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ML Based Safety Gear Compliance System

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Abstract— Wearing the appropriate protective gear is essential for worker safety and operational effectiveness in factories and other industrial settings. Manual checks are frequently labor-intensive and unreliable when used to enforce PPE regulations. Using machine learning and computer vision, this project presents an intelligent, automated system that watches live camera feeds and determines whether employees are wearing the necessary safety equipment, including gloves, helmets, vests, and protective eyewear. The system immediately flags the problem and records the incident for review if someone is discovered to be non-compliant. The solution's automation of this procedure lowers human error, enhances workplace safety, and fortifies compliance with safety rules.

I. INTRODUCTION

Staying to safety regulations is not always clear-cut in hectic factory environments. Especially when a shift is ending or the workload is high, employees might occasionally forego wearing a helmet or gloves to save time. No matter how watchful, supervisors cannot be everywhere at once. This project fits in there. We monitor things using the factory's current cameras and a smart computer vision system rather than depending on manual inspections. Clearly scanning live footage to check for missing key protective equipment—such as hard helmets, goggles, vests, and gloves—it notifies the safety team right away. The system also tracks every event, providing round-the-clock monitoring free from continuous human supervision.

II. PROBLEM STATEMENT

Additionally, when lapses in wearing protective gear can lead to major injuries or regulatory concerns, maintaining worker safety in manufacturing environments is both crucial and difficult. Traditionally, compliance has been monitored by manual checks, which are labor-intensive, inconsistent, and slow. This project offers a method that automatically checks whether employees are wearing the appropriate safety equipment—such as gloves, helmets, vests, and goggles-while on the job using machine learning and computer vision. The system can rapidly find any lacking equipment by means of live video analysis and notify the safety team in real time. This method guarantees that safety rules are being followed more consistently, helps to prevent accidents, and reduces the need for continuous human monitoring.

III. OBJECTIVE

The primary objective of this research is utilizing the cutting-edge object detection algorithm YOLOV11v11 to design and develop a machine learning-based Safety Gear Compliance Monitoring system. The goal of the system is to automatically detect and verify, in real-time, whether factory workers are wearing personal protective equipment (PPE) such as goggles, gloves, safety vests, and helmets. The system focuses on accurately and efficiently identifying safety equipment in a variety of factory settings by utilizing cutting-edge computer vision and machine learning techniques.

This project examines the main issues with manual inspection techniques, including labor-intensive monitoring, limited scalability, and human error. The system guarantees quicker, more dependable, and consistent enforcement of safety procedures by automating safety compliance checks. This helps companies meet regulatory requirements more easily, boosts workplace safety, lowers the chances of accidents, and encourages a culture where everyone takes responsibility and keeps improving on safety and health practices.

IV. LITERATURE REVIEW

In recent years, the use of computer vision (CV) and machine learning (ML) in workplace safety has received some attention. Many researchers have explored automated methods for monitoring personal protective equipment (PPE) compliance, particularly in industries where manual supervision is either inefficient or impractical.

A study by Singh et al. introduced a helmet detection system using Haar Cascade classifiers, which demonstrated the feasibility of lightweight models for basic safety checks. However, these classical approaches often lack the robustness needed in diverse real-world conditions, such as varying light, complex backgrounds or noisy image quality. To address this challenge, deep learning methods have gained popularity due to their superior accuracy and adaptability.

Chen and colleagues applied convolutional neural networks (CNNs) to detect safety gear in construction environments. Their model, trained on a labeled dataset of workers with and without PPE, achieved a notable improvement in accuracy compared to traditional techniques. However, their work was limited to helmet detection only.

Furthermore, advancements were observed in the work of Zhao et al., who employed the YOLOV11 (You Only Look Once) algorithm to enable real-time detection of multiple PPE items, such as gloves, vests, goggles/face-shields and boots. Their system showed promising results in terms of speed and accuracy, but the performance degraded in low-light conditions.

Other researchers have explored hybrid methods that combine deep learning with sensor data or rule-based systems to increase reliability. One instance is some systems integrate RFID or infrared sensors to cross-check visual detections, which increases the cost and complexity of implementation.

Most existing systems focus on specific environments and are not easily generalizable. There is also a gap in integrating alert mechanisms and automated reporting in a single, integrated, compact and end-to-end framework. These limitations highlight the need for a more comprehensive solution that balances accuracy, real-time performance, and ease of deployment

V. METHODOLOGY

The proposed system leverages machine learning and computer vision techniques to detect the presence or absence of essential safety gear/PPE on personnel in real-time. The methodology is structured into several key phases: data gathering, preprocessing/cleaning, model training, system integration, and real-time monitoring.

