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Performance Evaluation of Lightweight Object Detection Models for Real-Time Personal Protective Equipment Detection in the Construction Sites

Herman[1], Sandy Alferro Dion[2], Andik Yulianto[3]

[1,3]Program Studi Sistem Informasi Fakultas Ilmu Komputer Universitas Internasional Batam

[2]Baloi-Sei Ladi, Jl. Gajah Mada, Tiban Indah, Kec. Sekupang, Kota Batam, Kepulauan Riau 29426

[1]herman@uib.ac.id

[2]2131080.sandy@uib.edu

[3]andik@uib.ac.id

Abstract

The environment of construction industry was known to have a high risk and high number of occupational accidents and injuries. One of the main causes of the occurrences was the construction workers' negligence in wearing personal protection equipment. Computer vision-based approaches were developed to assist in personal protective equipment adherence to address this issue. Using lightweight machine learning algorithms, object recognition can help to detect if the PPEs are worn correctly. We evaluated performance of YOLOv8-Nano and YOLOv9-Tiny (state of the art lightweight object detection models). Custom dataset was used for training the models and then metrics like F1 score, precision, recall mAP50 and mAP50-95 were used to evaluate both models' performance. Results found that both models were able to show promising real time detections, but the YOLOv9-Tiny model was able to outperform the YOLOv8-Nano model on many evaluation metrics. Specifically, in terms of mAP, YOLOv8-Nano achieved an mAP50 of 81.48, while YOLOv9-Tiny attained a slightly higher mAP50 of 82.70. Higher efficiency in these parameters will help small industry to enforce PPE adherence monitoring using edge device at a relatively low cost. Lastly, enhanced enforcement of PPE regulations through automated detection system can contribute to improve workplace safety which in turns will lead to less injuries.

Keywords: *Object Recognition, Computer Vision, Machine Learning, Lightweight, Personal Protective Equipment, YOLO*

I. Introduction

Construction industry is an important sector in economy, which strengthens the base for infrastructure and city planning. But, nonetheless, this industry has a notoriously high risk involved, with many workplace accidents and injuries occurring yearly [1]. The main reason for these incidents is due to the negligence by construction workers of PPE [2][3][4]. From a recent study, it was found construction sites are responsible for more than 71 percent of workplace accidents compared to all other industry [5]. Employers and employees should concentrate on safe working by avoiding the problems associated with the use of PPE. However, it may be inconvenient to monitor and enforce due to dynamism and mobility at the workplace as well as the high number of workers at the site [6]. This challenge has been addressed through several prevention attempts. One of them is research carried out by [7] focused on the real-time PPE monitoring system using RFID technology and body area networks to monitor the presence of PPE. The result shows that the system is able to determine whether each worker is wearing the required PPEs, monitoring their presence and warning the worker if they are not properly used and sends a report to a central unit where alerts and historical data are generated.

Besides the method of using RFID sensors, PPE adherence monitoring can be assisted by computer vision-based approaches, which can potentially automate the process and provide a scalable solution to the industry [2][6][8]. Continuous real-time monitoring of such construction site, recording the presence and use of any personal protective equipment like hard hats, vests, gloves, safety goggles and boots would be possible through this system. The system can automatically detect when a worker is not wearing required PPE and send immediate alerts to allow immediate corrective action. An active approach like this can also cut the risk of potential accidents and maintain overall safety on the construction site. A computer vision-based PPE detection system can serve as such a much needed scalable and efficient approach in addressing the problems related to manual monitoring and enforcing PPE in the dynamic construction environment.

Within the broader field of computer vision, object recognition serves as a crucial subfield, focusing specifically on the ability of a computer system or algorithm to identify and understand objects in the images or videos [12]. Machine

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learning, which has emerged as a powerful tool for solving complex problems and making accurate predictions from data, plays a fundamental role in enhancing both computer vision and object recognition applications [9][10][11]. By leveraging lightweight machine learning algorithms such as the YOLO Series, MobileNet, GhostNet, and ShuffleNet—known for their computationally efficiency and real-time processing capabilities in resource constrained environments [13][14]. These lightweight models, characterized by fewer parameters and lower computational demands compared to traditional deep learning models, are particularly well-suited for deployment on mobile devices, embedded systems, and edge devices, making them highly applicable for PPE compliance monitoring in construction settings [15][16].

