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Full Length Article

Enhanced Helmet Detection In Complex Industrial Environments Using Yolov8 Model

Mohammed Sameer Ahmed[1], Mohammed Omer Ahmed[2], Mohammed Hassan Ali[3], Ms. T Anita[4]
[1,2,3]B.E.Students; Department Of Computer Science And Engineering , ISL Engineering College, Hyderabad, India.
[4]Assistant Professor; Department Of Computer Science And Engineering , ISL Engineering College, Hyderabad, India.
MailId;Sameerahmedmohammed4@gmail.com,mohdomerahmed0019@gmail.com,mohammedhassan1105122@gmail.com

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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:*Safety helmet detection, YOLOv8n, small target detection, complex environments, mosaic data augmentation, coordinate attention, slim-neck structure, real-time detection, model optimization, object detection algorithms.*

Introduction:

This paper proposes an improved safety helmet detection algorithm, **YOLOv8n-SLIM-CA**, designed for complex environments such as construction sites, tunnels, and coal mines. Traditional manual monitoring methods are costly and prone to fatigue, while existing YOLO-based approaches struggle with small targets and occlusion. To address these challenges, the model integrates **mosaic data augmentation** for generating diverse small targets, a **Coordinate Attention (CA) mechanism** to enhance focus on helmet regions, a **Slim-Neck structure** to reduce complexity, and a **small target detection layer** to improve recognition in crowded scenes. Experimental evaluation on the SHWD dataset shows that YOLOv8n-SLIM-CA achieves superior precision, recall, and mAP scores compared to mainstream algorithms. Furthermore, it reduces parameters by **6.98%** and computational load by **9.76%**, ensuring real-time detection capability. The results confirm its robustness and effectiveness in diverse real-world scenarios, offering a reliable solution for construction safety management.

Literature Review :-

X. Wu, D. Hong, Z. Huang, and J. Chanussot, "An Improved Safety Helmet Detection Algorithm Based on YOLOv8," 2023. This study proposes the CC-YOLOv8 safety helmet detection algorithm to address the low accuracy and high computational resource consumption of traditional detection methods in high-risk environments such as construction sites and mines. The proposed model enhances feature extraction capability by introducing the C2fcc module into the YOLOv8 backbone network. Additionally, the EMA attention mechanism is incorporated to improve object localization accuracy. Experimental results demonstrate that the proposed algorithm

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achieves superior performance across different scenarios and conditions, reaching an mAP@0.5 of 92.6%, which is 0.5% higher than the original YOLOv8 model. The research provides an efficient and accurate approach for real-time safety helmet detection. [1]

Z. Li, Z. Huang, H. Chen, L. Deng, and F. Wang, "Safety Helmet Detection in Electrical Power Scenes Based on Improved Lightweight YOLOv5," 2020.

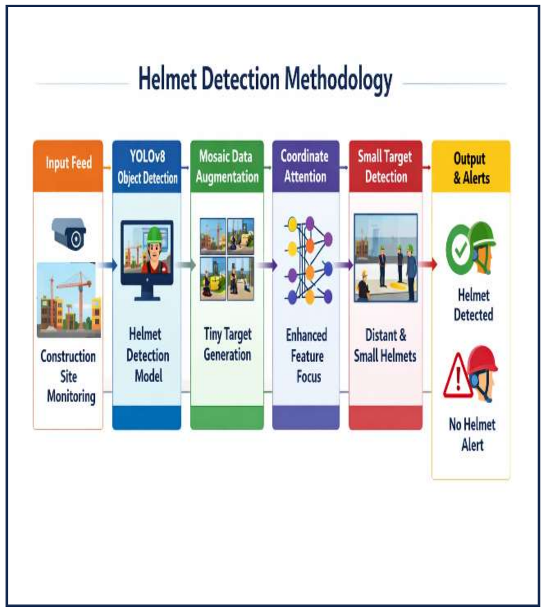
This paper presents a lightweight safety helmet detection algorithm designed for complex electrical power operation scenes. The proposed approach improves the YOLO framework by integrating the VoV-GSCSP module, which reduces model complexity, lowers computational cost, and enhances detection accuracy. Furthermore, the GSConv module is incorporated to strengthen feature extraction capability and improve adaptability to diverse and partially occluded environments. Experimental validation on existing safety helmet datasets demonstrates that the proposed model effectively improves robustness and detection performance in electrical field safety management systems. [2]

