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Full Length Article

Dual Detection Of License Plates And Helmets Using An Optimized YOLO And Neural Networks

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ABSTRACT:
This project presents an advanced computer vision system for real-time Safety Helmet Detection and License Plate Recognition using the latest YOLOv10 object detection architecture. The primary objective is to enhance workplace safety and vehicle monitoring by automatically identifying individuals without safety helmets in industrial zones and capturing vehicle license plates for surveillance and regulation purposes. YOLOv10, known for its superior accuracy and speed, enables efficient multi-object detection in complex environments. The system is trained on annotated datasets containing diverse helmet types and vehicle plates under varying conditions, ensuring robust performance. 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 YOLOv10.

Keywords: *YOLOv10, Computer Vision, Helmet Detection, License Plate Recognition, Deep Learning, Object Detection. YOLOv10 (Real-time detection) Attention Mechanism (Improves accuracy) Data Augmentation (Better raining)*

INTRODUCTION

In the modern industrial and transportation sectors, ensuring the safety of workers and maintaining effective vehicle monitoring systems are of paramount importance. This project introduces a cutting-edge computer vision system that leverages the power of the YOLOv10 object detection architecture for real-time Safety Helmet Detection and License Plate Recognition. The integration of these two critical applications addresses the growing need for intelligent surveillance systems that can operate accurately and efficiently in complex and dynamic environments. The primary goal of this system is to automatically identify individuals who are not wearing safety helmets in industrial and construction zones, thereby promoting workplace safety, and simultaneously recognize vehicle license plates for enhanced monitoring and regulatory compliance. The use of YOLOv10, renowned for its state-of-the-art performance in terms of detection accuracy and inference speed, enables the proposed system to perform multi-object detection with high precision, even in challenging conditions involving small targets and cluttered backgrounds. To achieve this, the model is trained on richly annotated datasets that include a wide range of helmet types and vehicle license plates captured under diverse lighting and weather conditions. Furthermore, the study introduces improvements to the standard YOLOv10 architecture to specifically address the challenges associated with detecting safety helmets in complex scenarios, where traditional algorithms often struggle with low accuracy. By incorporating advanced techniques and optimization strategies, the enhanced model demonstrates superior robustness and reliability in detecting both safety helmets and vehicle plates. This innovative approach not only contributes to reducing the risk of head injuries caused by falls in high-altitude construction work but also supports law enforcement and industrial management in maintaining safety standards and operational efficiency.

Literature Review

Safety helmet detection has become an important research area in computer vision due to its applications in construction sites, mining industries, traffic monitoring, and electrical field operations. Deep learning–based object detection models, especially the YOLO (You Only Look Once) family, have shown remarkable performance in real-time helmet detection tasks. Several researchers have proposed improved YOLO-based approaches to enhance detection accuracy, robustness, and computational efficiency in complex environments.
Wu et al. [1] proposed an improved safety helmet detection algorithm named CC-YOLOv8 based on the YOLOv8 framework. The study aimed to

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address the issues of low detection accuracy and high computational complexity in traditional helmet detection systems. The authors introduced the C2fcc module to strengthen feature extraction capabilities and integrated the EMA attention mechanism to improve object localization accuracy. Experimental results demonstrated that the proposed model achieved a mean Average Precision (mAP@0.5) of 92.6%, outperforming the original YOLOv8 model by 0.5%. The proposed method provided efficient and accurate helmet detection suitable for high-risk working environments such as construction sites and mines.

Li et al. [2] developed a lightweight safety helmet detection algorithm for electrical power operation environments using an improved YOLO-based architecture. The research focused on overcoming challenges such as diverse targets, complex backgrounds, and partial occlusions in electrical field scenes. The proposed model incorporated the VoV-GSCSP module to reduce computational complexity and the GSConv module to improve feature extraction capability. These enhancements enabled the network to adapt effectively to complex electrical environments while maintaining high detection accuracy and robustness. Experimental validation confirmed the effectiveness of the proposed lightweight detection framework for real-time safety monitoring.

