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AN OPTIMIZED YOLOV10 FRAMEWORK FOR DUAL DETECTION OF SAFETY HELMETS AND LICENSE PLATES

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ABSTRACT

This research uses the most recent YOLOv10 object detection architecture to demonstrate a sophisticated computer vision system for real-time safety helmet detection and license plate recognition. The main goal is to improve vehicle monitoring and workplace safety by automatically recognising people who are not wearing safety helmets in industrial zones and recording license plates for regulatory and surveillance purposes. Efficient multi-object identification in difficult situations is made possible by YOLOv10, which is renowned for its exceptional speed and accuracy. To ensure reliable performance, the system is trained using annotated datasets that include a variety of helmet types and car plates under various circumstances. Construction workers' risk of suffering head injuries in high-altitude falls can be significantly decreased by donning safety helmets. This study suggests an enhanced safety helmet detection method based on YOLOv10 to solve the low detection accuracy of current algorithms for small objects and complicated settings in different situations.

1. INTRODUCTION

Ensuring worker safety and maintaining efficient vehicle monitoring systems are critical in today's industrial and transportation sectors. This research presents a state-of-the-art computer vision system that uses the YOLOv10 object detection framework to recognise license plates and detect safety helmets in real time. The increasing demand for intelligent surveillance systems that can function precisely and effectively in complicated and dynamic contexts is addressed by the merging of these two crucial applications. This system's main objective is to automatically identify people who are not wearing safety helmets in industrial and construction zones, hence improving worker safety. At the same time, it recognises license plates from vehicles for improved monitoring and legal compliance. Even in difficult situations with small targets and crowded backgrounds, the suggested system can conduct multi-object recognition with high precision thanks to the usage of YOLOv10, which is well-known for its cutting-edge performance in terms of detection accuracy and inference speed. In order to do this, the model is trained using extensively annotated datasets that contain a variety of helmet types and car license plates taken in various lighting and weather scenarios. Additionally, the work presents modifications to the standard YOLOv10 architecture in order to explicitly address the difficulties of identifying safety helmets in complicated circumstances, where conventional algorithms frequently have poor accuracy. The improved model exhibits higher robustness and reliability in detecting both safety helmets and car plates by utilising cutting-edge methodologies and optimisation procedures. This creative strategy helps law enforcement and industrial management uphold safety regulations and operational effectiveness while also lowering the risk of head injuries brought on by falls during high-altitude construction operations.

OBJECTIVE

The primary objective of this project is to develop an intelligent and efficient real-time computer vision system capable of detecting safety helmets on individuals and recognizing vehicle license plates using the advanced YOLOv10 object detection algorithm. This dual-function system aims to enhance safety compliance in industrial and construction environments by automatically identifying workers who are not wearing protective helmets, thereby helping to prevent potential head injuries and promote a culture of safety. Simultaneously, the system is designed to capture and recognize vehicle license plates with high accuracy, facilitating effective monitoring and regulation of vehicular access within secured areas. A key focus is placed on improving detection performance in challenging scenarios involving small targets and occlusions, and variable lighting conditions. By training the YOLOv10 model on comprehensive and diverse datasets, the project seeks to ensure robust and reliable performance in real-world applications. Ultimately, the objective is to contribute to safer workplaces and more secure environments through the integration of cutting -edge AI and deep learning technologies.

PROBLEM STATEMENT

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Traditional safety helmet detection and license plate recognition systems rely on conventional image processing methods or earlier object detection models that struggle with small object detection, complex backgrounds, and varying lighting conditions. These systems often suffer from low detection accuracy, high false detection rates, and poor performance in real-time industrial environments. Additionally, class imbalance and occlusions further reduce their reliability in practical deployments. Therefore, there is a need to develop an efficient and intelligent deep learning–based computer vision system using an advanced object detection framework such as YOLOv10 to accurately detect safety helmet violations and recognize license plates in real time, while ensuring high precision, robustness, and scalability for real-world safety and surveillance applications.

