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# Safety Helmet Detection Based on Improved YOLOv8

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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, *YOLOv8n, mAP50, and mAP50-95*

## INTRODUCTION:

The use of a safety helmet is an essential safety step that should be taken in high-risk work areas such as construction sites, tunnels, and coal mines. Helmets are a crucial component in guaranteeing the safety of workers since they play a significant part in lowering the likelihood of head injuries, especially those that are caused by falls [1, 2], [3]. Over the years, compliance with helmet regulations has been checked via the use of video monitoring and human inspection. On the other hand, this approach is not only time-consuming and expensive, but it also has a significant risk of human mistake, which highlights the need of automated detection systems. Because of the significant breakthroughs that have been made in computer vision and deep learning, the possibility of automated helmet identification has rapidly increased. It has been established that deep learning models, particularly those belonging to the YOLO (You Only Look Once) family, are capable of striking a good balance between speed and accuracy, which makes them acceptable for use in real-time applications. In spite of their effectiveness, YOLO-based models continue to have difficulty reliably detecting helmets in real-world contexts. This is especially true when dealing with tiny targets, complicated backdrops, and occlusions. There are a number of factors that might contribute to missed detections or false positives. Some of these factors are consistent helmet colors, overlapping objects, and congested scenes. With the introduction of YOLOv8 in 2023, the Ultralytics team was able to bring about considerable improvements in detection speed and accuracy while still keeping a lightweight architecture. On the other hand, its effectiveness in helmet identification is still restricted when it is used to situations that include targets that are tiny, distant, or partly veiled for whatever reason. For the purpose of overcoming these obstacles, the YOLOv8n-SLIM-CA model, which is proposed in this study, is an improved safety helmet identification model. The mosaic data augmentation approaches are used in this upgraded strategy in order to raise the variety of tiny target samples and to boost the robustness of the model simultaneously. In addition to this, the model contains a mechanism known as Coordinate

Attention (CA), a structure known as Slim-Neck, and a tiny target detection layer in order to improve its ability to collect key characteristics and to limit interference from the background. Existing algorithms are outperformed by YOLOv8n-SLIM-CA, which delivers greater accuracy and stronger adaptability in complicated situations, as shown by experimental evaluations conducted on the SHWD dataset. This study makes a contribution to the advancement of automated safety monitoring systems by offering a method that is both efficient and real-time suitable for the detection of helmets in industrial settings that are practical.

## LITERATURE SURVEY:

**Title:** An improved safety helmet detection algorithm based on YOLOv8
**Author:** X. Wu, D. Hong, Z. Huang, and J. Chanussot
**Year:** 2023.
**Description:** To enhance helmet detection in high-risk environments, this study presents the CC-YOLOv8 algorithm, an improved variant of YOLOv8. It integrates the C2fcc module to strengthen feature extraction and incorporates the EMA attention mechanism for better object localization. These enhancements address the limitations of traditional models in terms of accuracy and computational efficiency. The algorithm achieved an mAP@0.5 of 92.6%, a 0.5% improvement over the base YOLOv8, demonstrating superior performance across diverse scenarios.

**Title:** Safety Helmet Detection in Electrical Power Scenes based on Improved Lightweight YOLOv5.
**Author:** Zuhe Li, Zhenwei Huang, Hongyang Chen, Lujuan Deng and Fengqin Wang.
**Year:** 2024.
**Description**: This study addresses the challenges of detecting safety helmets in complex and occluded electrical field environments. A lightweight algorithm based on improved YOLOv8 is proposed, integrating the VoV-GSCSP module to reduce model complexity and computational load, while maintaining accuracy. The GSConv module further enhances feature extraction, allowing the model to adapt effectively to diverse and challenging scenes. Validation using an existing safety helmet dataset confirms the model's improved robustness and efficiency for real-time detection in electrical operations.

**Title:** Real-time detection of coal mine safety helmet based on improved YOLOv8
**Author:** S Jie Li, Shuhua Xie, Xinyi Zhou, Lei Zhang ,
**Year:** 2024.
**Description:** To address the limitations of existing coal mine helmet detection systems—such as low accuracy, poor real-time performance, and high parameter count—this study introduces MH-YOLO, an improved YOLO-based algorithm. It integrates CBAM to enhance feature extraction, replaces subsampling with MaxPooling for better recall, and adds a small target detection layer. The ZoomCat and Scalseq (ZAS) module further improves detection of small and overlapping helmets. Trained on the CUMT-Helmet and DsLMF+helmet datasets, MH-YOLO achieves mAP50 scores of 92.4% and 97.8%, with a fast 10.1 ms detection time, making it suitable for real-time mining safety applications.

