scientific Reports*, *15*, 7226. https://doi.org/10.1038/s41598-025-89124-8

32. Hussain, M. (2023). YOLO-v1 to YOLO-v8, the Rise of YOLO and Its Complementary Nature toward Digital Manufacturing and Industrial Defect Detection. *Machines*, *11*, 677. https://doi.org/10.3390/machines11070677
33. Chen, W., Huang, H., Peng, S. et al. (2021). YOLO-face: a real-time face detector. *Visual Computing*, *37*, 805–813. https://doi.org/10.1007/s00371-020-01831-7
34. Vijayakumar, A., Vairavasundaram, S. (2024). YOLO-based Object Detection Models: A Review and its Applications. *Multimed Tools Appl*, *83*, 83535–83574. https://doi.org/10.1007/s11042-024-18872-y
35. Chen, C., Zheng, Z., Xu, T., Guo, S., Feng, S., Yao, W., Lan, Y. (2023) YOLO-Based UAV Technology: A Review of the Research and Its Applications. *Drones*, *7*, 190. https://doi.org/10.3390/drones7030190
36. Bakirci, M., Bayraktar, I. (2024). Comparative performance of YOLOv9 and YOLOv10 for vehicle detection towards real-time traffic surveillance with UAVs. In *2024 21st International Conference on Electrical Engineering, Computing Science and Automatic Control (CCE)* (pp. 1-6). IEEE Press. https://doi.org/10.1109/CCE62852.2024.10771048
37. Lee, J., Hwang, Ki. (2022). YOLO with adaptive frame control for real-time object detection applications. *Multimed Tools Appl*, *81*, 36375–36396. https://doi.org/10.1007/s11042-021-11480-0
38. Liang, H., Seo, S. (2023). UAV Low-altitude remote sensing inspection system using a small target detection network for helmet wear detection. *Remote Sensing*, *15*, 196. https://doi.org/10.3390/rs15010196
39. Zhang, F., Liu, H., Ma, Z., Yang, Y., Wan, X. (2020). Study of UAV Application in Wireless Sensor Networks. In *2020 3rd International Conference on Mechanical, Electronics, Computer, and Industrial Technology* (pp. 343-348). IEEE Press.
40. Li, B., Fei, Z., Zhang, Y. (2019). UAV Communications for 5G and Beyond: Recent Advances and Future Trends. *IEEE Internet of Things Journal*, *6*(2), 2241-2263.
41. Liu, D., Xu, Y., Wang, J., Chen, J., Yao, K. et al. (2020). Opportunistic UAV Utilization in Wireless Networks: Motivations, Applications, and Challenges. *IEEE Communications Magazine*, *58*(5), 62-68.
42. Bakirci, M., Toptas, B. (2022). Kinematics and Autoregressive Model Analysis of a Differential Drive Mobile Robot. In *2022 International Congress on Human-Computer Interaction, Optimization and Robotic Applications (HORA)*, (pp. 1-6). IEEE Press. https://doi.org/10.1109/HORA55278.2022.9800071
43. Maddikunta, P.K.R., Hakak, S., Alazab, M., Bhattacharya, S., Gadekallu, T.R. et al. (2021). Unmanned Aerial Vehicles in Smart Agriculture: Applications, Requirements, and Challenges. *IEEE Sensors Journal*, *21*(16), 17608-17619.
44. Chen, S., Lan, J., Liu, H., Chen, C., Wang, X. (2022). Helmet wearing detection of motorcycle drivers using deep learning network with residual transformer-spatial attention. *Drones*, *6*, 415. https://doi.org/10.3390/drones6120415