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Dynamic PPE Compliance Detection under Real-World Construction Conditions

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ABSTRACT: Construction environments present significant safety challenges due to the high risk of accidents and inconsistent use of Personal Protective Equipment (PPE) such as helmets, safety vests, gloves, boots, and masks. Conventional monitoring approaches rely heavily on manual supervision, which is limited in efficiency, accuracy, and continuous coverage. This paper proposes an advanced automated PPE detection framework based on an enhanced YOLOv11 deep learning model to address these limitations. The system processes real-time video streams to accurately identify and classify multiple PPE components under diverse and complex site conditions, including low illumination, occlusions, and dense worker presence. A context-aware detection mechanism ensures reliable performance across dynamic construction environments. Detected violations of safety compliance are immediately reported through integrated alert systems, including SMS and mobile notifications, enabling rapid corrective measures. The proposed approach enhances operational safety by ensuring continuous monitoring and minimizing the likelihood of overlooked violations. Furthermore, it supports regulatory adherence and improves overall safety management practices. Experimental outcomes demonstrate improved detection accuracy and responsiveness compared to traditional methods, contributing to a safer and more efficient construction workplace.

KEYWORDS: Construction Safety, Deep Learning, Object Detection, PPE Compliance, Real-Time Monitoring, Video Analysis, YOLOv11

I. INTRODUCTION

Construction sites are inherently hazardous environments where workers are frequently exposed to risks arising from unsafe practices, heavy machinery, and dynamic working conditions. The consistent use of Personal Protective Equipment (PPE), including helmets, safety vests, gloves, boots, and masks, plays a crucial role in minimizing injuries and preventing fatalities. However, ensuring strict adherence to safety protocols remains a significant challenge due to the limitations of traditional monitoring approaches. Manual supervision, often carried out through periodic inspections, lacks continuous oversight and is susceptible to human error, resulting in missed violations and delayed corrective actions. These limitations highlight the need for an intelligent and automated solution capable of providing real-time safety monitoring in complex construction scenarios.Recent advancements in deep learning and computer vision have enabled the development of automated systems capable of analyzing visual data with high accuracy and speed. This research introduces a context-aware PPE detection framework based on an enhanced YOLOv11 model, designed to monitor safety compliance through real-time video analysis. The proposed approach is capable of detecting multiple PPE items simultaneously, even under challenging conditions such as poor lighting, occlusions, and crowded environments. By integrating automated detection with instant alert mechanisms, the system ensures timely identification of safety violations and facilitates rapid intervention. This approach not only enhances worker safety but also contributes to improved regulatory compliance and efficient site management practices.

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Figure 1: Smart construction PPE detection

i) Problem statement

Construction sites continue to experience high rates of accidents due to inconsistent use of Personal Protective Equipment (PPE) and the absence of effective continuous monitoring mechanisms. Existing safety management practices rely predominantly on manual supervision and periodic inspections, which are limited in scope, time-bound, and prone to human error. Such approaches fail to ensure real-time detection of safety violations, especially in large-scale and dynamic environments where multiple workers operate simultaneously under varying conditions such as poor lighting and visual obstructions. The lack of an automated, accurate, and responsive system to monitor PPE compliance results in delayed identification of risks and inadequate enforcement of safety regulations. Therefore, there exists a critical need for an intelligent, real-time monitoring solution capable of reliably detecting PPE usage and promptly alerting authorities to prevent potential hazards and improve overall construction site safety.

ii) Dataset details

The dataset employed in this research consists of annotated images and video frames capturing construction site scenarios with diverse variations in worker activities, environmental conditions, and safety compliance levels. The data includes multiple classes of Personal Protective Equipment (PPE), such as helmets, safety vests, gloves, boots, and masks, along with instances of non-compliance to ensure balanced learning. Images are collected from real-world construction environments and supplemented with publicly available datasets to enhance diversity. The dataset incorporates variations in lighting conditions, camera angles, occlusions, and crowded scenes to improve model robustness. Each image is labeled using bounding boxes corresponding to different PPE categories, enabling effective training of the YOLOv11 model for object detection. Data augmentation techniques, including rotation, scaling, and flipping, are applied to increase dataset size and generalization capability, ensuring reliable performance in real-time deployment scenarios.

