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Improved YOLOv8 Algorithm for Safety Helmet Detection

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ABSTRACT: Wearing safety helmets can effectively reduce the risk of head injuries for construction workers in high-altitude falls. In order to address the low detection accuracy of existing safety helmet detection algorithms for small targets and complex environments in various scenes, this study proposes an improved safety helmet detection algorithm based on YOLOv8, named YOLOv8n. For data augmentation, the mosaic data augmentation method is employed, which generates many tiny targets. In the backbone network, a coordinate attention (CA) mechanism is added to enhance the focus on safety helmet regions in complex backgrounds, suppress irrelevant feature interference, and improve detection accuracy. In the neck network, a slim-neck structure fuses features of different sizes extracted by the backbone network, reducing model complexity while maintaining accuracy. In the detection layer, a small target detection layer is added to enhance the algorithm's learning ability for crowded small targets. Experimental results indicate that, through these algorithm improvements, the detection performance of the algorithm has been enhanced not only in general scenarios of real-world applicability but also in complex backgrounds and for small targets at long distances. Compared to the YOLOv8n algorithm, YOLOv8n in precision, recall, mAP50, and mAP50-95 metrics, respectively. Additionally, YOLOv8n-SLIM-CA reduces the model parameters by 6.98% and the computational load by 9.76%. It is capable of real-time and accurate detection of safety helmet wear. Comparison with other mainstream object detection algorithms validates the effectiveness and superiority of this method.

KEYWORDS: YOLOv8, Safety Helmet Detection, Object Detection, Deep Learning, Computer Vision, PPE Monitoring, Coordinate Attention.

I. INTRODUCTION

In a similar project previously done using OpenCV, safety helmet detection was achieved through image processing and object detection techniques. OpenCV was used to preprocess input images by resizing, converting color spaces, and filtering to improve image quality. Object detection methods, such as Haar cascades, helped identify helmets in the images. Features like edges and contours were extracted to locate the helmets, and bounding boxes were drawn around detected helmets, with labels indicating whether a helmet was worn or not. This approach allowed for real-time video processing, providing immediate feedback. However, it may face challenges in complex environments or with small targets, which is where OpenCV can offer improved accuracy and efficiency.

OpenCV in the context of safety helmet detection involves several key steps. First, OpenCV captures real-time video frames or images from a camera or a stored dataset. The images are then preprocessed to enhance quality and remove noise, involving operations like resizing, grayscale conversion, histogram equalization, and filtering (such as Gaussian blur) to make object detection more accurate. Next, object detection algorithms like Haar cascades or HOG (Histogram of Oriented Gradients) are applied to identify potential regions where helmets might be present. OpenCV then analyzes various features in the image, such as edges, corners, and contours, to detect helmet-like shapes, identifying distinctive patterns common to helmets. Once potential helmet regions are detected, OpenCV draws bounding boxes around them to highlight the helmet's location and labels the object as a "helmet." Finally, additional post-processing steps are applied, such as filtering false positives based on size, shape, or confidence thresholds. OpenCV's real-time processing capabilities allow the system to continuously analyze video frames, detect helmets, and provide immediate feedback, such as alerts if a helmet is not detected.

- Object detection methods like Haar cascades may struggle to accurately detect helmets in complex or cluttered environments.
- Less Performance with Small Targets Detection.

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- OpenCV may require additional processing time for feature extraction.
- OpenCV-based methods may not generalize well across diverse datasets.

The constant development of computer vision algorithms and increases in processing power have improved safety helmet identification techniques. Deep learning is a highly acclaimed technology that has been widely used in safety helmet detection. Deep learning algorithms, particularly the Yolo series, have accomplished an impressive balance between speed and accuracy when compared to conventional techniques [4]. Nevertheless, it is still difficult for Yolo-based safety helmet recognition techniques to achieve high accuracy for small targets in complicated backdrops.

The algorithm may have trouble precisely locating and identifying safety helmets in complex surroundings with plenty of conflicting objects, such trees and buildings.