Li et al. [3] presented MH-YOLO, an improved YOLOv8-based real-time coal mine safety helmet detection algorithm. The study highlighted the limitations of existing detection methods, including poor real-time performance, low detection accuracy, and sensitivity to environmental conditions. To improve performance, the authors integrated the Convolutional Block Attention Module (CBAM) into the backbone network to enhance feature extraction. Additionally, MaxPooling layers replaced partial subsampling convolutions to improve recall rates, while a small-object detection layer and the ZoomCat and ScaleSeq (ZAS) feature extraction module were introduced to improve small and overlapping object detection. The proposed MH-YOLO achieved mAP50 scores of 92.4% and 97.8% on the CUMT-Helmet and DsLMF+Helmet datasets, respectively, with a detection speed of 10.1 ms, demonstrating excellent real-time performance.

Suma et al. [4] proposed an automated helmet detection system for two-wheeler riders in India using the YOLOv8 algorithm. The system aimed to improve road safety by identifying riders who were not wearing helmets. The model was trained using a dataset generated through RoboFlow and incorporated Convolutional Neural Network (CNN) architectures for improved feature learning. The proposed approach demonstrated higher accuracy and efficiency compared to earlier helmet detection models. The authors emphasized that further improvements in bounding box precision and detection accuracy could significantly enhance practical deployment in intelligent traffic monitoring systems.

Li et al. [5] introduced YOLO-PL, a lightweight helmet-wearing detection algorithm based on YOLOv4. The study addressed challenges such as small helmet sizes, occlusions, and complex backgrounds commonly encountered in workplace environments. The authors proposed the YOLO-P algorithm to improve small-object detection capability and optimize anchor assignment strategies. Furthermore, an Enhanced Path Aggregation Network (E-PAN) structure was designed to fuse high-level semantic information with low-level spatial features, thereby improving detection accuracy. The proposed YOLO-PL model reduced the number of parameters while maintaining high performance, making it suitable for practical deployment in workplace safety systems.

From the reviewed literature, it is evident that significant advancements have been achieved in safety helmet detection using YOLO-based models. Existing studies have focused on improving detection accuracy, computational efficiency, lightweight architectures, and small-object detection capabilities. However, challenges related to real-time deployment, high-speed inference, robustness under varying environmental conditions, and overall detection efficiency still remain. These limitations motivate the development of more advanced architectures such as YOLOv10, which aims to provide enhanced speed, accuracy, and real-time performance for intelligent safety helmet detection systems.

Methodology

Modules Name:

- Input Image/Video
- Object Detection Using YOLOv10
- Data Augmentation
- Coordinate Attention (CA) Mechanism:
- Small Target Detection
- Output Detection

MODULES EXPLANATION:

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 YOLOv10:

YOLOv10, 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. YOLOv10 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

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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:
YOLOv10 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.

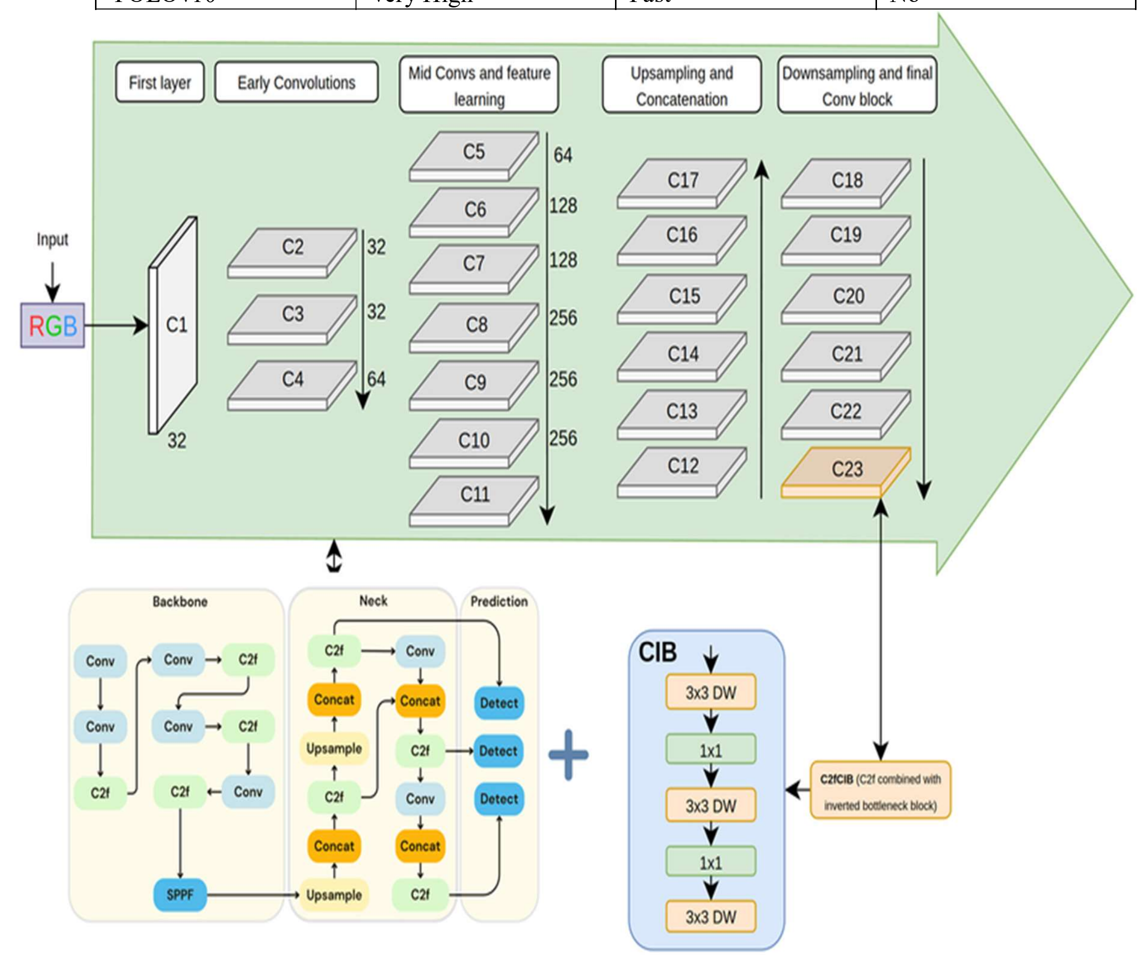
5) Small Target Detection:
A small target detection layer is added in the detection layer to improve the model's ability to detect helmets that may be small or located far away in the frame. This addition enables better performance in real-world environments where helmets may be partially obscured or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