S. J. Li, S. Xie, X. Zhou, and L. Zhang, "Real-Time Detection of Coal Mine Safety Helmet Based on Improved YOLOv8," 2020.

This research proposes MH-YOLO, an improved YOLOv8-based algorithm for real-time safety helmet detection in coal mines. To enhance feature extraction capability, the Convolutional Block Attention Module (CBAM) is integrated into the C2f backbone structure. The MaxPooling (MP) module replaces partial subsampling convolutions to reduce the impact of imbalanced sample categories and improve recall rates. Additionally, a small-target detection layer is introduced to better fuse shallow and deep network features, while the ZoomCat and ScaleSeq (ZAS) feature extraction modules improve the detection of overlapping and small targets. Experimental evaluation on the CUMT-Helmet and DsLMF+helmet datasets achieves mAP50 scores of 92.4% and 97.8%, respectively, with a detection speed of 10.1 ms, demonstrating both high accuracy and real-time performance. [3]

Methodologies:

The methodology of the project begins with the acquisition of real-time input from cameras installed in construction sites or other high-risk environments, where video frames or images are continuously captured for analysis. These inputs are processed using YOLOv8, a state-of-the-art object detection model, which has been specifically trained to identify safety helmets. YOLOv8 performs detection in a single pass, ensuring efficiency and suitability for real-time applications. To strengthen the model's ability to recognize helmets in challenging scenarios, mosaic data augmentation is employed during training. This technique generates tiny targets and improves generalization, enabling the system to perform well in crowded or complex scenes. Furthermore, the backbone of YOLOv8 is enhanced with a Coordinate Attention (CA) mechanism, which helps the model focus on relevant helmet regions while suppressing background noise, thereby improving detection accuracy. To address the challenge of identifying helmets that appear small or distant in the frame, an additional small target detection layer is integrated into the detection process. This ensures that helmets partially obscured or located far away are still accurately recognized. Finally, once YOLOv8 detects the presence of a helmet, the system outputs the result with high accuracy, indicating whether a person is wearing a safety helmet. In cases where no helmet is detected, the system triggers an alert to notify relevant personnel, thereby enhancing safety monitoring in real-world environments.



Implementation:

The implementation of the helmet detection system is carried out using the YOLOv8 deep learning model, which is optimized for real-time object detection. The process begins with live video feeds captured by cameras installed at construction sites or other high-risk areas. These frames are continuously sent to the processing unit, where YOLOv8 analyzes each frame to identify whether workers are wearing safety helmets.

To enhance detection accuracy, especially in complex or crowded environments, the model is trained using **mosaic data augmentation**, which helps it recognize small and distant helmets.