A. Data Collection and Preprocessing

The system begins with the collection of image and video datasets containing individuals both complying with and violating PPE norms. These datasets include varied scenarios, lighting conditions, and camera angles, image noise variations to ensure model robustness. Each image is custom annotated to mark whether safety gear such as helmets, safety vests, and gloves are properly worn. The images are then resized, transformed, normalized, and augmented to improve the model's generalization.

B. Model Selection and Training

A convolutional neural network (CNN)-based architecture is selected due to its effectiveness in image classification tasks. Pretrained models like YOLOV11 (You Only Look Once) may be fine-tuned for PPE detection. The model is trained on the custom annotated dataset to learn distinguishing features of compliant and non-compliant employees. Hyperparameters such as learning rate, batch size, and epoch count are tuned for optimal performance.

C. Detection and Classification

During operation, the system captures live video streams from surveillance cameras installed in the workspace. These streams are passed through the trained model, which detects and classifies whether the required PPE items are present on everyone. Bounding boxes are generated around detected personnel along with compliance labels.

D. Alert and Reporting Mechanism

If a violation is detected, the system immediately triggers an alert, which may be in the form of visual indicators, audio warnings, notifications to supervisors or DOS (Denial of service or operation without proper PPE). A log of all detections, including timestamps and images, is maintained for further review and documentation.

E. System Deployment

The final model is deployed on an IOT edge device or server, depending on the scale of operation. The system is optimized for low-latency inference to support real-time compliance monitoring without significant delays.