6) Output Detection:
Once YOLOv10 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.

Block Diagram (Text Representation)
Input → Preprocessing → YOLOv10 Detection → Feature Extraction
→ Attention Mechanism → Detection Output → Alert System

SYSTEM ARCHITECTURE:

Model	Accuracy	Speed	NMS Required
YOLOv8	High	Medium	Yes
YOLOv10	Very High	Fast	No



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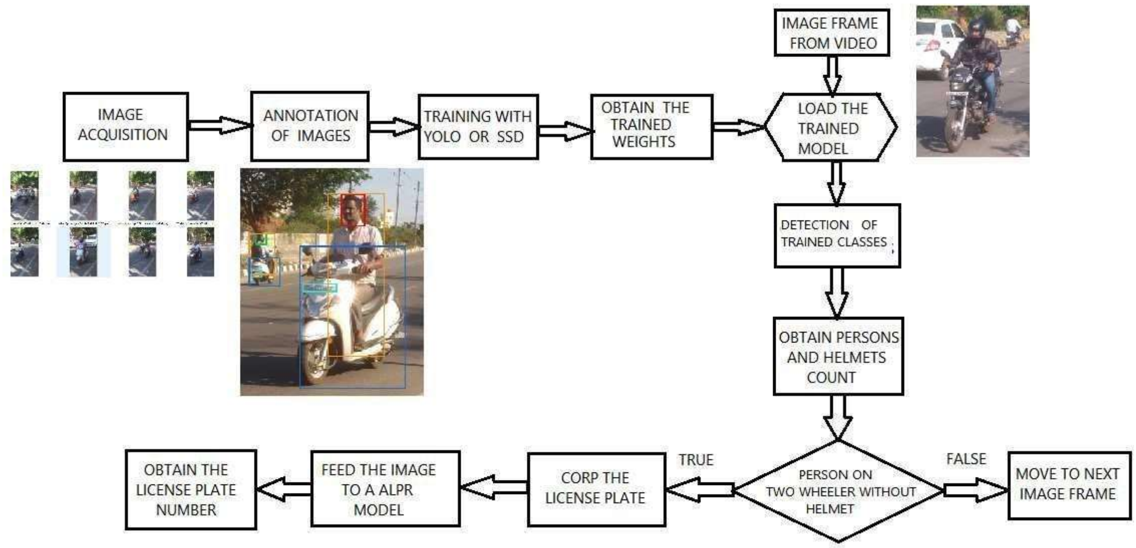

Implementation

The implementation of the proposed Safety Helmet Detection System is carried out using the YOLOv10 object detection framework to ensure accurate and real-time detection of helmets and license plates from images and video streams. The system is designed to improve road safety and automate helmet compliance monitoring through advanced computer vision techniques.

