International Journal of Engineering Research and Science & Technology

ISSN 2319-5991 www.ijerst.com
© 2026 IJERST. All Rights Reserved
Peer Reviewed, Referred & Indexed Journal

Research Paper

SAFETY HELMET DETECTION BASED ON IMPROVED YOLOV8

VANGALA SWATHI [1], YAARA VYSHNAVI [2], MERUGU SAI CHARAN [3], SAMUDRALA SUSHVAN [4]

[1]Assistant Professor, Dept. of CSE, Guru Nanak Institutions Technical Campus, Ibrahimpatnam, Telangana, India

[2, 3, 4] B.Tech, Dept. of CSE, Guru Nanak Institutions Technical Campus, Ibrahimpatnam, Telangana, India

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.

Index Terms – Safety helmet detection, YOLOv8, object detection, deep learning, computer vision, coordinate attention (CA), mosaic data augmentation, small object detection, construction safety, real-time detection, occupational safety, feature fusion.

I. INTRODUCTION

In work environments such as construction sites, tunnels, and coal mines, wearing a safety helmet is one of the fundamental requirements to ensure personnel safety. It effectively reduces the risk of head injuries when construction workers fall from heights, providing crucial protection [1], [2], [3]. Monitoring whether individuals are wearing safety helmets as per regulations relies on video data collected by cameras and assessed through manual supervision. However, traditional monitoring methods face increased labor costs, surveillance fatigue, and subjective judgments. Therefore, the development of high-performance safety helmet detection algorithms holds significant importance. Safety helmet detection methods have been enhanced with the continuous advancement of algorithms in computer vision and improvements in computational capabilities. As a highly regarded technology, deep learning has found widespread application in safety helmet recognition. Compared to traditional methods, deep learning algorithms, especially the YOLO series, have achieved a remarkable balance between accuracy and speed [4]. However, Yolo-based safety helmet detection methods still encounter challenges in achieving high accuracy for small targets in complex backgrounds. Complex environments may feature numerous interfering objects, such as buildings and trees, making it difficult for the algorithm to locate and identify safety helmets accurately Additionally, safety helmets' small and monochromatic features make them susceptible to interference from other objects in complex backgrounds, leading to misjudgments. Complex backgrounds may also involve occlusion phenomena, such as overlapping crowds and passing vehicles, causing the safety helmet's shape to be incomplete or partially obscured, making it challenging for the algorithm to identify. Since the introduction of the YOLO single-stage object detection algorithm, it has garnered widespread attention from industry

scholars. In recent years, the YOLO algorithm has undergone continuous optimization. In 2023, the Ultralytics team proposed the YOLOv8 version, which, while meeting real-time requirements, exhibits high detection accuracy and a lightweight network structure suitable for object detection. The progress in object detection has inspired the development of safety helmet detection methods using deep learning. Numerous researchers assert that deep learning technology represents a crucial avenue for tackling construction security management challenges. YOLOv8 employs deep learning technology, enabling it to learn and comprehend complex visual features. This capability ensures robust execution of helmet detection tasks under varying lighting, angles, and background conditions. However, the current usage of YOLOv8 in safety helmet detection is limited, and its effectiveness in detecting small targets in complex backgrounds could be better. Therefore, based on the YOLOv8 algorithm, we optimized the model to enhance its accuracy, introducing the novel YOLOv8n-SLIM-CA safety helmet detection algorithm. The main contributions of this paper are as follows substantially boost the algorithm's detection accuracy, this approach utilizes the mosaic data augmentation method. By employing random augmentation and diverse scaling techniques on the dataset, numerous small targets are generated. This deliberate augmentation and unpredictable scaling contribute to strengthening the network's overall robustness. (2) This paper introduces the YOLOv8n-SLIM-CA model. The model incorporates three key enhancements: the integration of a Coordinate Attention (CA) mechanism, the adoption of a Slim-Neck structure, and the addition of a small target detection layer. These improvements collectively strengthen the model's detection capabilities for complex background objects and small targets. (3) The model proposed in this paper is tested on the SHWD dataset in comparison with various algorithms. The results indicate that the algorithm surpasses other algorithms in terms of detection performance. The algorithm exhibits higher robustness in real-world scenarios and across different working environments.