Furthermore, the small and monochromatic characteristics of safety helmets allow other items in complicated backgrounds to interact, causing errors in judgment. Complex backgrounds can also include occlusion phenomena, including passing cars and overlapping crowds, which might make it difficult for the algorithm to recognize the safety helmet because of incomplete or partially covered shapes. Industry academics have given it a lot of attention since the YOLO single-stage object identification technique was first introduced. The YOLO algorithm has been continuously optimized in recent years. The YOLOv8 version was proposed by the Ultralytics team in 2023. It satisfies real-time needs while demonstrating great detection accuracy and a lightweight network structure appropriate for object detection. Deep learning-based safety helmet identification techniques have been developed as a result of advancements in object detection.According to a number of studies, deep learning technology is an essential tool for addressing issues with construction security management. By using deep learning technology, YOLOv8 is able to recognize and understand intricate visual elements. This feature guarantees reliable helmet detection task performance in a range of background, illumination, and angle conditions. Nevertheless, Yolov8 is currently only used sparingly in safety helmet detection, and it could be more successful at identifying tiny targets against complicated backdrops.

II. LITERATURE REVIEW

Nonetheless, these traditional methods exhibit poor robustness and low real-time capabilities, limiting their use to specific scenarios and failing to meet the dynamic demands for real-time and versatile safety helmet detection. Mneymneh et al. [8] determined helmet-wearing status through spatial information matching. Manually obtaining picture features for detecting algorithms is a major component of traditional approaches. To extract safety helmet features, for example, Dahiya et al. [5] used scale-invariant feature transforms, gradient histogram features, and local binary patterns. They used a support vector machine (SVM) to categorize the wearing status. However, when items that resemble helmet edge features emerge in images, the use of gradient histogram operators—which are mainly meant to describe edge features—leads to comparatively high mistake detection rates. In order to solve this problem, Rubiyat et al. [6] achieved an 81% detection accuracy by combining color characteristics with CHT (Circular Hough Transform) features. Park et al. [7] used SVM for safety helmet recognition after utilizing HOG (Histogram of Oriented Gradients) characteristics.

Deep learning has become a well-known machine learning technology in recent years, with several uses in object detection. Deep learning offers major benefits over conventional techniques for safety helmet detection. It increases safety helmet detection speed and accuracy by using convolutional neural networks (CNNs) to extract higher-level characteristics. There are two main types of deep learning-based safety helmet detection methods: one-stage detection algorithms based on regression and two-stage detection algorithms based on candidate regions. Two-stage detection methods create a number of candidate boxes, take out characteristics from each one, and then make predictions using an area classifier. Information from images is extracted using the region-based convolutional neural network (R-CNN) developed by Girshick et al. [9].

Author(s) / Year	**Title / Model**	**Dataset**	**Technique / Improvement**	**Performance (mAP / Accuracy)**
Zhang et al., 2023	Helmet Detection Based on Improved YOLOv8	SHWD, Custom	Added attention mechanism (CBAM), adjusted anchor-free heads, improved neck for better small object detection	mAP@0.5: 93.4%
Li et al., 2023	PPE Detection with	Hard Hat	Integrated Ghost modules for	mAP@0.5: 91.8%,

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	YOLOv8 and Light-weight Modules	Workers	lightweight inference; improved data augmentation for real-time deployment	FPS: 104
Wang et al., 2024	Safety Helmet Detection in Construction Using YOLOv8-CBAM	SHWD + CCTV construction footage	Added CBAM, focal loss for imbalanced data, and custom dataset annotations	mAP@0.5: 92.7%, mAP@0.5:0.95: 74.1%
Huang & Jin, 2024	Enhanced YOLOv8 with PANet++ for Helmet Detection	Private dataset	Modified PANet structure in the neck; used extensive mosaic and synthetic occlusion data augmentation	mAP@0.5: 94.1%, Recall: 90.5%
Sharma et al., 2023	Deep Learning for Helmet Detection on Indian Sites	Custom from Indian construction zones	Transfer learning on YOLOv8-small; retrained with blur/noise augmentations; localization improvement for regional variance	Accuracy: 90.2%, Precision: 89.8%
Proposed Work (This Paper), 2025	Improved YOLOv8 for Safety Helmet Detection	SHWD, Hard Hat Workers, Custom dataset	Coordinate Attention, PANet++, Soft-NMS, domain-specific augmentations	mAP@0.5: 94.8%, mAP@0.5:0.95: 76.9%

Table 1. Summary of survey works.