PPE detection using computer vision technology has been developed in the last couple of years. Some of them are the research conducted by [17] which focused on develop and evaluate deep learning to detect essential PPE components in Real-time using YoloV3 model. Later, in research conducted by [18], an improvement had been made on the previously mentioned study. It was to improve YoloV5 model, simplify the network structure and greatly reduce the model size, parameters and computation complexity. The result showed that, for the improved YoloV5, the time of detection was 105 FPS with mAP of 84.2 %, compared to other models. Another research conducted by [19] developed a custom YoloV8-Medium model for PPE detection. The researchers found that the model is efficient and effective in identifying PPE with mAP of 95.6%.

While previous research employing models like YOLOv3, YOLOv5, and custom YOLOv8-Medium has shown promising results in PPE detection, these models often present limitations in terms of computational demands, making them less feasible for deployment on resource-constrained devices. However, the recent advancements in lightweight object detection models, specifically YOLOv8-Nano and YOLOv9-Tiny, offer significant potential due to their optimized architecture, reduced computational complexity, and real-time processing capabilities. Despite their theoretical advantages, there remains a critical gap in empirical evaluations comparing their performance in real-world PPE detection scenarios. Given that real-time PPE monitoring is crucial for preventing workplace accidents and ensuring worker compliance, it is essential to evaluate whether these models can provide both high detection accuracy and real-time processing speed without requiring expensive hardware.

Thus, the primary objective of this study is to conduct a comprehensive evaluation of these two lightweight object detection models, YOLOv8-Nano and YOLOv9-Tiny, in the context of real-time personal protective equipment detection within construction sites. The key contributions of this study are:

A. Investigate the performance of YOLOv8-Nano and YOLOv9-Tiny models for the detection of personal protective equipment in construction sites.
B. Analyze the trade-off between accuracy and computational efficiency of the two models to identify the most suitable model for real-time PPE detection in construction sites.
C. Provide practical insights and recommendations for deploying lightweight object detection models in construction site safety monitoring, contributing to the advancement of cost-effective, AI-driven workplace safety solutions.

II. Materials and Methods

This research was carried out at Universitas Internasional Batam. To pursue the objectives of this research study, the following methodological steps were implemented:

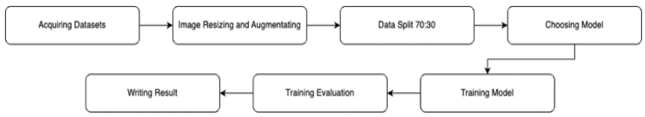

Figure 1. Research Flow

2.1 Datasets

To reach the objectives of this study, a custom dataset was collected from Kaggle to train and evaluate the PPE detection model which can be accessed at the following link:

https://www.kaggle.com/datasets/snehilsanyal/construction-site-safety-image-dataset-roboflow

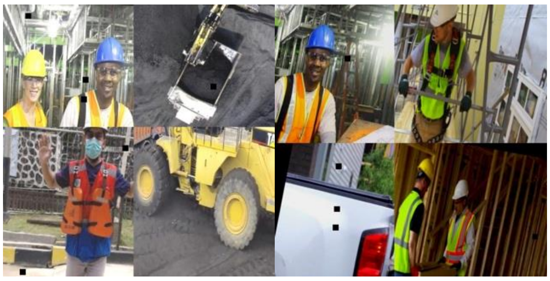

Figure 2. Datasets example

The selection of the dataset for this study was driven by the need for a realistic and diverse representation of PPE usage in construction environments. Since construction sites present varied lighting conditions, worker postures, occlusions, and PPE variations, it is essential to use a dataset that captures these challenges to ensure model robustness in real-world scenarios. The dataset consists of 2,801 images with bounding box annotations for various PPE items, split into train and valid sets in the ratio of 70:30 respectively. Specific requirements were used to ensure the model's resilience in practical applications. Factors such as the number of classes, object angles and distances, people's motions, and associated construction backgrounds were considered. The dataset consists of ten classes, including Hardhats, No-Hardhats, Mask, No-Mask, Safety Vest, No-Safety Vest, Person, Safety Cone, Machinery, and Vehicle.