EXISTING SYSTEM

The goal of the YOLOv8 algorithm is to precisely identify safety helmets in real-time, especially in difficult settings like building sites. The core of the detection technique is YOLOv8, which recognises helmets even when they are tiny or far away. Because of its high-speed object detection capabilities, which allow the system to process video frames in real-time, the algorithm is especially effective. YOLOv8's performance is improved by key features such the Coordinate Attention (CA) method and tiny target detection layer, which enable it to minimise background noise and concentrate on pertinent helmet features. Because of this, YOLOv8 is perfect for identifying safety helmets in a variety of intricate environments, guaranteeing worker safety by sending out instant alerts when helmets are not found.

Disadvantages Of Existing System

- YOLOv8 includes a specialized layer for small target detection.
- Improved Detection in Complex Environments.
- YOLOv8 can handle large datasets and work efficiently in different scenarios.
- YOLOv8 is optimized for performance, reducing computational load without sacrificing accuracy.

PROPOSED SYSTEM

The most recent development in the YOLO family of real-time object detection models, YOLOv10 (You Only Look Once version 10), offers notable gains in efficiency and performance. YOLOv10 incorporates state-of-the-art improvements to enable greater accuracy and faster inference times while retaining a lightweight architecture appropriate for deployment on edge devices, building on the fundamental ideas of earlier iterations.

YOLOv10's enhanced head and backbone architecture, which is intended to extract robust and rich information from input images, is one of its primary advancements. Even in difficult situations with occlusions or dim lighting, this leads to improved object localisation and classification. Additionally, YOLOv10 uses optimised anchor-free detection methods and sophisticated attention mechanisms to improve detection accuracy over a broad range of object sizes while lowering processing costs.

Advantages Of Proposed System

- No Need for Non-Maximum Suppression
- Faster Inference (Real-Time Performance)
- Fewer Parameters and Computations
- Higher Accuracy
- Better Multi-Scale Object Detection

2.RELATED WORK

A. OBJECT DETECTION METHODS

One of the core objectives in computer vision is object detection, which seeks to locate and classify certain items in pictures or videos. Conventional object detection techniques, including the Viola-Jones detector [16] and HOG+SVM [17], are usually dependent on manually created features and sliding window operations.

Nevertheless, these techniques are computationally costly and have low adaptation to complicated settings. Deep learning-based object detection algorithms have advanced significantly in recent years due to the growth of deep learning. These techniques can provide end-to-end object detection by autonomously learning image attributes. Among these, two-stage detectors based on convolutional neural networks (CNNs), as FasterR-CNN [18], produce candidate regions and carry out classification and regression to attain higher detection accuracy.

B. AUTOMATIC RECOGNITION OF LICENSE PLATES

The automated recognition of car license plate numbers and the regions that correspond with them is known as Automatic License Plate Recognition (ALPR) technology. Character segmentation, picture preprocessing, license plate localisation, and character recognition are common components of traditional license plate identification techniques [21]. These techniques are sensitive to lighting, angles, and noise because they frequently rely on manually created features and rules.

Deep learning-based license plate recognition techniques have progressively gained popularity in recent years [22].

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These techniques enable the direct identification and recognition of license plate information from photos by treating license plate recognition as an object detection and recognition task. For example, Dalarmelina et al. and Singh and Bhushan [23]

3. METHODOLOGY

The proposed system employs an optimized YOLOv10 deep learning model for the real-time dual detection of safety helmets and vehicle license plates. Initially, images and video frames captured from surveillance cameras are preprocessed through resizing, normalization, and data augmentation techniques such as mosaic augmentation, rotation, flipping, and brightness adjustment to improve dataset diversity and reduce overfitting. The preprocessed data is then fed into the enhanced YOLOv10 architecture, which utilizes an improved backbone network to extract rich multi-scale features for accurate object localization and classification. To further enhance detection performance, a Coordinate Attention (CA) mechanism is incorporated to emphasize important spatial information while suppressing irrelevant background features, enabling reliable detection in complex environments. Additionally, the anchor-free detection strategy of YOLOv10 improves localization accuracy and computational efficiency, allowing the system to detect both safety helmets and license plates in a single forward pass. The detected objects are displayed with bounding boxes, class labels, and confidence scores, and an alert is generated whenever a helmet is not detected. Finally, the model's performance is evaluated using standard object detection metrics such as Precision, Recall, F1-score, and mAP, demonstrating its effectiveness for real-time intelligent surveillance and workplace safety monitoring.