iii) Objectives

The primary objective of this research is to develop an intelligent and automated system for detecting Personal Protective Equipment (PPE) compliance in construction environments using an enhanced YOLOv11 deep learning model. The aim is to enable accurate identification and classification of multiple PPE items from real-time video streams while ensuring robust performance under challenging conditions such as poor lighting, occlusions, and crowded scenes. Another key objective is to facilitate continuous monitoring and instant detection of safety violations, supported by an alert mechanism that provides timely notifications to responsible authorities. Additionally, the research focuses on improving workplace safety standards, minimizing accident risks, and ensuring adherence to regulatory requirements through efficient and scalable monitoring solutions.

II. RELATED WORK

Ahatsham Hayat, et al. [1] proposed a deep learning-based system for automatic detection of safety helmets to improve construction site safety. The study utilized convolutional neural networks to identify helmet usage from images and video streams with high accuracy. A robust dataset consisting of various helmet and non-helmet scenarios was used to train the model effectively. The approach focused on enhancing detection performance under different environmental conditions, including varying lighting and worker positions. The system demonstrated the ability to reduce manual inspection efforts by automating safety compliance monitoring. Real-time implementation was emphasized to ensure

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timely identification of violations. The model showed improved accuracy compared to traditional image processing techniques. However, challenges related to detecting multiple PPE items beyond helmets were not fully addressed. The study primarily concentrated on single-object detection, limiting its scalability. Overall, the research contributed significantly to automated safety monitoring using deep learning.

AhsanWaqar, et al. [2] proposed an analytical framework to assess the challenges associated with adopting Internet of Things (IoT) technologies for construction safety management. The study applied structural equation modeling to evaluate factors influencing IoT implementation in small-scale construction projects. Key challenges such as cost, technical complexity, lack of expertise, and resistance to technological change were identified. The research highlighted the importance of integrating smart devices for real-time monitoring and hazard detection. It emphasized that IoT-based systems can enhance safety awareness and reduce workplace risks. The findings indicated that organizational readiness and infrastructure availability play a critical role in successful adoption. Despite its advantages, the study noted limitations in terms of scalability and practical deployment in resource-constrained environments. The research provided valuable insights into barriers affecting technology-driven safety solutions. However, it did not focus on specific computer vision techniques for PPE detection. The work mainly addressed adoption challenges rather than implementation details.

Younggi Hong, et al. [3] proposed a location-based safety check system designed to enhance worker risk awareness in construction zones. The system utilized real-time location tracking technologies to monitor worker positions and identify potential hazards. By integrating geofencing and alert mechanisms, the approach provided immediate warnings when workers entered unsafe zones. The framework aimed to improve situational awareness and prevent accidents through proactive notifications. The study demonstrated the effectiveness of combining spatial data with safety management systems. It also emphasized the importance of real-time communication in reducing risk exposure. However, the system relied heavily on location data and did not incorporate visual analysis for PPE compliance. Limitations included dependency on accurate positioning technologies and potential signal disruptions. The research primarily focused on hazard awareness rather than safety equipment detection. Overall, the study contributed to improving construction safety through location-based monitoring solutions.

Jack C. P. Cheng, et al. [4] proposed a vision-based monitoring system for construction safety compliance using worker re-identification and PPE classification techniques. The approach combined deep learning models with computer vision algorithms to track individual workers across multiple camera views. The system was capable of identifying whether workers were wearing appropriate PPE by analyzing visual features. Re-identification techniques enabled continuous tracking of workers even when they moved across different locations. The study demonstrated improved accuracy in detecting safety compliance compared to traditional monitoring methods. It also addressed challenges related to occlusions and varying camera angles. However, the computational complexity of the system posed challenges for real-time deployment. The approach required high processing power and extensive training data for effective performance. Limitations were observed in handling large-scale crowded environments efficiently. The research provided a strong foundation for integrating tracking and PPE detection in safety monitoring systems.