**Title:** Helmet Detection Based On Improved YOLO V8
**Author:** Sahir Suma, ANOOP G L, MITHUN B N,
**Year:** 2022
**Description**: This study introduces an automated helmet detection system for two-wheeler riders in India, leveraging the YOLOv8 algorithm to enhance road safety. The model, trained on a curated dataset using RoboFlow, integrates CNN and NN architectures for improved accuracy and efficiency. Compared to earlier methods, it delivers superior performance, with ongoing enhancements aimed at refining accuracy and bounding box precision. The system shows strong potential for real-world deployment in traffic monitoring applications across India.

**Title:** YOLO-PL: Helmet wearing detection algorithm based on improved YOLOv4.
**Author**:
Haibin Li [a b], Dengchao Wu [a b], Wenming Zhang
**Year:** 2019**.**
**Description:** Workplace safety remains a global concern, with approximately 67.95% of construction accidents linked to the absence of helmets. Existing helmet detection models often struggle in real-world conditions due to challenges like small helmet sizes, complex backgrounds, and occlusions. To overcome these limitations, the study proposes YOLO-PL—a lightweight algorithm based on YOLOv4. YOLO-PL enhances small object detection and anchor assignment through a refined network structure. The introduction of an Enhanced Path Aggregation Network (E-PAN) further improves detection by effectively combining high-level and low-level feature information, resulting in better accuracy and practical deployment feasibility.

**DEVELOPING METHODOLOGIES**: The testing process begins with a comprehensive plan to evaluate general functionality and special features across multiple platforms. Strict quality control

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ensures the application meets system requirements and is bug-free. These considerations guide the framework for developing testing methodologies.

## SYSTEM ARCHITECTURE:

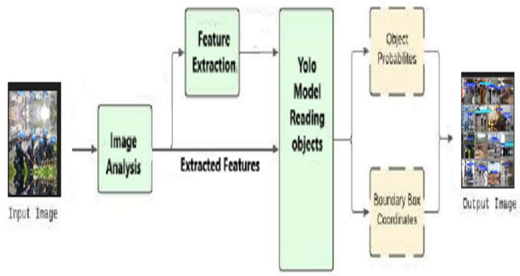


Fig 4.11: System Architecture

## IMPLEMENTATION (ALGORITHM):

**EXISTING SYSTEM:** In a similar project using OpenCV, safety helmet detection was done through image processing and object detection. Images were preprocessed by resizing, color conversion, and filtering. Haar cascades were used to detect helmets, with features like edges and contours helping to locate them. Bounding boxes and labels indicated helmet use, enabling real-time video feedback. However, this approach may struggle in complex environments or with small targets—where YOLOv8 offers improved accuracy and efficiency.

**PROPOSED SYSTEM:** 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.

**SOFTWARE TESTING:** The primary purpose of software testing is to identify errors, defects, or weaknesses in a system. Testing ensures that individual components, sub-assemblies, and the complete system function correctly and meet both the specified requirements and user expectations. It involves systematically exercising the software to verify that it performs as intended and does not fail under defined conditions. Various types of testing are employed, each targeting specific aspects of the system to ensure overall quality, reliability, and performance.

**Unit testing** : Unit testing focuses on verifying individual components or modules of a software system. It checks whether each part functions correctly and produces the expected output. This testing helps detect errors early by validating internal logic, decision branches, and data flow before integration with other components.

**Functional test:** Functional tests provide systematic demonstrations that functions tested are available as specified by the business and technical requirements, system documentation, and user manuals.

Functional testing is centered on the following items:

Valid Input : identified classes of valid input must be accepted.

Invalid Input : identified classes of invalid input must be rejected.

Functions : identified functions must be exercised.

Output : identified classes of application outputs must be exercised.

Systems/Procedures: interfacing systems or procedures must be invoked.

**System Test:** System testing ensures that the entire integrated software system meets requirements. It tests a configuration to ensure known and predictable results. An example of system testing is the configuration oriented system integration test. System testing is based on process descriptions and flows, emphasizing pre-driven process links and integration points.

**Performance Test:** The Performance test ensures that the output be produced within the time limits,and the time taken by the system for compiling, giving response to the users and request being send to the system for to retrieve the results.