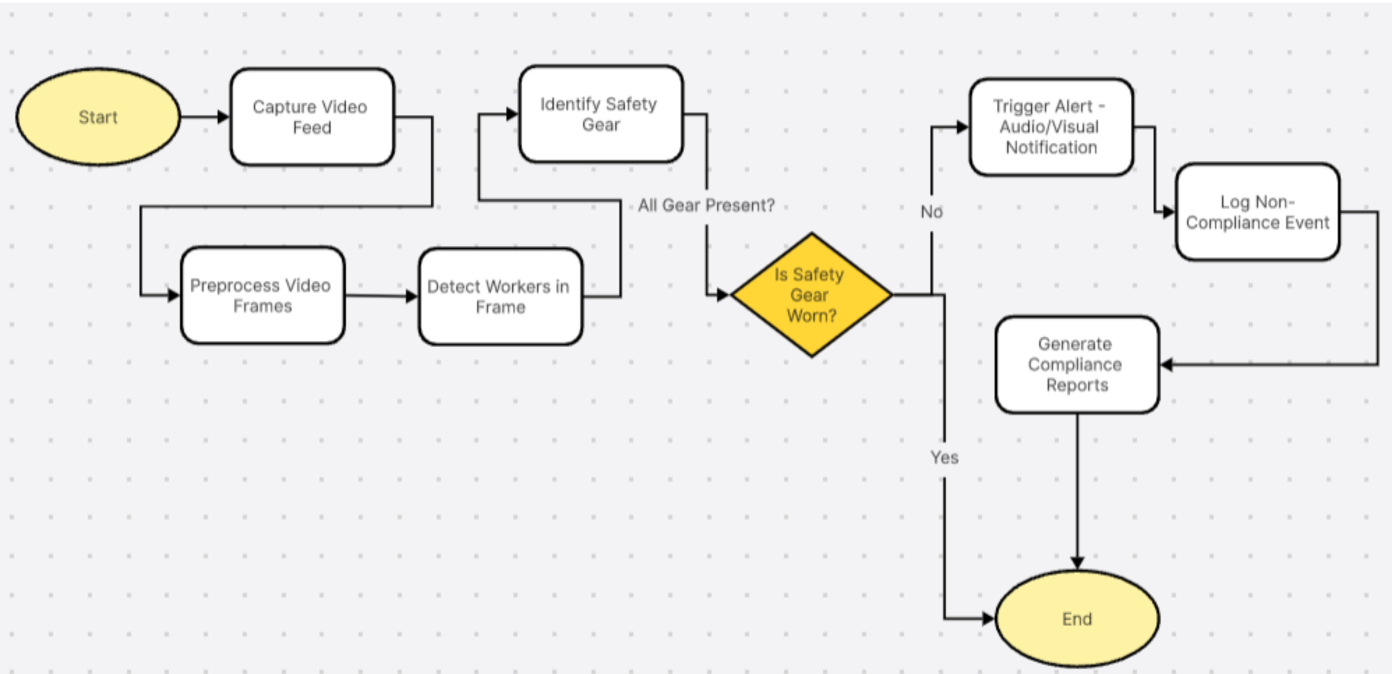

Fig 5.1 Methodology flowchart

VI. TESTING AND EVALUATION

The safety equipment/PPE compliance detection model underwent thorough testing to evaluate its precision and reliability. The dataset was divided into training, validation, and testing sets, where the test set included factory surveillance images that the model had not encountered ever before during training phase. Assessment metrics like accuracy, precision, recall, and F1-score were utilized to evaluate the model's capability to identify different types of Personal Protective Equipment (PPE), including helmets, safety vests, gloves, masks, protective goggles/Face Shields and Safety Boots.

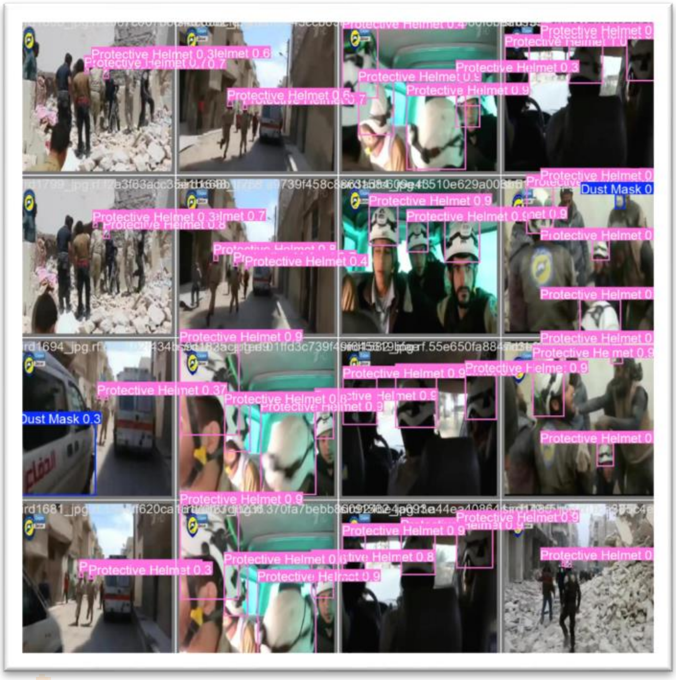

Fig 6.1 Model test output

A confusion matrix was used to evaluate prediction accuracy across PPE categories, showing strengths such as better detection rates for "Helmet" and "Safety Vest," while showing areas for enhancement, like differentiating between "Gloves" and "Bare Hands" in low-light and noisy scenarios. These performance metrics confirmed the model's strength and pointed out areas for additional improvement and optimization.

Fig 6.2 Model detecting safety gear

VII. RESULTS AND DISCUSSION

The safety gear compliance monitoring system was developed using YOLOV11v11 and trained on a custom dataset it showed strong performance in accurately detecting the presence or absence of Personal Protective Equipment (PPE) such as helmets, safety vests, gloves, masks, and glasses. The model was tested using real-world factory footages including variable lighting, diverse backgrounds, demonstrating its working and practical utility. The results confirm the model's potential for deployment in industrial safety environments hence enabling real-time compliance monitoring. It would help us in improved worker safety, and reduced dependency on manual supervision.

- **Confusion Matrix:** The confusion matrix demonstrates the classification precision for every PPE category. High accuracy was seen in identifying helmets and safety vests, although there were some errors in classifying gloves and bare hands. This indicates that though the model excels with commonly seen gear, there is potential for better performance in detecting less common classes or visually similar categories. Enhancing **dataset diversity could help mitigate such errors.**