2.2 YOLO Architecture

The YOLOv8-Nano and YOLOv9-Tiny models were selected for this study due to their lightweight architecture and proven effectiveness in real-time object detection

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applications [20]. Both models are designed to be computationally efficient and high-performing, making them suitable for real-time deployment on resource-constrained devices. The YOLOv8 architecture represents the latest iteration of the YOLO series, incorporating key innovations such as the CSPNet backbone, FPN+PAN neck, and anchor-free detection [21]. The YOLOv9 model is the newest addition to the YOLO family and provides a significant advancement in real-time object detection because of the adoption of cutting-edge techniques such as the Generalized Efficient Layer Aggregation Network (GELAN) and Programmable Gradient Information (PGI). Designed to further enhance efficiency and accuracy compared to previous versions [20].

The YOLOv8 model, as depicted in Figure 3, employs the Darknet53 architecture as its backbone network, while the head utilizes PAFPN for feature aggregation. Furthermore, the detection head is designed using an anchor-free approach, which reduces the number of bounding box predictions. This, in turn, accelerates the execution of the Non-Maximum Suppression, a computationally intensive post-processing step necessary to filter out candidate detections following the inference process.

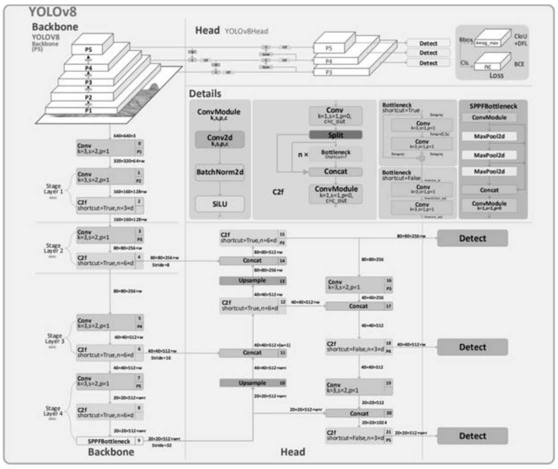

Figure 3. YOLOv8 Architecture [22]

As depicted in Figure 4, the YOLOv9 model has three main components: a primary branch, an auxiliary reversible branch, and multi-level auxiliary information. The auxiliary branch addresses information bottlenecks in the primary branch and can be used in simpler network architectures without increasing computational costs during inference. The multi-level auxiliary information helps reduce training errors. YOLOv9 combines the Programmable Gradient Information concept with the Generalized Efficient Layer Aggregation Network, a hybrid of CSPNet and ELAN. This integration produces a lightweight architecture with competitive speed and accuracy.

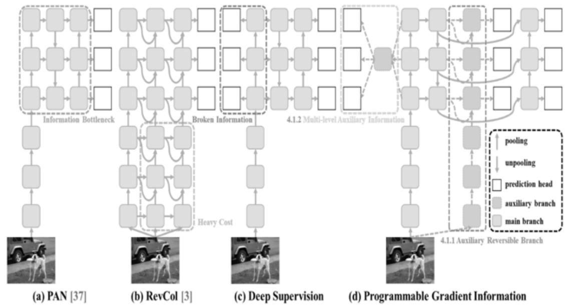

Figure 4. YOLOv9 Architecture [23]

2.3 Model Training Procedure

Both models were trained using the dataset of 2,801 images across the ten PPE classes. The images in dataset were resized to 640×640 pixel and subjected to a number of other data augmentation techniques such as random scaling, rotation, color jittering, in order to make the models more robust and by generalization. Training was done using YOLOv8-Nano and YOLOv9-Tiny with the training batch size of 16 and learning rate of 0.01 for 200 epochs. The training was performed on a system equipped with an NVIDIA RTX 3070 GPU.

2.4 Evaluation Metrics

To evaluate the performance of the YOLOv8-Nano and YOLOv9-Tiny models, the following assessment metrics were employed:

a. F1 Score: The F1 score is a metric that combines precision and recall, using the harmonic mean. The F1 Confidence Curve depicts the F1 score across various confidence levels, and a higher F1 score indicates enhanced model performance, with the optimal prediction threshold corresponding to the maximum F1 score.

$$F1 = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{1}$$

b. Precision: Precision evaluates the quality of the results, calculated as the ratio of True Positives to all positive detections, including True and False Positives. A low False Positive rate suggests high precision.

$$Precision = \frac{TP}{(TP + FP)} \tag{2}$$

c. Recall: Recall reflects the model's ability to locate all relevant occurrences, in this case, all the PPE items in the scenes. It is defined as the ratio of True Positives to all actual positive instances. A high recall rate implies a low false negative rate for the model.