II. RELATED WORK

A. An improved safety helmet detection algorithm based on YOLOv8

Safety helmets are very important for the life safety of operators in construction sites, mines and other high-risk operating environments. Therefore, based on the YOLOv8 framework, this study proposes the

CC-YOLOv8 safety helmet detection algorithm, optimizing the issues of low accuracy and high computational resource consumption faced by traditional detection methods. By introducing the C2fcc module, the backbone network feature extraction capability of the algorithm is significantly enhanced. Meanwhile, the EMA attention mechanism is added to the algorithm, which effectively improves the object localization accuracy. The experimental results show that the algorithm demonstrates superior performance in a variety of scenarios and conditions, and its mAP0.5 reaches 92.6%, which is improved by 0.5% compared with the original algorithm. This research result provides an efficient and accurate new method for safety helmet detection.

B. Safety Helmet Detection in Electrical Power Scenes based on Improved Lightweight YOLOv5

To tackle the challenges of diverse targets, complex scenes, and partial occlusion in safety management during electrical field operations, the YOLO series algorithm, recognized for its exceptional accuracy and swift processing capabilities, has been applied to various scene detection tasks. To ascertain if workers have donned safety helmets and ensure the safety of electrical field operations, we propose a lightweight algorithm based on the improved YOLOv8 for constructing a digital safety helmet detection system. By incorporating the VoV-GSCSP module, we reduced model complexity, decreased computational load, and improved detection accuracy. Simultaneously, by combining the GSConv module, we enhanced the network's feature extraction capability, enabling the network to adapt more rapidly and accurately to various complex electrical scenes, thereby strengthening the network's robustness in safety helmet detection. Finally, we validated the effectiveness of the proposed model using the pre-existing dataset for safety helmet detection.

C. Real-time detection of coal mine safety helmet based on improved YOLOv8

The existing coal mine safety helmet detection method has problems such as low detection accuracy, susceptibility to environmental impact, poor real-time performance, and a large number of parameters. So, this paper proposes a Miner Helmet detection algorithm based on YOLO, abbreviated as MH-YOLO. First, the convolutional block attention mechanism (CBAM) is applied to improve the CSPDarkNet53 to 2-Stage FPN (C2f) module of the backbone network and enhance feature-extraction capability. Second, the

MaxPooling (MP) module is used to replace the partial subsampling convolution of YOLOv8 to reduce the impact of unbalanced sample categories and improve the recall rate. In addition, a small target detection layer is added to further improve the small target characteristics by fusing shallow network features with deep network features. Finally, the ZoomCat and Scalseq Module (ZAS) feature-extraction module is used to improve the detection accuracy of small and overlapping targets. Training and testing were conducted on the public dataset CUMT-Helmet from China University of Mining and Technology and DsLMF + helmet from Xi'an University of Science and Technology. The proposed MH-YOLO achieves mAP50 values of 92.4% and 97.8%, respectively, surpassing the comparative networks. The detection time is 10.1 ms, enabling accurate and real-time detection of whether coal miners are wearing safety helmets.

D. Helmet Detection Based On Improved YOLO V8

This paper presents an automated Helmet Detection system for two-wheeler riders in India, using the advanced YOLO v8 algorithm for improved road safety. The system employs the Ultralytic YOLO algorithm and is trained on a carefully curated dataset generated via Robo Flow. It incorporates Convolutional Neural Network (CNN) and Neural Network (NN) architectures, demonstrating superior accuracy and efficiency compared to previous models. Ongoing refinements aim to enhance accuracy further and bounding box precision, highlighting the system's potential to significantly improve road safety in India.

III. PROPOSED METHODOLOGY

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.