**Integration Testing:** Integration testing is performed to ensure that multiple software components work together as intended. It involves incrementally combining individual modules and testing them as a group to identify any interface

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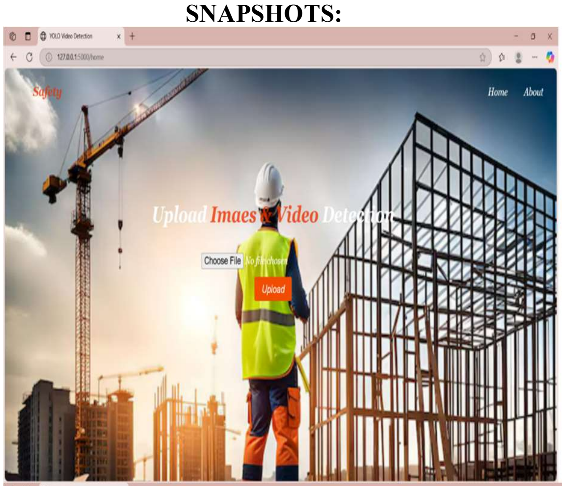
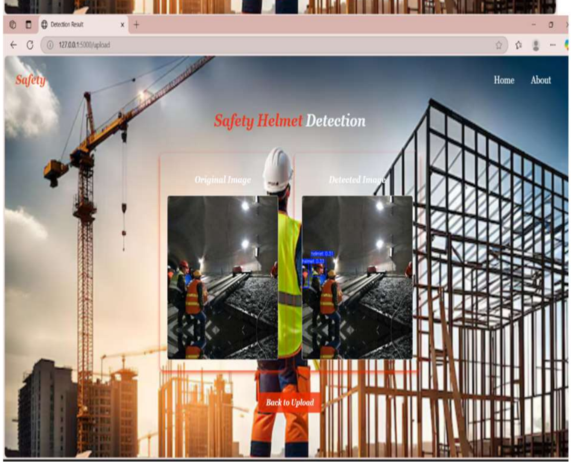
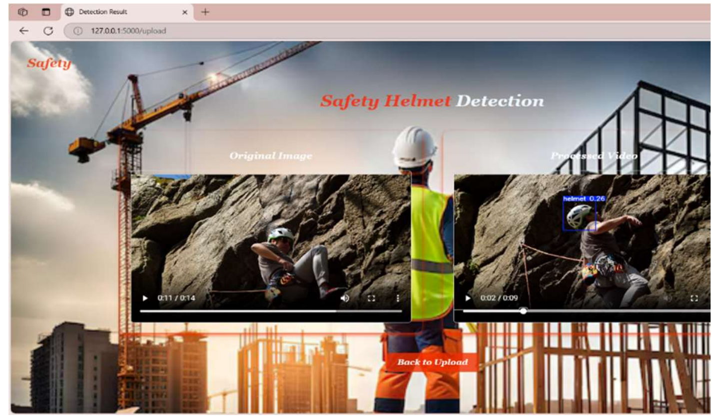
defects. This type of testing verifies that data is correctly exchanged between components and that they interact seamlessly. Whether at the system level or higher, such as between applications in an enterprise environment, integration testing ensures reliable communication and functionality across the entire system.

**Acceptance Testing:** User Acceptance Testing is a critical phase of any project and requires significant participation by the end user. It also ensures that the system meets the functional requirements.

## SNAPSHOTS:




## CONCLUSION:

This study highlights the positive impact of the YOLOv8n-SLIM-CA algorithm in improving helmet detection accuracy, especially in complex environments and with small targets. To address existing challenges, the model incorporates a Slim-Neck architecture that reduces FLOPs by 9.76% and parameters by 6.98%, while improving speed by 9.52% with minimal accuracy loss. The use of Mosaic data augmentation generates more small-object samples, enhancing generalization. Additionally, the small target detection layer and Coordinate Attention (CA) module contribute to better feature focus and reduced background interference. Overall, YOLOv8n-SLIM-CA achieves a 2.15% mAP@0.5 improvement over baseline YOLOv8n, with performance suited for real-time detection on mobile and edge devices in safety-critical applications like construction monitoring.

**FUTURE ENHANCEMENTS:** Future improvements to the YOLOv8-based helmet detection system focus on enhancing its robustness and deployment efficiency. The Coordinate Attention (CA) mechanism improves focus on helmet regions, reducing background noise interference. The small target detection layer ensures accurate detection of distant or partially obscured helmets. Mosaic data augmentation further strengthens model performance in complex scenes by enriching the training dataset. The Slim-Neck structure optimizes the model by reducing complexity while preserving accuracy. These enhancements not only improve detection precision but also enable real-time performance on resource-constrained devices, making the model well-suited for deployment in dynamic, real-world environments such as construction sites.

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