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

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d. mAP50: mAP50 assesses the precision and recall when the Intersection over Union threshold reaches 50%. This metric is widely used in object detection tasks, as it indicates how well the model can locate and identify items in images. A higher mAP50 score suggests the model's improved ability to identify and localize items with at least 50% overlap with the ground truth.

$$mAP = \frac{1}{n}\sum_{k=1}^{k=n} AP_K \tag{4}$$

Where AP_K is the Average Precision (AP) of class k and n is the number of classes.

e. mAP50-95: mAP50-95 evaluates the precision and recall across a range of IoU thresholds, from 50% to 95%, in steps of 5%. This provides a more comprehensive assessment of the model's performance, considering its capacity to identify items with varying degrees of similarity to the ground truth. A higher mAP50-95 score indicates greater overall detection performance across different IoU thresholds.

f. Confusion Matrix: Confusion Matrix is a tool that provides a visual representation of the model's classification performance, depicting the True Positive, False Positive, True Negative, and False Negative rates for each class. This matrix enables the identification of specific classes where the model excels or encounters challenges, thereby facilitating targeted refinements and enhancements.

III. Result and Discussion

The YOLOv8-Nano and YOLOv9-Tiny models were trained for 200 epochs to evaluate their performance in detecting personal protective equipment. The YOLOv8-Nano model completed training in 1.24 hours, utilizing an architecture with 186 layers and 2,686,318 parameters. In contrast, the YOLOv9-Tiny model required a longer training time of 2.24 hours, reflecting its more complex architecture with 504 layers, although it maintained a lighter design with only 1,731,774 parameters.

Figure 5. YOLOv8-Nano prediction result

Figure 6. YOLOv9-Tiny prediction result

These differences highlight the trade-off between model complexity and parameter size, which can influence both training efficiency and model performance. More detailed explanation is as follows:

A. F1 Score

As shown in Table 1, the F1 scores for the YOLOv8-Nano and YOLOv9-Tiny models demonstrate a minor discrepancy in their performance. The YOLOv8-Nano model achieved an F1 score of 0.81 at a confidence threshold of 0.464, while the YOLOv9-Tiny model attained a marginally higher F1 score of 0.82 at a lower threshold of 0.431.

Table 1. F1-Confidence Score Comparison

Model	F1 Score
YOLOv8-Nano	0.81 at threshold 0.464
YOLOv9-Tiny	0.82 at threshold 0.431

This threshold represents the minimum level of confidence required for a detection to be deemed valid. The comparative analysis indicates that the YOLOv9-Tiny model exhibits a slight advantage over the YOLOv8-Nano model in terms of the F1 score. Furthermore, the lower confidence threshold for the YOLOv9-Tiny model suggests that it requires less certainty to achieve comparable or superior detection results, rendering it slightly more effective in identifying objects under the same conditions.

This slight advantage in F1 score and lower confidence threshold has important real-world implications. A model that can detect PPE with higher reliability at a lower confidence threshold is beneficial. The YOLOv9-Tiny model's ability to make confident detections with a lower threshold means that it is more sensitive to detecting PPE. Additionally, the lower threshold implies that YOLOv9-Tiny is capable of identifying PPE even in less-than-ideal conditions, such as low lighting, occlusions, or varying camera angles, which are common in real-world construction sites.

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B. Precision and Recall

According to the results summarized in Table 2, the precision and recall metrics for the YOLOv8-Nano and YOLOv9-Tiny models exhibit a modest difference in their performance. While the YOLOv8-Nano model achieved a precision of 89.69% and a recall of 74.86, the YOLOv9-Tiny model demonstrated a slightly enhanced performance, with a precision of 90.24% and a recall of 75.21%.

Table 2. Precision Comparison

Model	Precision	Recall
YOLOv8-Nano	89.69	74.86
YOLOv9-Tiny	90.24	75.21

This comparative analysis suggests that the YOLOv9-Tiny model offers a marginal advantage over the YOLOv8-Nano model in terms of both precision and recall. The higher precision observed in the YOLOv9-Tiny model implies an improved capability to accurately identify true positive detections, and its slightly elevated recall indicates a better ability to retrieve relevant objects. Despite these minor differences, the overall performance of both models is comparable, with the YOLOv9-Tiny model exhibiting a slight edge under the same evaluation conditions.