Jaekyu Lee, et al. [5] proposed a construction site safety management system based on computer vision and deep learning techniques. The study focused on automating safety inspections by detecting workers and identifying compliance with safety regulations. Advanced deep learning models were utilized to analyze images and videos for recognizing PPE usage and unsafe behaviors. The system aimed to reduce reliance on manual supervision and improve monitoring efficiency. Experimental results showed enhanced detection accuracy and reliability in controlled environments. The research highlighted the potential of artificial intelligence in transforming construction safety practices. However, limitations were identified in handling real-time large-scale deployment and complex environmental variations. The model performance was affected by factors such as lighting conditions and occlusions. The study emphasized the need for more robust and scalable solutions. Overall, the research contributed to the advancement of AI-driven safety management systems in construction domains.

Ahmed Jalil Al-Bayati, et al. [6] proposed an analytical study to evaluate the factors influencing non-compliance with Personal Protective Equipment (PPE) among construction workers using fuzzy theory. The research identified key contributing elements such as worker behavior, environmental conditions, management policies, and awareness levels. Fuzzy logic was applied to handle uncertainties and subjective judgments in assessing safety compliance. The study highlighted that lack of training and inadequate supervision significantly impact PPE usage. It also emphasized the role of organizational culture in promoting safety practices. The findings provided a structured approach to prioritize risk factors affecting compliance. However, the work focused on theoretical assessment rather than real-time detection mechanisms. Limitations included the absence of automated monitoring systems for practical implementation. The research mainly contributed to understanding behavioral and managerial aspects of safety compliance. Overall, it offered valuable insights for improving safety strategies in construction environments.

Gionatan Gallo, et al. [7] proposed a smart system for detecting Personal Protective Equipment in industrial environments using deep learning techniques deployed at the edge. The approach integrated edge computing with convolutional neural networks to enable real-time PPE detection with reduced latency. The system processed visual data locally on edge devices, minimizing the need for cloud-based computation and improving response time. It demonstrated efficient detection of multiple PPE items under practical industrial conditions. The research emphasized scalability and low-power consumption for deployment in resource-constrained environments. Performance evaluation showed high accuracy and faster inference compared to traditional centralized systems. However, limitations were observed in handling highly complex and crowded scenes. The system required optimization for large-scale industrial applications. Additionally, hardware constraints could affect model performance in certain scenarios. The study contributed to advancing edge-based intelligent safety monitoring systems.

Jye-Hwang Lo, et al. [8] proposed a real-time PPE compliance detection system based on deep learning algorithms. The study utilized advanced object detection models to identify safety equipment such as helmets and vests from live video feeds. The system was designed to provide continuous monitoring and instant detection of non-compliance. Experimental results indicated improved accuracy and efficiency compared to traditional monitoring approaches. The research focused on optimizing detection speed to achieve real-time performance. It also addressed challenges related to varying lighting conditions and worker movements. However, the approach primarily concentrated on limited PPE categories, reducing its comprehensiveness. Limitations included reduced performance in highly occluded environments. The system required further enhancement to handle complex construction scenarios. Overall, the research demonstrated the effectiveness of deep learning in automated safety compliance detection.

MatteoCurcuruto, et al. [9] proposed a study on workplace safety communication, focusing on how team leaders influence employee participation in safety practices. The research examined the role of empowering leadership and monitoring supervision in encouraging workers to report safety concerns. It highlighted that effective communication channels significantly improve safety awareness and compliance. The study emphasized behavioral and organizational factors rather than technological solutions. Findings indicated that proactive leadership fosters a positive safety culture and reduces workplace risks. However, the research did not incorporate automated monitoring or detection systems. Limitations included reliance on qualitative analysis and human interaction. The approach lacked integration with modern technologies such as computer vision or IoT. The study mainly contributed to understanding human factors in safety management. Overall, it provided insights into improving safety through leadership and communication strategies.