MODULES:

1. Input Image/Video

The system takes pictures or video frames in real time from cameras, which are usually placed in high-risk areas or on building sites.

2. Object Detection Using YOLOv10

The input photos are scanned by YOLOv10, a cutting-edge object detection model, to identify different things. It is specially trained to recognise safety helmets in this instance. This is accomplished in a single pass by YOLOv10, which makes it extremely effective for real-time detection.

3. Data Augmentation

The approach employs mosaic data augmentation to enhance the model's capacity to identify small and far-off helmets. By producing small targets, this method improves the model's performance in cluttered and complicated environments and ensures improved generalisation.

4. Coordinate Attention (CA) Mechanism

A Coordinate Attention (CA) method in the backbone network improves YOLOv10. By successfully eliminating unimportant characteristics and increasing detection accuracy, this approach enables the model to concentrate on safety helmet regions in complicated backdrops.

5. Small Target Detection

To enhance the model's capacity to identify helmets that might be small or far away in the frame, a small target detection layer is added to the detection layer. Better performance in real-world situations when helmets may be partially hidden or visible from a distance is made possible by this feature.

6. Output Detection

The system delivers the result with great accuracy, indicating if the person is wearing a safety helmet, after YOLOv10 has identified the helmet. An alert is set out to notify the appropriate personnel if the helmet is not found.

4. ALGORITHM

YOLOV10

YOLOv10 improves localization accuracy and computational efficiency, allowing the system to YOLOv10 (You Only Look Once Version 10) is a state-of-the-art object detection algorithm that is specifically designed for real-time detection tasks with high accuracy and efficiency YOLOv10 employs a deep neural network architecture consisting of a backbone, neck, and detection head. The backbone extracts important visual features from the input image, while the neck combines information from different feature levels to improve object localization. The detection head predicts object classes and bounding box coordinates with high precision. During training, the model learns from annotated datasets containing images of safety helmets and license plates captured under diverse conditions. This enables the system to generalize effectively to unseen data and maintain robust performance in real-world scenarios.The ability of YOLOv10 to process images rapidly while maintaining excellent detection accuracy makes it an ideal solution for workplace safety monitoring and intelligent vehicle surveillance systems. Furthermore, the model can identify important visual patterns and features associated with helmets and license plates, allowing authorities and safety personnel to take timely actions when safety violations or unauthorized vehicle entries are detected.

5. DATA FLOW DIAGRAM

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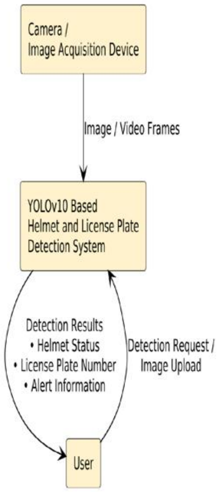
LEVEL 0