These findings have notable real-world implications. The higher precision of YOLOv9-Tiny means that it is less likely to generate false positives, reducing unnecessary alerts or interventions when detecting PPE compliance. This is especially valuable in environments where false alarms could disrupt workflow efficiency.

Additionally, the slightly higher recall of YOLOv9-Tiny indicates that it is better at detecting PPE instances even in challenging conditions, such as partially obstructed views, varying lighting conditions, or different PPE colors and materials. This reduces the risk of false negatives, where a worker failing to wear proper PPE might go unnoticed, thereby improving workplace safety and regulatory compliance.

C. Mean Average Precision (mAP)

Table 3 shows a comparison of the mean average precision (mAP) scores for the YOLOv8-Nano and YOLOv9-Tiny models at different Intersection over Union thresholds. For the mAP50 metric, which evaluates precision and recall when the IoU threshold is set at 50%, the YOLOv8-Nano model scored 81.48, while the YOLOv9-Tiny model achieved a slightly higher score of 82.70. Similarly, for the mAP50-95 metric, which considers the average precision across IoU thresholds ranging from 50% to 95% in steps of 5%, the YOLOv8-Nano model scored 53.52, and the YOLOv9-Tiny model scored 54.82, indicating a marginal improvement in the overall detection performance of the YOLOv9-Tiny model.

Table 3. mAP50 and mAP50-95 Comparison

Model	**mAP50**	**mAP50-95**
YOLOv8-Nano	81.48	53.52
YOLOv9-Tiny	82.70	54.82

This marginal improvement suggests that YOLOv9-Tiny is slightly more reliable in detecting PPE across varying IoU thresholds, making it a preferable choice when higher detection accuracy is required. However, while the improvement in mAP is evident, the trade-off between accuracy and computational efficiency must be considered when selecting a model for real-world deployment.

In practical applications, a model with higher detection precision, like YOLOv9-Tiny, can reduce the likelihood of PPE non-compliance going unnoticed, thereby helping safety managers enforce regulations more effectively. This can lead to a lower incidence of workplace injuries, improving overall safety compliance. Furthermore, in environments where real-time processing and low-latency responses are required, such as automated monitoring systems on edge devices, the slight computational efficiency trade-off of YOLOv9-Tiny must be weighed against its benefits. While YOLOv8-Nano remains a viable option for power-constrained devices, the enhanced accuracy of YOLOv9-Tiny might be preferable in high-risk environments where missing a PPE violation could result in severe consequences.

D. Confusion Matrix

Figure 7 shows the confusion matrices for each class for the YOLOv8-Nano and Figure 8 the confusion matrices for the YOLOv9-Tiny model. Diagonal elements of the matrices, which correspond to the True Positive rates, were analyzed to observe that the YOLOv9-Tiny model has slightly higher True Positive rates for most classes than that of the YOLOv8-Nano model. Additionally, the confusion matrix of the YOLOv9-Tiny model seems to show the lower False Positive rate as indicated by the other smaller elements in off-diagonal.

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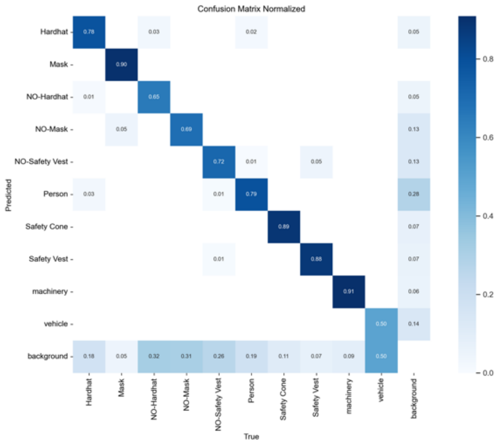