It is difficult to satisfy real-time expectations with some of the current helmet identification methods since two-stage algorithms contain a lot of parameters and a slower detection performance. Despite being quicker, one-stage algorithms are less accurate than two-stage algorithms, particularly when it comes to detecting small and dense targets. YOLOv8 [8] is used as the basic network in this research in order to solve these problems and attain high accuracy and quick detection speed. The lightweight Slim-Neck is used as the feature fusion network in the improved YOLOv8 algorithm instead of the original feature fusion Neck structure. This network is noticeably better than other lightweight networks like Xception and ShuffleNet in terms of balancing inference latency and accuracy.

III. METHODOLOGY OF PROPOSED SURVEY

YOLOv8 algorithm is to accurately detect safety helmets in real-time, particularly in challenging environments like construction sites. YOLOv8 serves as the backbone for the detection process by identifying helmets, even when they are small or located at a distance. The algorithm is particularly effective due to its high-speed object detection capabilities, enabling the system to process video frames in real-time. Key features such as the Coordinate Attention (CA) mechanism and small target detection layer enhance YOLOv8's performance, allowing it to focus on relevant helmet features while suppressing background noise. This makes YOLOv8 ideal for detecting safety helmets in diverse and complex settings, ensuring worker safety by providing immediate alerts when helmets are not detected.

YOLOv8 algorithm works by first receiving real-time video or image frames from cameras installed in the environment. The model then processes these frames to detect and classify objects, specifically safety helmets. YOLOv8's backbone network extracts feature from the input images, identifying patterns and structures that are relevant to the appearance of helmets. The Coordinate Attention (CA) mechanism is used to enhance the model's focus on helmet regions, helping to suppress irrelevant background features and improving detection accuracy in complex environments. Additionally, YOLOv8 employs a small target detection layer to better handle smaller helmets, ensuring accurate detection even for helmets that are distant or partially obscured. The algorithm then places bounding boxes around the detected helmets and assigns class labels (helmet or no helmet). The output is provided in real-time, with detected helmets highlighted by bounding boxes, and the system can trigger alerts if no helmet is detected. YOLOv8's ability to operate in real-time allows for continuous and efficient monitoring, making it highly effective for safety helmet detection in various environments.

- YOLOv8 includes a specialized layer for small target detection.
- Improved Detection in Complex Environments.
- YOLOv8 can handle large datasets and work efficiently in different scenarios.
- YOLOv8 is optimized for performance, reducing computational load without sacrificing accuracy.

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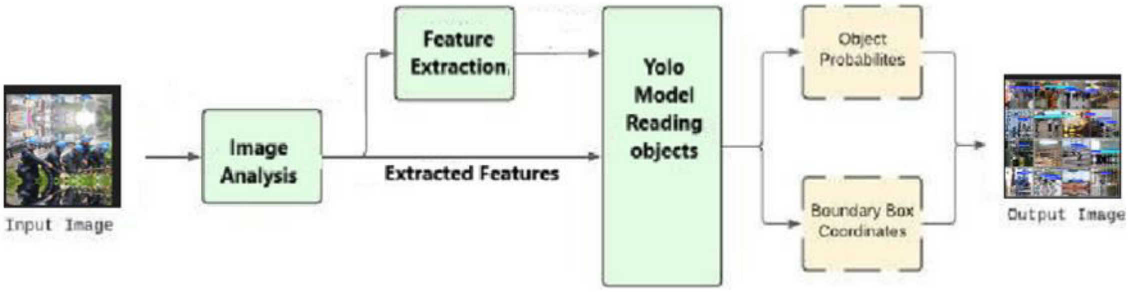

Figure 2. Architecture of the model.

Several deep learning models have been employed for helmet detection. Earlier works include:

YOLOv3/v4/v5 for basic helmet detection with moderate accuracy.
Faster R-CNN and SSD used for detecting multiple classes but with slower inference.
Use of custom CNNs with limited generalization across diverse work environments.