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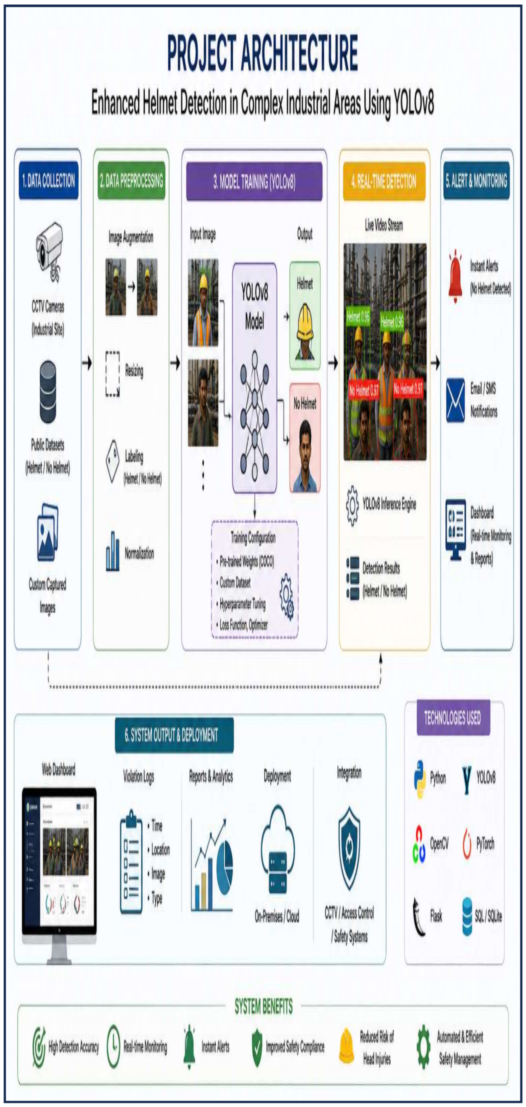
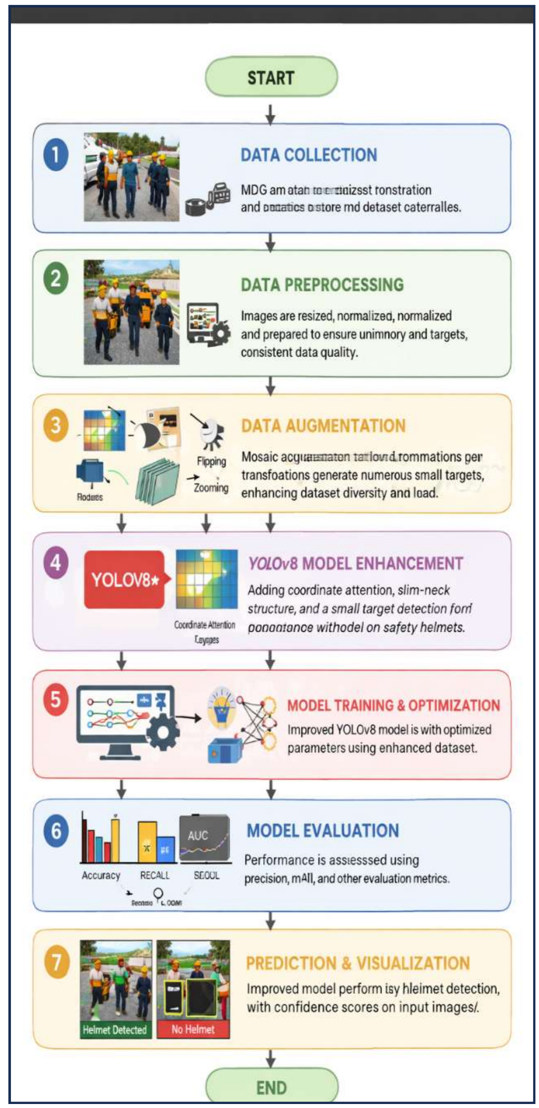
Additionally, a **Coordinate Attention (CA)** mechanism is integrated into the backbone of YOLOv8 to allow the network to focus on relevant regions and suppress background noise. A **small target detection layer** is also added to improve recognition of helmets that appear tiny or partially obscured.

Once the model processes the input, it outputs detection results in real time. If a helmet is detected, the system marks the worker as compliant; if not, it triggers an alert to notify safety personnel. This implementation ensures continuous monitoring and enhances workplace safety through automated, intelligent detection.