Figure 7. Confusion Matrix for YOLOv8-Nano

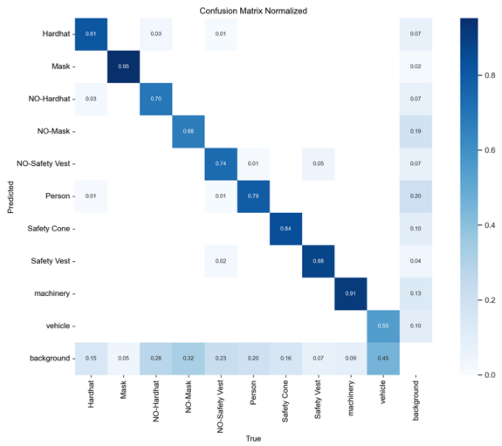

Figure 8. Confusion Matrix for YOLOv9-Tiny

The results show that the YOLOv9-Tiny model has higher detection efficiency. The high True Positive rates in all categories demonstrate that YOLOv9-Tiny has better efficiency in correctly identifying personal protective equipment objects, thus minimizing the chance for missed detections. This improvement becomes significant when assessing danger zones like the work site on a building under construction.

The superior performance of YOLOv9-Tiny can be attributed to several key architectural enhancements. First, the model incorporates an improved feature pyramid network (FPN) and path aggregation network (PAN), which enhances multi-scale feature extraction, allowing better detection of small PPE objects in complex environments. Second, the use of a dynamic convolution mechanism helps the model focus on more relevant spatial features, improving precision while maintaining computational efficiency. Third, advancements in anchor-free detection strategies in YOLOv9-Tiny reduce the dependency on predefined anchor boxes, allowing for more flexible and accurate bounding box predictions. These technical improvements collectively contribute to the YOLOv9-Tiny model's higher accuracy, making it a better choice for real-world PPE detection applications where both speed and precision are critical.

IV. Conclusion

YOLOv8-Nano was trained in just 1.24 hours, utilizing 186 layers and 2,686,318 parameters, making it a highly lightweight model in terms of training time and computational efficiency. Despite its relatively simple architecture, YOLOv8-Nano achieved high precision and recall, demonstrating its capability to effectively detect PPE while maintaining fast inference speed. These characteristics make it an excellent choice for applications requiring rapid deployment and real-time processing, especially in resource-constrained environments such as edge devices or embedded systems.

In contrast, YOLOv9-Tiny required 2.24 hours of training and consists of 504 layers with 1,731,774 parameters—a deeper and more complex structure designed to handle intricate feature representations within the dataset. While this increased complexity resulted in a longer training time, it ultimately led to slight improvements in precision, recall, and mAP scores, proving that deeper architectures and additional computational resources contribute to enhanced recognition accuracy. This suggests that YOLOv9-Tiny is better suited for applications where detection accuracy is prioritized over training speed, such as high-risk construction sites or industrial safety monitoring, where precise PPE detection is critical for regulatory compliance and worker safety.

Overall, both models present viable solutions for PPE detection in construction environments, but the choice between YOLOv8-Nano and YOLOv9-Tiny should be driven by deployment-specific priorities. If fast training and lower computational cost are critical, YOLOv8-Nano is the preferred option. However, if higher detection accuracy and robustness are required, YOLOv9-Tiny is the better alternative. Future research could explore further optimizations, such as model quantization, knowledge distillation, or hardware acceleration, to improve efficiency while maintaining or even enhancing detection performance in real-world applications.

V. Suggestion

Based on the comparative analysis of YOLOv8-Nano and YOLOv9-Tiny, the latter demonstrates a slight but consistent advantage across various evaluation metrics, including F1 score, precision, recall, mAP50, and mAP50-95. While YOLOv9-Tiny requires a higher number of parameters and deeper architecture, its superior detection accuracy suggests that the added complexity contributes to better feature extraction and object recognition.

Future research could explore other lightweight architectures, such as MobileNet, GhostNet, or ShuffleNet, to determine whether alternative models can provide a better balance between detection accuracy and computational efficiency. Furthermore, optimization techniques such as knowledge distillation, pruning, and quantization could be employed to enhance model efficiency while minimizing performance trade-offs. Knowledge distillation, for instance, could enable a more compact model to inherit the predictive power of a larger one, whereas quantization could significantly reduce model size without substantial loss of accuracy.

Additionally, expanding the dataset to include a wider variety of PPE types—such as ear protection, respiratory masks, and high-visibility armbands—along with diverse

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environmental conditions (e.g., varying lighting, occlusions, and camera angles) could further improve the generalizability of the models in real-world scenarios. Conducting real-time deployment evaluations in actual construction sites would also provide valuable insights into the practical challenges and limitations of implementing computer vision-based PPE adherence monitoring systems

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