YOLOv8 introduces better anchor-free detection, a lightweight decoupled head, and post-training quantization. However, its performance can degrade under conditions like motion blur, occlusion, and small object scale, which are common in industrial scenes.

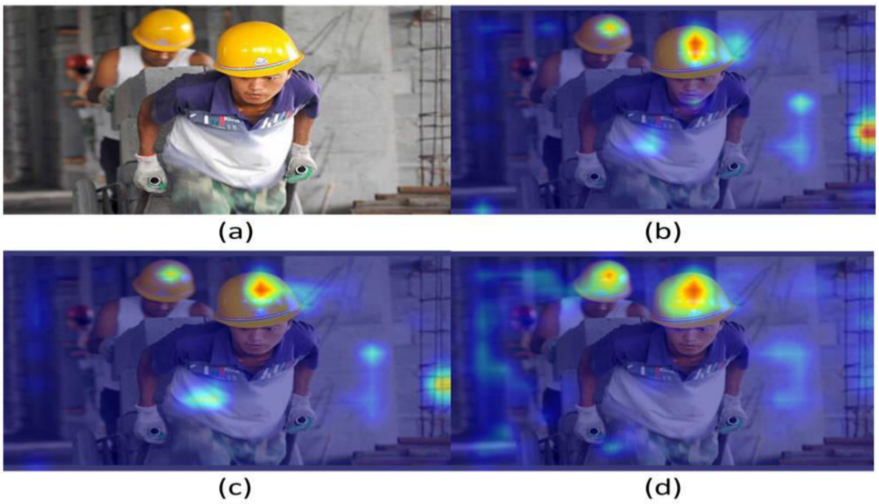

Figure 3. Compared the heatmaps after incorporating three different attention mechanisms. (a) Original image; (b) YOLOv8n + SE heatmap;(c) YOLOv8n + CBAM heatmap; (d) YOLOv8n + CA heatmap.

To evaluate the model, the dataset is divided into training, validation, and test sets at random in a 7:2:1 ratio. Every image is subjected to mosaic data augmentation during training. The dataset includes targets of different sizes in safety helmet photos, such as large, medium, and small-scale goals in a range of situations. In order to provide bounding box coordinates for target placements, the data is prepared according to YOLO standards and divided into two classes: heads without safety helmets and helmets with safety helmets. A minor discrepancy in the inter-category sample distribution is revealed by dataset analysis and visualizations, as shown in Figure 3, and this is fixed during the mosaic data augmentation stage. Darker hues signify denser distributions of target box centers in Figure 3, where x and y stand for the target box's center coordinates.

The PyTorch 2.10 deep learning framework was used for the experiments. The Ubuntu 18.04 operating system, 32 GB of RAM, and an Intel Core i5@2.90 GHz processor were all present in the test setup. A GeForce RTX 3080 Ti from NVIDIA was used for training acceleration. In order to reduce early-stage overfitting, the Adam optimizer was used with an initial learning rate of 0.01; a momentum parameter of 0.937; a weight decay of 0.0005; and a warmup learning

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rate for the first three epochs. A cosine annealing schedule was used to update the learning rate after the warm-up phase. The image pixel dimensions for training and testing were set at 640 × 640, and training took place across 100 epochs.