Initially, the system captures input data in the form of images, recorded videos, or live camera feeds. The captured input is then passed through a preprocessing stage, where image resizing, normalization, and noise reduction techniques are applied to improve image quality and ensure compatibility with the YOLOv10 model requirements. Preprocessing also enhances detection accuracy by standardizing the input dimensions and improving feature visibility.

After preprocessing, the input image or video frame is provided to the trained YOLOv10 model. The model performs real-time object detection by analyzing the visual features within each frame and identifying relevant objects such as helmets and vehicle license plates. YOLOv10 utilizes advanced deep learning techniques and optimized feature extraction layers to achieve high-speed and accurate detection performance.

Once the objects are detected, the system classifies them into predefined categories such as "Helmet" and "No Helmet." Bounding boxes are generated around the detected objects along with confidence scores to visually indicate the prediction results. These bounding boxes help in locating and tracking the detected objects within the video frame.

If the system identifies a rider without a helmet, an alert mechanism is triggered automatically. The alert may include warning notifications, image capture, or license plate recording for further action. This functionality enables automated traffic monitoring and assists authorities in enforcing road safety regulations effectively.

Algorithm Steps

Step 1: Capture Input Image or Video

The system captures real-time video streams or input images from surveillance cameras or external devices for processing.

Step 2: Preprocess the Input

The captured input is preprocessed using resizing, normalization, and enhancement techniques to improve image quality and model compatibility.

Step 3: Pass Input to YOLOv10 Model

The preprocessed image or video frame is forwarded to the YOLOv10 deep learning model for object detection.

Step 4: Detect Helmets and License Plates

The YOLOv10 model detects helmets, riders, and vehicle license plates from the input frame using trained object detection capabilities.

Step 5: Classify Detected Objects

Detected objects are classified into categories such as "Helmet" and "No Helmet" based on learned visual patterns.

Step 6: Display Bounding Boxes

The system displays bounding boxes and confidence scores around the detected objects for visual interpretation.

Step 7: Trigger Alert for Violations

If a rider without a helmet is detected, the system automatically triggers an alert and stores the detected information for monitoring and reporting purposes.

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Software Testing

Software testing is an essential phase in system development that aims to identify errors, weaknesses, and functional issues within the software application. The primary objective of testing is to ensure that the developed system operates according to the specified requirements and performs reliably under different operating conditions. Testing provides a systematic approach to verify the functionality, efficiency, accuracy, and stability of the software components and the overall application.