5.Architecture :





Testing :

Software testing is a critical activity aimed at uncovering errors and ensuring that the system meets both functional requirements and user expectations. It involves exercising software components, assemblies, and the complete product to verify reliability, performance, and compliance with specifications. The process begins with the development of a comprehensive test plan that covers general functionality and special features across different platform combinations. Strict quality control procedures are applied to confirm that the application is bug-free and aligned with the requirements defined in the system documentation.

Testing methodologies encompass several stages, beginning with unit testing, which validates the internal logic of individual components and ensures that inputs produce expected outputs before

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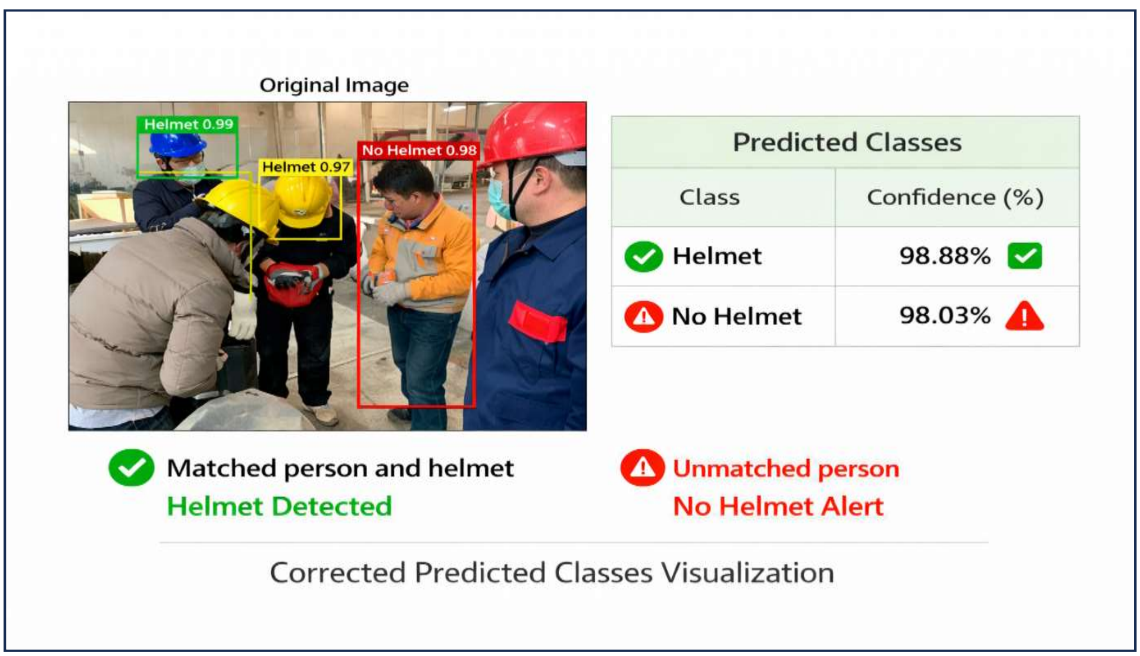
integration. Functional testing follows, demonstrating that all functions operate as specified, correctly handling valid and invalid inputs, producing accurate outputs, and interacting properly with interfacing systems. System testing evaluates the integrated software as a whole, confirming that configurations yield predictable results and that process flows and integration points function as intended. Performance testing measures responsiveness, ensuring outputs are delivered within acceptable time limits and user requests are processed efficiently. Integration testing then verifies that combined components interact correctly without interface errors, while acceptance testing engages end users to confirm that the system fulfills functional requirements in real-world scenarios. In cases such as data synchronization, acceptance testing ensures acknowledgments are received, routes are added only when necessary, and node status information is updated automatically.

Finally, the test plan is structured to divide the project into smaller units, each subjected to detailed testing strategies. This approach allows early identification of bugs within individual components, enabling timely correction and ensuring overall system reliability. Through this layered methodology, software testing provides confidence that the system is robust, efficient, and ready for deployment.