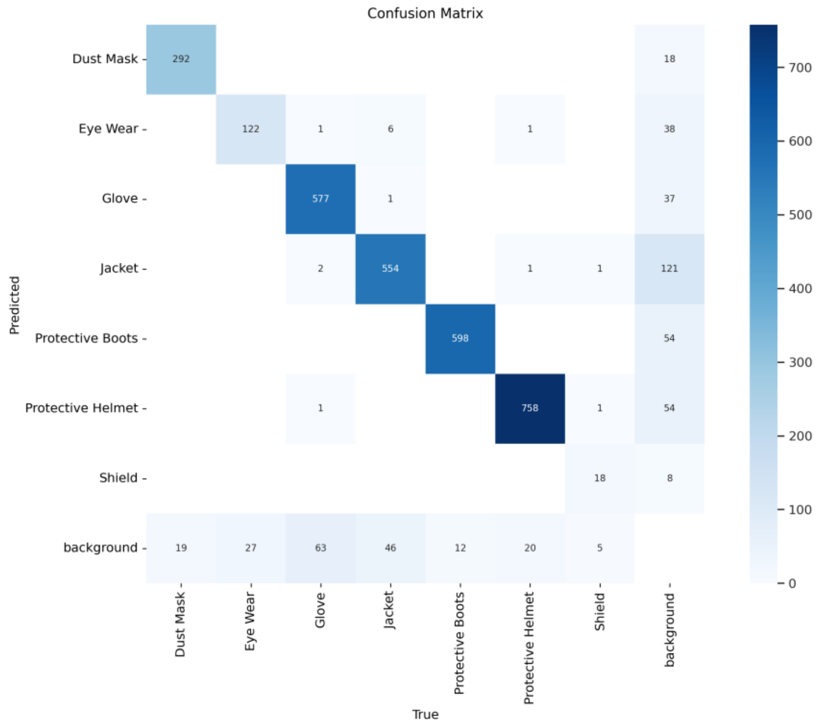

Fig 7.1 Confusion matrix

- **Training and Validation Loss:** The training loss reduced consistently across the epochs, showcasing successful learning of the model. The validation loss, while normally witnessing a similar reduction, showed minimal changes, likely caused because of varying background scenes within the dataset. This shows that there is a requirement for more training data to help increase generalization and reduce overfitting.

- **Precision, Recall, and map:** These results show that the model is good at correctly finding the safety gear (PPE). Precision and recall improved over time during training, but later stayed the same, which means the model may not get much better unless changes are made. The mAP@50 and mAP@50-95 scores show that the model works well overall, but there is still room to make it better by improving the dataset.

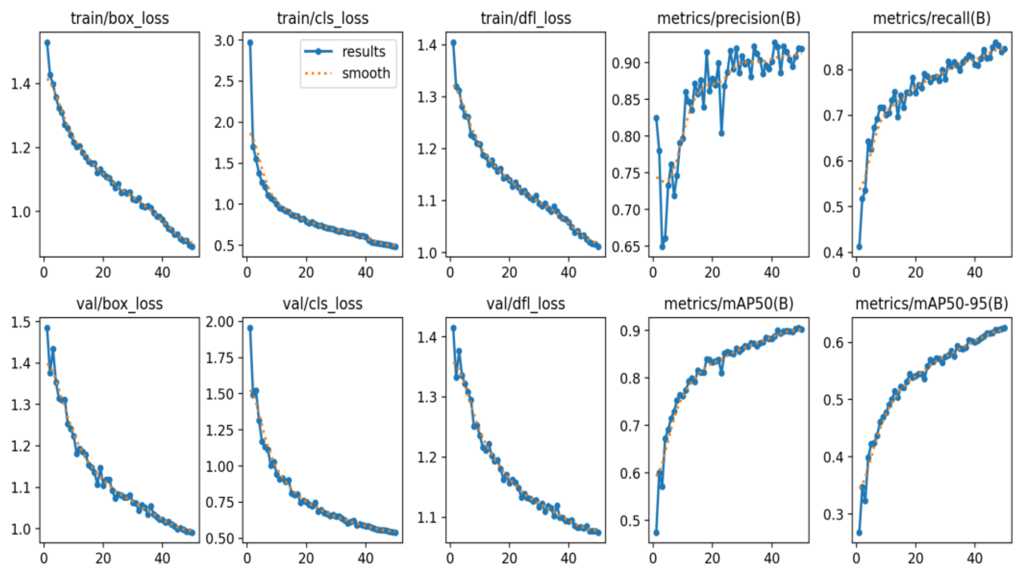

Fig 7.2 Precision, Recall, and mAP

VIII.CONCLUSION

In conclusion, the safety gear detection model built using YOLOV11v11 is effective in identifying and classifying different types of PPE like helmets, vests, gloves, masks, and glasses. The model works well in most situations, especially when detecting commonly used gear. It also performed well under different real-world conditions such as varying lighting and backgrounds, showing that it can be used in actual factory settings. Overall, this technology can help improve workplace safety by reducing the need for manual monitoring and making the process faster and more reliable. This automation can lead to fewer workplace accidents, enhanced regulatory compliance, and overall operational efficiency

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