LEVEL 1

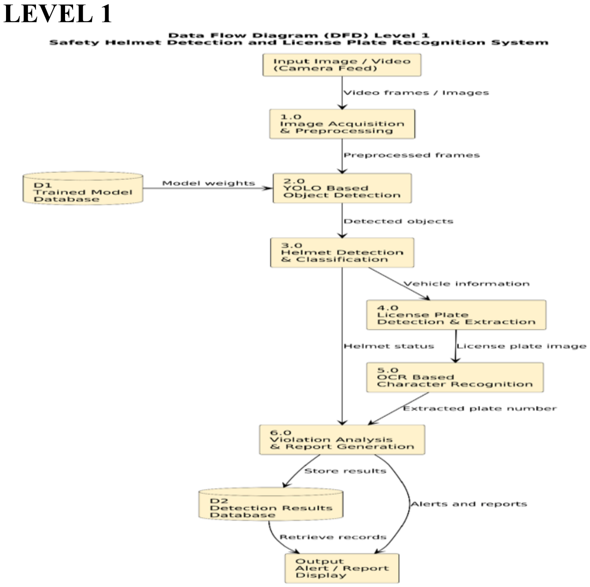


Fig 5: Data flow diagram

6. SYSTEM ARCHITECTURE

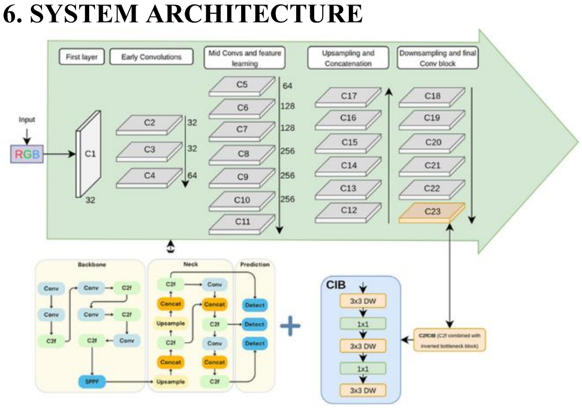
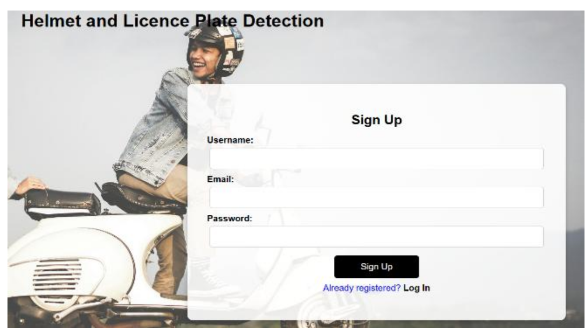
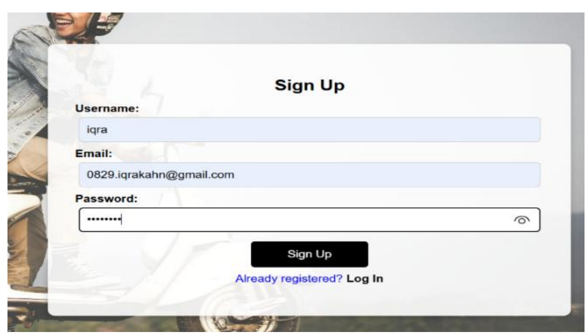


Fig 6: System Architecture

7. RESULTS

The above figure illustrates the output of the proposed Helmet and License Plate Detection system. The left side displays the original uploaded image, while the right side shows the detection results generated by the optimized YOLO model. The system successfully identifies the motorcyclist with a confidence score of 0.77 and accurately detects the vehicle license plate with a confidence score of 0.94 by drawing bounding boxes around the detected objects. These results demonstrate the model's ability to perform real-time multi-object detection with high accuracy, even in a busy traffic environment containing multiple vehicles and pedestrians. The generated confidence scores indicate the reliability of the detections, highlighting the effectiveness of the proposed system for intelligent traffic monitoring and safety surveillance applications.