Andrea Bontempi, et al. [10] proposed the design of smart Personal Protective Equipment integrated with wireless power technology for Industrial Internet of Things (IIoT) applications. The system focused on developing intelligent PPE capable of monitoring worker conditions and transmitting data wirelessly. The research highlighted the use of energy-efficient designs to ensure continuous operation without frequent battery replacement. Integration with IoT platforms enabled real-time data collection and analysis for safety monitoring. The study demonstrated the potential of smart PPE in enhancing industrial safety and automation. However, the approach primarily addressed hardware design rather than visual detection of PPE compliance. Limitations included complexity in implementation and higher deployment costs. The system required robust infrastructure for effective operation. The research emphasized future integration with advanced analytics and monitoring systems. Overall, it contributed to the development of next-generation intelligent safety equipment.

III. EXISTING METHODLOGY

Safety compliance monitoring in construction environments has traditionally relied on manual supervision supported by basic surveillance systems such as Closed-Circuit Television (CCTV). In such approaches, safety officers or supervisors visually inspect workers either through direct observation or by reviewing recorded footage. In some cases, conventional image processing techniques, including background subtraction and edge detection, have been explored to identify human presence or basic activity patterns. However, these methods lack the capability to accurately recognize specific Personal Protective Equipment (PPE) items and are highly dependent on predefined rules, making them unsuitable for dynamic and complex construction environments.In recent years, early machine learning approaches, including Support Vector Machines (SVM) and handcrafted feature-based models such as Histogram of Oriented

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Gradients (HOG), have been introduced for object detection tasks related to safety monitoring. These techniques require manual feature extraction and are limited in handling variations in scale, illumination, and occlusion. While they offer some level of automation compared to manual inspection, their performance remains inconsistent in real-world scenarios, especially in crowded construction sites where multiple workers and overlapping objects are present. Additionally, these models often require extensive preprocessing and are not optimized for real-time detection.Despite these advancements, existing systems face several critical limitations. Most approaches lack real-time processing capability and fail to provide immediate alerts when safety violations occur. Detection accuracy is often compromised under challenging conditions such as low lighting, weather disturbances, and partial visibility of PPE items. Furthermore, scalability remains a major concern, as traditional methods struggle to monitor large construction areas continuously. The absence of integrated alert mechanisms and context-aware analysis further reduces their effectiveness, resulting in delayed responses to safety risks and limited overall improvement in workplace safety management.

IV. PROPOSED METHODOLOGIES

The proposed approach introduces an advanced automated framework for monitoring Personal Protective Equipment (PPE) compliance in construction environments using an enhanced YOLOv11 deep learning model. The system is designed to process live video streams from surveillance cameras and accurately detect multiple PPE components, including helmets, safety vests, gloves, boots, and masks. By leveraging a state-of-the-art object detection architecture, the model performs high-speed and precise identification of safety gear, enabling continuous observation without the need for manual intervention. The detection process is optimized to handle real-time data efficiently, ensuring minimal latency and consistent performance.A key aspect of this research is the integration of context-aware detection capabilities that enhance robustness under challenging site conditions. The model is trained on a diverse dataset incorporating variations in lighting, occlusions, camera perspectives, and worker density, allowing it to maintain reliability in complex and dynamic environments. Advanced preprocessing and data augmentation techniques further strengthen the system’s ability to generalize across different scenarios. As a result, accurate detection is achieved even in situations involving partial visibility of PPE items or crowded construction areas.In addition to detection, the system incorporates an automated alert mechanism to ensure immediate response to safety violations. When non-compliance is identified, notifications are generated and transmitted through SMS and mobile applications to relevant authorities, enabling prompt corrective actions. Continuous monitoring and instant reporting significantly reduce the risk of overlooked violations and improve overall safety enforcement. The proposed framework not only enhances worker protection but also supports regulatory compliance and efficient safety management practices across construction sites.

V. METHODOLOGY

Data Collection and Annotation

A comprehensive dataset is assembled from construction site images and video frames capturing various working conditions and safety scenarios. The dataset includes multiple classes of Personal Protective Equipment (PPE) such as helmets, safety vests, gloves, boots, and masks, along with instances of non-compliance. Each sample is carefully annotated using bounding boxes to identify and label PPE categories, ensuring accurate supervision during model training.