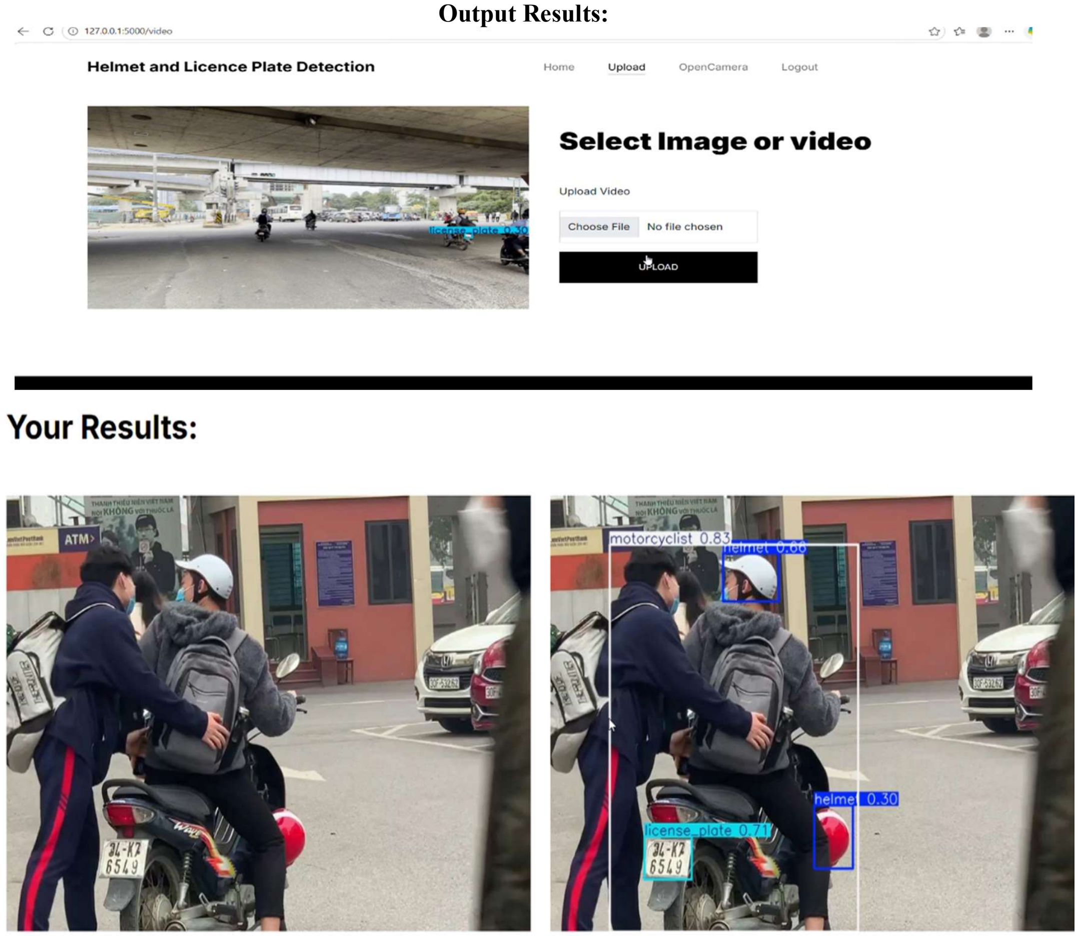
The testing process involves executing the software with the intention of identifying defects and ensuring that the system meets user expectations without producing unacceptable failures. Different testing methods are applied to validate individual modules, integrated components, and the complete system. These tests help ensure that all functionalities perform correctly and that the application behaves consistently across different scenarios and environments.

Developing Methodologies

The testing methodology for the proposed system is developed through a structured and comprehensive approach to evaluate both general functionality and specialized features of the application. A detailed testing plan is prepared to examine the system performance across various platform configurations and operational conditions. Strict quality control procedures are followed throughout the testing process to ensure software reliability and accuracy.

The testing framework is designed to verify that the developed application satisfies all functional and non-functional requirements specified in the system requirements document. Various testing techniques, including functional testing, integration testing, system testing, and performance testing, are conducted to identify and eliminate software bugs. The methodology also ensures that the YOLOv10-based detection system performs effectively in real-time scenarios with accurate helmet detection, efficient object classification, and reliable alert generation mechanisms.

Output Results:



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CONCLUSION

In conclusion, this project successfully demonstrates the potential of leveraging advanced deep learning techniques, particularly the YOLOv10 object detection algorithm, to develop an efficient and accurate real-time system for Safety Helmet Detection and License Plate Recognition. By addressing critical challenges such as small object detection, environmental variability, and multi-object recognition, the proposed system significantly contributes to enhancing workplace safety and vehicle monitoring in industrial and construction settings. The integration of these functionalities into a single, unified framework ensures improved compliance with safety regulations and streamlined surveillance operations. With its high performance, scalability, and potential for further enhancements, this system represents a forward-thinking solution that aligns with the growing demand for intelligent automation in safety-critical environments. The outcomes of this project pave the way for future advancements in smart surveillance systems, contributing to safer and more secure operational spaces.

FUTURE ENHANCEMENTS:

In the future, this project can be enhanced by incorporating additional safety features and expanding its capabilities to create a more comprehensive intelligent surveillance system. One potential enhancement is the integration of facial recognition technology to identify and track individual workers, ensuring personalized safety compliance and attendance monitoring. The system can also be extended to detect other personal protective equipment (PPE) such as safety vests, gloves, and goggles, making it suitable for broader occupational safety applications. Another promising direction is the integration with Internet of Things (IoT) devices and cloud-based platforms for real-time alerts, remote monitoring, and centralized data storage and analysis. Moreover, employing edge computing devices can improve processing efficiency and reduce latency, allowing for seamless real-time performance in low-bandwidth environments. The system could also benefit from multilingual optical character recognition (OCR) for reading license plates from different regions and countries. Continuous model refinement using transfer learning and real-time feedback loops would further enhance the accuracy and adaptability of the system to evolving environments and requirements.

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