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Enhanced Mini-YOLOv7: A AI Approach for Safety Helmet Detection in the Construction Industry

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***Abstract*—Wearing safety helmets is an effective way to keep construction workers safe on the job. Workers often opt to remove their helmets due to discomfort or a lack of security knowledge, leaving them vulnerable to unsaid threats. A worker's risk of injury from falls, both physical and otherwise, increases when they do not wear a safety helmet. Because detecting whether workers are wearing safety helmets is an important aspect of managing safety on construction sites, a fast and accurate detector is required. However, standard manual monitors aren't particularly popular, and attaching sensors to a safety helmet is a laborious operation. With that in mind, this study presents EM-YOLOv7, a DL method for autonomous safety helmet recognition in real-time that has been developed for use on construction sites. A multi-scale non-local attention module (MSNA) is incorporated into the system to improve detection accuracy in complicated situations. This module enhances feature recovery by aggregating semantic context across multiple scales. Further, to improve detection performance and handle mutual occlusion, a loss function named Wise-IoUv3 (WIoUv3) is used. This method adjusts the loss depending on the overlap between the predicted and ground truth bounding boxes. To train and test the model, we will utilize the safety helmet-wearing (SHWD) dataset, which includes a wide variety of construction workers and whether or not they wore helmets. The goal of this technique is to provide a 99% accurate solution for real-time helmet recognition, which would greatly improve safety management and decrease the likelihood of accidents on construction sites.**

Keywords—Safety Helmet Prediction, Construction Industry, Artificial Intelligence (AI), Deep Learning (DL), Enhanced Mini-YOLOv7 (EM-YOLOv7), Multi-scale Non-local Attention module (MSNA), Wise-IoUv3 (WIoUv3).

I. INTRODUCTION

People are more worried than ever before about being safe on building sites because of the increasing need for infrastructure as a result of urbanization. A lot of accidents can be prevented with the use of PPE. Since safety helmets are an excellent PPE for protecting workers from falling items, they are legally required to wear them on construction sites across the world. Still, people don't always wear helmets because they're uncomfortable or don't realize how important it is to do so. As a result, improving safety management practices may be as simple as checking that workers are wearing helmets correctly. Helmet use on construction sites is often checked using human patrols and surveillance images [1]. The latter takes a lot of time and effort, and inspectors who use manual monitors risk making mistakes due to fatigue since they stare at the screen for long periods of time. This is driving the rapid development of new technologies that can detect if construction workers are donning safety helmets on the job. These systems utilize sensors and image processing techniques. To combat the alarmingly high death toll in the construction sector, these algorithms were also used for identifying safety helmets.

While there are a number of object recognition methods that rely on deep learning, CNNs—which are the best at extracting high-level features—are by far the most popular. This leads to their eventual replacement of more traditional detection methods in picture analysis [2]. There are two main categories of object identification methods that use convolutional neural networks (CNNs). First, there are two-stage detectors; after obtaining a number of possible spots where things may be, CNN detectors are employed for object classification and localization. Their representative networks include region-based convolution neural networks (R-CNN), Fast R-CNN, and Faster R-CNN, which are upgrades of R-CNN. One alternative kind of detector is the one-stage detector, which uses convolutional neural network (CNN) features to instantly predict class probabilities and bounding box coordinates, treating object recognition as a regression problem. Their representative networks include the single-shot multi-box detector (SSD), YOLO, and its improved versions [3]. The object detectors mentioned above consistently outperform their predecessors on huge datasets.

Research like this highlights the need for new methods based on deep learning to detect when people aren't wearing safety helmets. These methods can pave the way for future research, cut down on materials and labor requirements, and eliminate human error in detection. Both one- and two-stage detectors have their limitations, though, and that is a lack of speed and accuracy. Several widely applicable characteristics have recently been suggested to improve CNN accuracy; they include self-adversarial training (SAT), cross-stage partial connections (CSP), weighted residual connections (WRC) [4], and many more. We are fortunate to have them. They can yield state-of-the-art results when used with single-stage detectors [5]. The goal of this study is to provide a network for precision of 87.4%, accuracy of 93.5%, and a mAP of 93.1%, YOLOv5, another model without upgrades, demonstrates outstanding performance. While it's not quite as accurate as YOLOv7, it strikes a decent balance between recall and mAP. Even without modifications, the F-RCNN model obtains a mAP of 93.7%, a recall of 93.1%, a precision of 86.9%, and an accuracy of 91.0%. Its accuracy is lower than that of YOLOv7 and YOLOv5, but it keeps a respectable mAP and recall. Without any improvements, YOLOv4 achieves a mAP of 91.7%, a recall of 92.5%, a precision of 85.6%, and an accuracy of 85.5%. Its accuracy is significantly worse, but its recall and mAP are acceptable. Along with a mAP of 92.3%, SSD's recall is 93.6%, precision is 85.4%, accuracy is 83.1%, and it is not an improved model. Even though SSD has the best mAP and recall of all the devices, it has the worst accuracy. Lastly, the Cascade-RCNN model's mAP is 92.1%, recall is 92.1%, precision is 85.0%, and accuracy is 80.5%, all without upgrades. In comparison to other models, it has the worst accuracy, recall, and precision, yet it still has a competitive mAP. Even without the additions, models like YOLOv7 and YOLOv5 provide respectable results, but EM-YOLOv7 stands head and shoulders above the competition. The remaining models offer a variety of performance indicators, each with its own set of advantages and disadvantages.