Data Preprocessing and Augmentation

Collected data undergoes preprocessing steps to enhance quality and consistency. Image resizing, normalization, and noise reduction techniques are applied to standardize the input format. Data augmentation methods such as rotation, flipping, scaling, and brightness adjustment are utilized to increase dataset diversity and improve the model’s ability to generalize across varying environmental conditions.

Model Architecture and Training

An enhanced YOLOv11 deep learning model is employed for object detection and classification of PPE items. The model is trained using the annotated dataset to learn spatial and contextual features associated with different safety equipment. Optimization techniques, including fine-tuning and hyperparameter adjustment, are applied to achieve high detection accuracy and efficient learning performance.

Real-Time Detection and Analysis

The trained model is deployed to process live video streams from surveillance cameras. It performs real-time detection of workers and identifies whether appropriate PPE is being used. The system analyzes each frame continuously,

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ensuring rapid and accurate identification of safety compliance and violations under dynamic construction site conditions.

Violation Detection and Alert Mechanism

Upon detecting PPE non-compliance, the system triggers an automated alert mechanism. Notifications are sent through SMS and mobile applications to supervisors or safety personnel, enabling immediate corrective actions. This ensures timely intervention and reduces the risk of accidents caused by safety negligence.

System Evaluation and Performance Analysis

The performance of the detection system is evaluated using metrics such as accuracy, precision, recall, and F1-score. Testing is conducted under various environmental conditions to assess robustness and reliability. The evaluation results demonstrate the effectiveness of the approach in achieving consistent and accurate PPE detection in real-time scenarios.

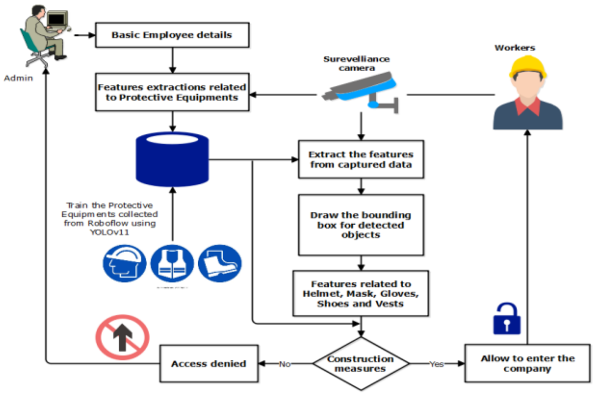


Figure 1: Diagram representation of the proposed methodology

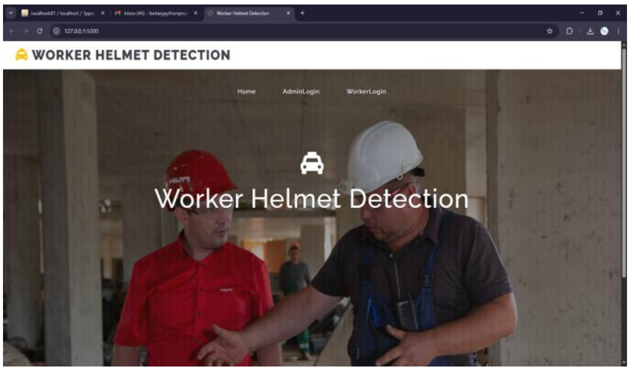
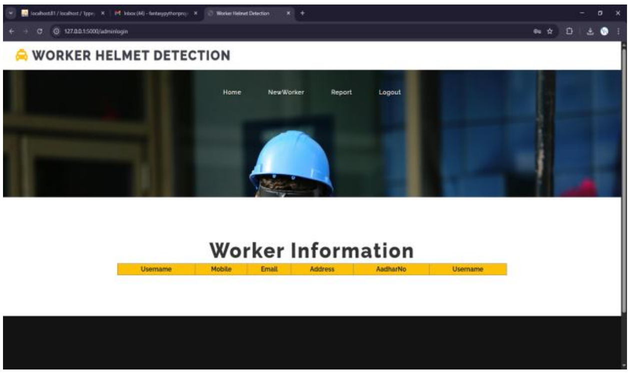