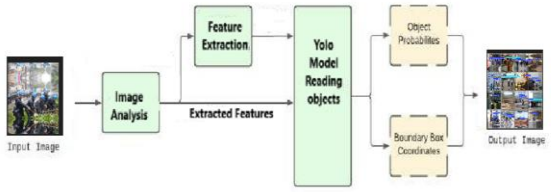


Fig. 1: System Overview

1. Input Image/Video

The system processes real-time input from cameras, typically installed on construction sites or high-risk environments, capturing images or video frames.

2. Object Detection Using YOLOv8

YOLOv8, a state-of-the-art object detection model, scans the input images to detect various objects. In this case, it is specifically trained to detect safety helmets. YOLOv8 performs this in a single pass, making it highly efficient for real-time detection.

3. Data Augmentation:

To improve the model's ability to detect small and distant helmets, the system uses mosaic data augmentation.

This technique helps generate tiny targets, ensuring better model generalization and enhancing its performance in crowded and complex scenes.

4. Coordinate Attention (CA) Mechanism:

YOLOv8 is enhanced with a Coordinate Attention (CA) mechanism in the backbone network.

This mechanism allows the model to focus on safety helmet regions in complex backgrounds, effectively suppressing irrelevant features and improving detection accuracy.

5. Small Target Detection:

A small target detection layer is added in the detection layer to improve the model's ability to detect helmets that may be small or located far away in the frame. This addition enables better performance in real-world environments where helmets may be partially obscured or seen from a distance.

6. Output Detection:

Once YOLOv8 identifies the helmet, the system outputs the result with high accuracy, showing whether the person is wearing a safety helmet. If the helmet is not detected, an alert is triggered, warning the relevant personnel.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

The experimental results show that the proposed improved YOLOv8 model achieves higher precision, recall, and mAP than the original YOLOv8n for safety helmet

detection. The integration of Coordinate Attention (CA), mosaic data augmentation, and a small-object detection layer improves detection accuracy in complex environments and for distant targets. The model also reduces parameters by 6.98% and computational cost by 9.76%, enabling efficient real-time performance. Overall, the proposed framework provides accurate and lightweight safety helmet detection for construction site monitoring.

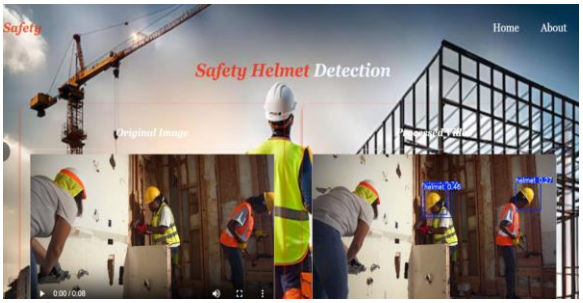


Fig. 2: Helmet Detection-1



Fig. 3: Helmet Detection-2

V. CONCLUSION

Its positive impact on helmet wearing detection for enhanced workplace safety is evident. However, existing helmet detection models face challenges in recognizing small targets and complex backgrounds. This study proposes and implements an improved algorithm named YOLOv8n-SLIMCA to address these issues. Through a series of comparative and ablation experiments, the following conclusions are drawn: Adopting the Slim-Neck structure for feature fusion in the backbone network significantly reduces the model's size and computational load. Specifically, FLOPs decreased by 9.76%, parameters decreased by 6.98%, and speed improved by 9.52%, with minimal compromise on accuracy. Hence, the Slim-Neck structure proves to be an excellent lightweight module. Secondly, introducing Mosaic data augmentation, a small target detection layer, and the CA module effectively improves accuracy. Mosaic data augmentation enriches the dataset with small scale helmet samples; the small target detection layer aids the model in focusing on multiscale features, especially for small sized targets, thereby enhancing the accuracy of small target helmet detection. The CA attention module outperforms SE and CBAM attention mechanisms, allowing more focused attention on crucial regions and reducing interference from complex backgrounds. In summary, the proposed YOLOv8n-SLIM-CA algorithm, compared

to the YOLOv8n algorithm, achieves a 2.151% improvement in mAP@0.5, reaching 94.361%. Its detection performance surpasses other algorithms in scenarios involving small targets, dense targets, and complex environments. This algorithm meets real-time and accuracy requirements for helmet detection and has low computational demands, with 11.3GB FLOPs, 2.74MB parameters, and 2.3 ms inference speed. It is suitable for deployment on mobile and edge devices, making it applicable for monitoring construction site videos and having broad applications in the industrial sector.