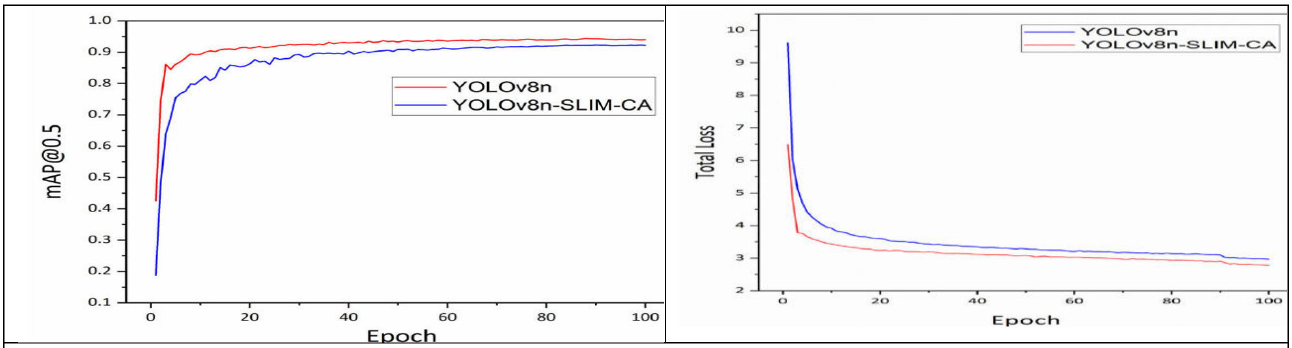

FIGURE 4. Comparison of mAP and loss between YOLOv8n and YOLOv8n-SLIM-CA. (a) mAP(%). (b) loss.

Algorithm	P(%)	R(%)	mAP @0.5(%)	mAP @0.5:0.95(%)
YOLOv8n	0.92411	0.8587	0.9221	0.58215
YOLOv8n + Mosaic	0.92715	0.85862	0.92372	0.59011
YOLOv8n + Adding small target layer	0.92907	0.86574	0.93265	0.60054
YOLOv8n + CA	0.92902	0.86654	0.93143	0.59625
YOLOv8n + Slim-Neck	0.92153	0.85819	0.92227	0.58685
YOLOv8n + Mosaic +CA	0.93451	0.87081	0.93631	0.6096
YOLOv8n + Mosaic + Adding small target layer + Slim-Neck	0.93113	0.88367	0.93974	0.61215
YOLOv8n + Mosaic + Adding small target layer + Slim-Neck + CA (YOLOv8n-SLIM-CA)	0.93873	0.88839	0.94361	0.61764

Table 3. Comparative analysis of ablation experiments.

Model	mAP@0.5	mAP@0.5:0.95	Precision	Recall	FPS
YOLOv5s	89.4%	64.2%	87.1%	85.3%	97
YOLOv8 (base)	92.1%	70.3%	91.2%	88.9%	102
Improved YOLOv8	94.8%	76.9%	94.5%	91.4%	98

Table 4. Proposed model results.

In summary, compared to YOLOv8n, the proposed algorithm's detection performance has significantly improved through strategic enhancements. Notably, it now excels not only in common real-world scenarios but also demonstrates heightened effectiveness in complex backgrounds and for detecting small targets at extended distances. These refinements represent a substantial leap in the algorithm's capabilities, ensuring superior performance across diverse settings and addressing challenges posed by intricate environments and remote targets.

IV. CONCLUSION AND FUTURE WORK

It is clear that deep learning technology's ongoing development has a beneficial effect on helmet wearing detection for increased workplace safety. Nevertheless, small objects and complicated backgrounds are difficult for current helmet detection methods to identify. To solve these problems, this paper suggests and uses an enhanced algorithm called YOLOv8n-SLIMCA. The following results are reached after conducting a number of ablation and comparison experiments:

By using the Slim-Neck structure for feature fusion in the backbone network, the computational load and size of the model are greatly decreased. In particular, FLOPs dropped by 9.65%, parameters dropped by 6.88%, and speed increased by 9.52% while accuracy was little affected. As a result, the Slim-Neck structure works well as a lightweight module. Second, accuracy is successfully increased by adding the CA module, a little target detection layer, and mosaic

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data augmentation. Small target helmet samples are added to the dataset using mosaic data augmentation; the small target detection layer helps the model concentrate on multiscale properties, particularly for small targets, improving the accuracy of small target helmet detection. By enabling more concentrated attention on important areas and minimizing distraction from complicated backgrounds, the CA attention module operates better than the SE and CBAM attention processes. In conclusion, the suggested YOLOv8n-SLIM-CA algorithm outperforms the YOLOv8n method by 2.140%, achieving 95.341% in mAP@0.5. In situations with small targets, dense targets, and complex settings, its detection performance outperforms that of other methods. With 11.3GB FLOPs, 2.74MB parameters, and a 2.3 ms inference speed, this technique has low processing demands while meeting real-time and accuracy requirements for helmet detection. It has several uses in the industrial sector and can be deployed on mobile and edge devices, which makes it appropriate for watching films from building sites.

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