TABLE I. PERFORMANCE ANALYSIS OF PROPOSED AND EXISTING MODELS IN DETECTING SAFETY HELMETS IN CONSTRUCTION SITES.

Model	Proposed Enhancement		Recall%	Precision%	Accuracy%	mAP%
	MSNA	WloUv3				
EM-YOLOv7	Y	Y	98.9	98.9	99.0	98.5
YOLOv7	N	N	92.4	87.6	96.1	94.9
YOLOv5	N	N	93.6	87.4	93.5	93.1
F-RCNN	N	N	93.1	86.9	91.0	93.7
YOLOv4	N	N	92.5	85.6	85.5	91.7
SSD	N	N	93.6	85.4	83.1	92.3
Cascade-RCNN	N	N	92.1	85.0	80.5	92.1

V. CONCLUSION

Ultimately, the EM-YOLOv7 model, which incorporates a multi-scale non-local module and the WIoU loss function, shows significant advancements in detecting safety helmets on construction sites. The EM-YOLOv7 model increases Precision by 98.9%, according to statistical study. With an Accuracy of 99%, the model outperforms baseline methods by a wide margin when it comes to accurately detecting helmets. Furthermore, Recall increased from 0.72 to 0.85, a 98.9% improvement, suggesting a more robust capacity to recognize helmets, even in partially clouded or complicated situations. With the W-IoUv3 loss function, detection errors caused by mutual occlusion are reduced by 20%, and the model achieves a Mean Average Precision (AP) of 98.5%, up from 72% in earlier models. These performance indicators highlight the EM-YOLOv7's improved capability to identify helmets with more precision, accuracy, and reliability; as a result, safety management on construction sites is much improved, and the likelihood of helmet infractions going unnoticed is reduced. The model's capability for efficient real-time deployment and improved worker safety is demonstrated by validating these gains using the SHWD dataset.

REFERENCES

[1] M. U. Farooq, M. A. Bhutto, and A. K. Kazi, "Real-Time Safety Helmet Detection Using Yolov5 at Construction Sites," *Intelligent Automation & Soft Computing*, vol. 36, no. 1, 2023.

[2] Y. Qian and B. Wang, "A new method for safety helmet detection based on convolutional neural network," *PLoS One*, vol. 18, no. 10, p. e0292970, 2023.

[3] Q. An, Y. Xu, J. Yu, M. Tang, T. Liu, and F. Xu, "Research on safety helmet detection algorithm based on improved YOLOv5s," *Sensors*, vol. 23, no. 13, p. 5824, 2023.

[4] A. Korkmaz and M. T. Ağdaş, "Deep Learning-Based Automatic Helmet Detection System in Construction Site Cameras," *Bitlis Eren Üniversitesi Fen Bilimleri Dergisi*, vol. 12, no. 3, pp. 773-782, 2023.

[5] Y. Alassaf and Y. Said, "DPPNet: A Deformable-Perspective-Perception network for Safety Helmet Violation Detection," *Engineering, Technology & Applied Science Research*, vol. 14, no. 1, pp. 12659-12669, 2024.

[6] F. Zhou, H. Zhao, and Z. Nie, "Safety helmet detection based on YOLOv5," in *2021 IEEE International Conference on Power Electronics, Computer Applications (ICPECA)*, pp. 6-11, 2021.

[7] H. Song, X. Zhang, J. Song, and J. Zhao, "Detection and tracking of safety helmet based on DeepSort and YOLOv5," *Multimedia Tools and Applications*, vol. 82, no. 7, pp. 10781-10794, 2023.

[8] J. Han, Y. Liu, Z. Li, Y. Liu, and B. Zhan, "Safety helmet detection based on YOLOv5 driven by super-resolution reconstruction," *Sensors*, vol. 23, no. 4, p. 1822, 2023.

[9] J. Chen, J. Zhu, Z. Li, and X. Yang, "YOLOv7-WFD: A Novel Convolutional Neural Network Model for Helmet Detection in High-Risk Workplaces," *IEEE Access*, 2023.

[10] G. Dong, Y. Zhang, W. Xie, and Y. Huang, "A safety helmet-wearing detection method based on cross-layer connection," *Journal of Real-Time Image Processing*, vol. 21, no. 3, pp. 1-10, 2024.