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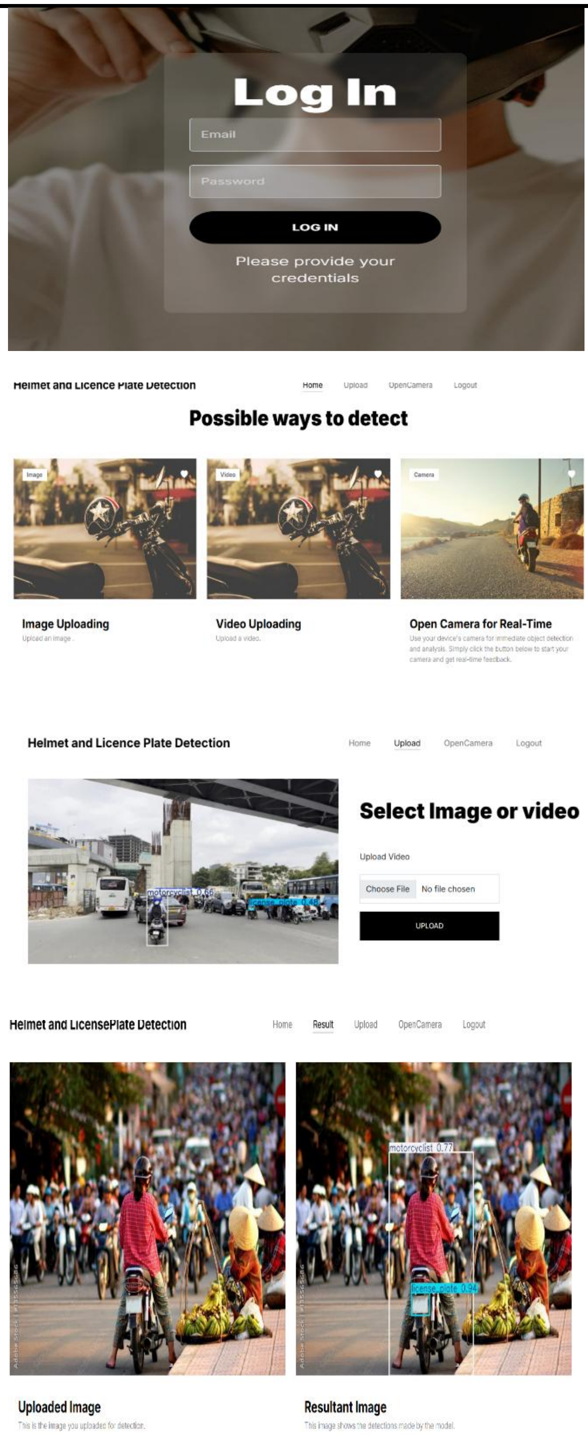

Fig 7: Resultant Image

8. FUTURE ENHANCEMENT

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.

9. CONCLUSION

In summary, this study effectively illustrates the potential of utilising cutting-edge deep learning techniques, specifically the YOLOv10 object identification algorithm, to create a precise and effective real-time system for license plate recognition and safety helmet detection. The suggested method greatly improves workplace safety and vehicle monitoring in industrial and construction environments by tackling important issues including small item detection, ambient unpredictability, and multi-object recognition. Streamlined surveillance activities and better adherence to safety requirements are guaranteed by the integration of various functions into a single, cohesive structure. This system is an innovative response to the increasing need for intelligent automation in safety-critical settings because of its high performance, scalability, and possibility for additional improvements. The project's results open the door for further developments in intelligent surveillance systems, making operating environments safer and more secure.

In order to develop a more complete intelligent surveillance system, this project can be improved in the future by adding more safety features and increasing its capabilities. The use of facial recognition technology to track and identify specific employees, guaranteeing individual safety compliance and attendance tracking, is one possible improvement. The system is appropriate for more extensive occupational safety applications since it can be expanded to identify other personal protective equipment (PPE) such safety jackets, gloves, and goggles. Integrating Internet of Things (IoT) devices and cloud-based systems for centralised data storage and analysis, remote monitoring, and real-time alerts is another promising avenue. Additionally, using edge computing devices can lower latency and increase processing efficiency, enabling smooth real-time performance in low-bandwidth settings. Multilingual optical character recognition (OCR) for reading license plates from many nations and areas would also be beneficial to the system. The accuracy and flexibility of the system to changing settings and requirements would be further improved by ongoing model improvement employing transfer learning and real-time feedback loops. the future by adding more safety features and increasing its capabilities. The use of facial recognition technology to track and identify specific employees, guaranteeing individual safety compliance and attendance tracking, is one possible improvement. The system is appropriate for more extensive occupational safety applications since it can be expanded to identify other personal protective equipment (PPE) such safety jackets, gloves, and goggles. Integrating Internet of Things (IoT) devices and cloud-based systems for centralised data storage and analysis, remote monitoring, and real-time alerts is another promising avenue. Additionally, using edge computing devices can lower latency and increase processing efficiency, enabling smooth real-time performance in low-bandwidth settings. Multilingual optical character recognition (OCR) for reading license plates from many nations and areas would also be beneficial to the system. The accuracy and flexibility of the system to changing settings and requirements would be further improved by ongoing model improvement employing transfer learning and real-time feedback loops.

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