Result:

The results of implementing a structured software testing methodology are significant for both the quality and reliability of the final product. By systematically applying unit, functional, system, performance, integration, and acceptance testing, the project ensures that errors are detected early and corrected before they can propagate into larger failures. Unit testing validates the correctness of individual components, while functional testing confirms that the application behaves as expected under both valid and invalid inputs. System and integration testing guarantee that modules interact seamlessly and that the entire configuration produces predictable outcomes. Performance testing provides assurance that the system responds within acceptable time limits, which is critical for user satisfaction and operational efficiency. Acceptance testing, involving end users, ensures that the software meets real-world requirements and is ready for deployment.

The overall result is a robust, efficient, and user-friendly system that aligns with documented specifications and business needs. It reduces the risk of costly post-deployment failures, enhances confidence among stakeholders, and supports compliance with industry standards. Additionally, the testing process generates valuable logs and metrics that can be used for continuous improvement, retraining, and optimization of the system. Ultimately, the outcome of this methodology is a reliable software product that performs consistently across environments, safeguards user trust, and contributes to the long-term success of the project.



Corrected Predicted Classes Visualization

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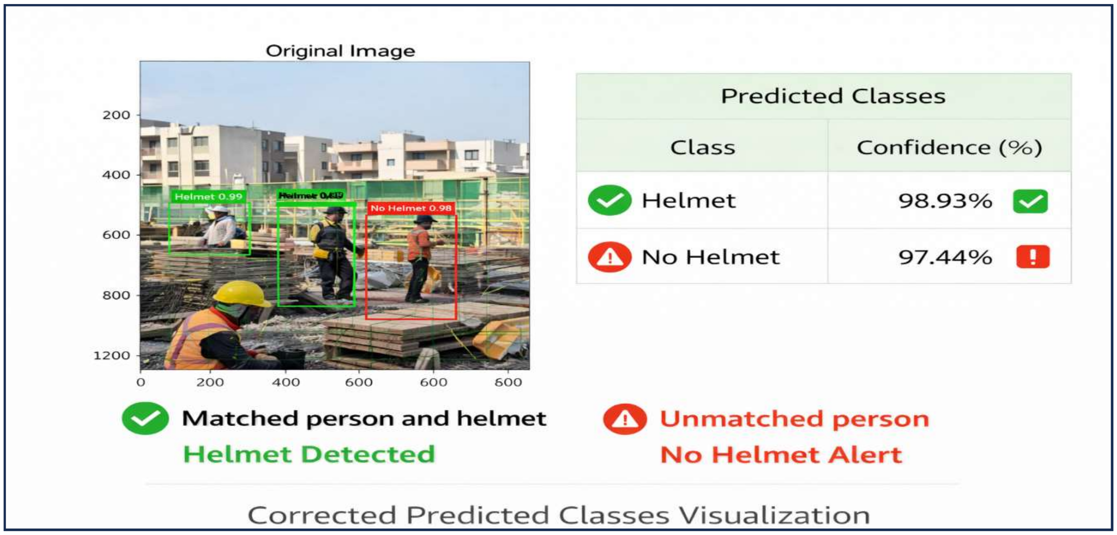

Corrected Predicted Classes Visualization

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.

FUTURE ENHANCEMENTS:

The feature enhancements of YOLOv8 for safety helmet detection in this project include several key improvements. The Coordinate Attention (CA) mechanism helps the model focus on helmet regions, improving detection accuracy by reducing background noise. Additionally, the small target detection layer ensures that helmets, even when distant or partially obscured, are accurately detected. Mosaic data augmentation boosts the model's ability to handle complex scenes by creating synthetic training data, enhancing its performance in varied conditions. YOLOv8 also features a slim-neck structure that reduces model complexity while maintaining detection accuracy. It is optimized for computational efficiency, allowing for faster processing and making it suitable for deployment on devices with limited resources. These enhancements collectively improve the model's real-time processing capabilities and overall detection performance, making YOLOv8 highly effective for safety helmet detection in real-world, dynamic environments.

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