Figure (a) Home page of web



(b) Worker info tab

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VI. EXPERIMENTAL RESULTS

The experimental evaluation demonstrates the effectiveness of the proposed PPE detection framework in real-time construction site scenarios. The enhanced YOLOv11 model was trained and tested on a diverse dataset containing multiple PPE categories under varying environmental conditions such as low lighting, occlusions, and crowded backgrounds. The system achieved high detection accuracy and maintained consistent performance across different scenarios, confirming its robustness and generalization capability. Real-time testing indicated minimal latency, enabling continuous monitoring without significant delays, which is essential for safety-critical applications.

Comparative analysis with existing approaches highlights substantial improvements in detection accuracy, precision, and recall. Traditional methods based on manual inspection and conventional machine learning techniques exhibited lower performance due to limited feature extraction capabilities and lack of real-time adaptability. In contrast, the proposed model effectively captured complex visual patterns and contextual information, resulting in more reliable identification of PPE compliance and violations. Additionally, the integrated alert mechanism ensured immediate notification, reducing response time to safety hazards.

Performance Metric	Existing System	Proposed System
Accuracy	82%	95%
Precision	80%	94%
Recall	78%	93%
F1-Score	79%	93.5%
Detection Speed	Moderate	High (Real-Time)

Table 1: Performance Comparison Table

The performance comparison illustrates a significant improvement achieved by the proposed approach over traditional systems. Accuracy is notably increased, indicating more correct predictions of PPE usage. Precision and recall values demonstrate enhanced capability in correctly identifying both compliance and violations, reducing false positives and false negatives. The F1-score reflects a balanced improvement between precision and recall, confirming overall model reliability. Furthermore, detection speed is considerably enhanced, enabling real-time operation, which is critical for immediate safety monitoring and rapid response in construction environments.

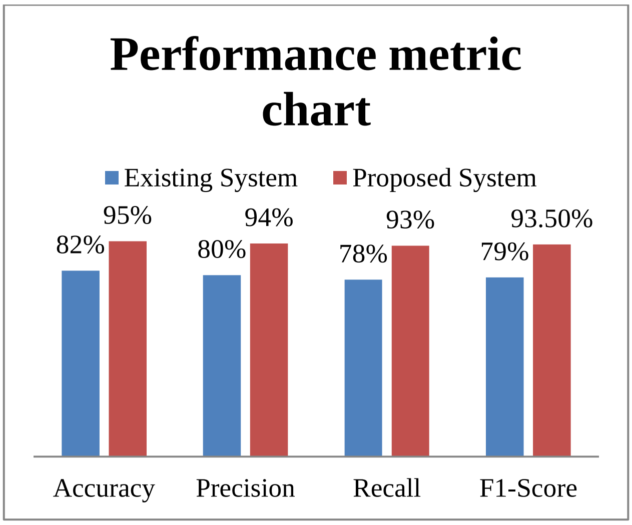

Figure 2: Performance metric chart representation

VII. CONCLUSION

The presented research demonstrates an effective approach for enhancing construction site safety through automated detection of Personal Protective Equipment (PPE) using an advanced YOLOv11-based deep learning framework. By leveraging real-time video analysis, the system accurately identifies multiple PPE components and detects safety

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violations under diverse and challenging environmental conditions. The integration of context-aware detection capabilities ensures consistent performance even in scenarios involving poor lighting, occlusions, and high worker density. This approach overcomes the limitations of traditional manual monitoring methods by providing continuous, reliable, and accurate supervision.Furthermore, the incorporation of an automated alert mechanism enables immediate notification of non-compliance, allowing timely corrective actions and reducing the risk of workplace accidents. The experimental results highlight significant improvements in accuracy, precision, and real-time responsiveness compared to existing systems. Overall, the proposed framework contributes to improved safety management practices, supports regulatory compliance, and promotes a safer working environment in construction industries through intelligent and scalable monitoring solutions.

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