REFERENCES

[1] F. Zhou, H. Zhao, and Z. Nie, ‘‘Safety helmet detection based on YOLOv5,’’ in Proc. IEEE Int. Conf. Power Electron., Comput. Appl. (ICPECA), Jan. 2021, pp. 6–11.

[2] L. Huang, Q. Fu, M. He, D. Jiang, and Z. Hao, ‘‘Detection algorithm of safety helmet wearing based on deep learning,’’ Concurrency Comput., Pract. Exper., vol. 33, no. 13, p. e6234, Jul. 2021.

[3] S. Sanjana, S. Sanjana, V. R. Shriya, G. Vaishnavi, and K. Ashwini, ‘‘A review on various methodologies used for vehicle classification, helmet detection and number plate recognition,’’ Evol. Intell., vol. 14, no. 2, pp. 979–987, Jun. 2021.

[4] M. U. Farooq, M. A. Bhutto, and A. K. Kazi, ‘‘Real-time safety helmet detection using YOLOv5 at construction sites,’’ Intell. Autom. Soft Comput., vol. 36, no. 1, pp. 911–927, 2023. [5] K. Dahiya, D. Singh, and C. K. Mohan, ‘‘Automatic detection of bike-riders without helmet using surveillance videos in real-time,’’ in Proc. Int. Joint Conf. Neural Netw., Jul. 2016, pp. 3046–3051.

[6] A. H. M. Rubaiyat, T. T. Toma, M. Kalantari-Khandani, S. A. Rahman, L. Chen, Y. Ye, and C. S. Pan, ‘‘Automatic detection of helmet uses for construction safety,’’ in Proc. IEEE/WIC/ACM Int. Conf. Web Intell. Workshops (WIW), Oct. 2016, pp. 135–142.

[7] M.-W. Park, N. Elsafty, and Z. Zhu, ‘‘Hardhat-wearing detection for enhancing on-site safety of construction workers,’’ J. Construct. Eng. Manage., vol. 141, no. 9, Sep. 2015, Art. no. 04015024.

[8] B. E. Mneymneh, M. Abbas, and H. Khoury, ‘‘Automated hardhat detection for construction safety applications,’’ Proc. Eng., vol. 196, pp. 895–902, Jan. 2017.

[9] R. Girshick, J. Donahue, T. Darrell, and J. Malik, ‘‘Rich feature hierarchies for accurate object detection and semantic segmentation,’’ in Proc. IEEE Conf. Comput. Vis. Pattern Recognit., Jun. 2014.

[10] Akinapalli, S. (2024). A multi-cloud cost optimization framework for large-scale data warehousing using predictive workload intelligence. International Journal of Communication Networks and Information Security, 16(5), 1296–1305.

AUTHORS Profile



Mrs. VANGALA SWATHI has received his B.Tech from JNTUH, Hyderabad in 2005, M.Tech degree in Computer science from JNTUH, Hyderabad in 2010 and Pursuing Ph.D degree in Computer Science from Saveetha university, Chennai. He is dedicated to teaching field from the last 14 years. His research area Cloud Computing. At present he is working as Assistant Professor in CSE Department at Guru Nanak Institutions Technical Campus ,Ibrahimpatnam, Telangana, India.



Ms. YAARA VYSHNAVI pursuing B.Tech degree in Computer Science and Engineering at Guru Nanak Institu-tions Technical Campus affiliated to JNTUH in 2022-2026.



Mr. MERUGU SAI CHARAN pursuing B.Tech degree in Computer Science and Engineering at Guru Nanak Institutions Technical Campus affiliated to JNTUH in 2022-2026.



Mr. SAMUDRALA SUSHVAN pursuing B.Tech degree in Computer Science and Engineering at Guru Nanak Institutions Technical Campus affiliated to JNTUH in 2022-2026.