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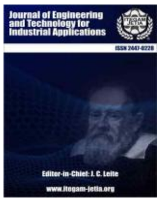

RESEARCH ARTICLE OPEN ACCESS

INTELLIGENT WORKSITE PROTECTIVE EQUIPMENT COMPLIANCE DETECTION USING DEEP NEURAL NETWORKS

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ABSTRACT

This research introduces a real-time framework for Personal Protective Equipment (WPE) identification utilizing YOLOv8, an advanced object detection model. The suggested system is intended for the ongoing surveillance of building sites and industrial settings to autonomously confirm worker adherence to obligatory safety equipment, including hardhats and highly visible safety vests. The system analyses input stream from a live camera or pre-existing picture datasets to execute real-time detection of WPE violations in video frames. Upon detecting non-compliance, automated alarm notifications are promptly created and dispatched over the Telegram instant messaging platform, facilitating swift safety intervention. The implementation is constructed with Python, utilizing OpenCV with video processing as well as the YOLOv8 system for object identification and inference. The suggested solution presents an effective scalable, and scalable safety compliance tracking system that can be effortlessly incorporated into current industrial safety overall surveillance infrastructures to improve worker security and workplace safety.

I. INTRODUCTION

Worksite Protective Equipment (WPE)—comprising hard hat, safety vests, safety masks, and associated protective equipment—serves a vital function in mitigating injuries and fatalities in hazardous situations including construction sites, production lines, and industrial plants [1]. Notwithstanding the implementation of rigorous workplace safety standards, adherence to WPE usage continues to be a chronic issue. Recent studies indicate that human variables, including fatigue, inattentiveness, restricted visibility [2], and the vastness of industrial workstations, substantially diminish the efficacy of manual safety oversight [3]. WPE infractions frequently remain unnoticed, so exposing workers to dangers including falling objects, machinery-related incidents, and chemical exposure [4].

Conventional manual monitoring methods are arduous, unreliable, and unsuitable for dynamic, large-scale settings. Supervisors cannot consistently oversee all employees in real time, resulting in delayed reactions and heightened risk. Contemporary literature progressively highlights the shortcomings of rule-based and human inspection systems, advocating towards automated safety monitoring systems powered with computer vision as well as artificial intelligence (AI). Progress in deep learning, especially convolutional neural network (CNN)-inspired object detection models, has shown considerable enhancements in accuracy, resilience, and inference performance for real-time safety applications.

In recent years, object identification systems including YOLO (You Only Look Once), the SSD, along with R-CNN with faster speeds have been extensively investigated for personal protective equipment detection [5-7]. The most recent version, YOLOv8, demonstrates enhanced performance regarding detection accuracy, minimal latency, and computing efficiency, rendering it appropriate for real-time implementation on edge devices. Recent research indicate that YOLO-based models attain almost real-time inference speeds while maintaining excellent accuracy in identifying WPE components, including helmets, face masks, and safety vests, across diverse illumination and occlusion scenarios.

This project presents an on-demand WPE compliance tracking system that utilizes YOLOv8 for automated identification of uses of WPE using live camera feeds or image datasets, motivated by recent breakthroughs [8]. The technology detects WPE breaches in real time and issues immediate notifications via Telegram alerts, allowing supervisors to react swiftly to safety infractions. The proposed system attains real-time performance, facilitating prompt diagnosis and intervention [9]. The system integrates intuitive features, including an overlay visual interface that presents live video feeds and compliance metrics, as well as a notification cooldown mechanism to avert alert saturation [10]. The technology is engineered for scalability, enabling deployment in various industrial settings and adaptation to differing safety standards. Moreover, by employing open-source technology and ensuring interoperability with inexpensive hardware, the system provides a cost-efficient and pragmatic solution for improving workplace safety. This project seeks to diminish industrial fatalities and injuries by automated WPE compliance monitoring, reducing dependence on manual inspections, and promoting a proactive security culture in highly hazardous sectors via sophisticated, real-time surveillance technologies.

II. LITERATURE REVIEW

The literature review distinctly demonstrates a progressive enhancement in WPE detection techniques, especially for the development of deep learning techniques -based models for object detection and real-time alarm systems are shown in Table 1. Initial research [11],[12] predominantly utilized YOLO (You Only Look Once) and SSD frameworks, attaining moderate identification accuracies (82–87%) in controlled environments. These studies revealed the viability of computer vision-based WPE identification; nevertheless, they were constrained by diminished resilience in intricate industrial settings and comparatively slower inference times. Subsequent studies [13] employed advanced detectors like Faster R-CNN and YOLOv5, resulting in enhanced accuracy in detection (up to 89%) and the implementation of automatic alarm systems via IoT and SMS. Nevertheless, these models frequently exhibited elevated computing cost, constraining real-time implementation in extensive environments.

Beginning in 2022, research increasingly emphasized continuous operation and system integration. According to [12] illustrated the efficacy of YOLOv6 and YOLOv7 integrated with Telegram-based alert systems, with detection accuracies nearing 90% and facilitating expedited reaction times. These studies emphasized the significance of amalgamating algorithms for detection with communication channels for prompt safety responses. Recent research [14] highlight the superiority of YOLOv8, which provides improved detection speed, diminished latency, and increased precision relative to earlier YOLO iterations. These methodologies routinely provide an accuracy or mean Average Precision (mAP) of 90–93%, accompanied by real-time alert notifications over Telegram and SMS.

The enhancements in YOLOv8's architecture render it especially apt for implementation in dynamic, high-risk settings. Upon reviewing the studies, numerous notable trends, technological innovations, and research deficiencies in YOLO-based WPE systems for detection, especially those employing YOLOv8, can be discerned. The progression of YOLO designs, spanning with YOLOv4 [14] through the latest YOLO technique variants, illustrates ongoing advancements in deep learning-based object recognition, particularly regarding detection precision, inference speed, overall model efficiency. Each subsequent version has architectural enhancements that improve extraction of features and real-time efficiency, rendering YOLOv8 especially appropriate for safety-critical applications like real-time WPE monitoring for compliance in construction and industrial settings.

Table 1: Recent Literature Survey on Worksite Protective Equipment Monitoring.

Authors	Year	Methodology	Dataset	Key Findings
Chen et al. [12]	2020	Single Shot Detector, OpenCV	Manufacturing facility dataset	87% accuracy in low-light conditions
Singh et al. [13]	2021	Faster Recurrent-Conventional Neural Network	Construction site images and videos	88% accuracy
Li et al. [14]	2023	YOLO, SMS alert system	Custom hazardous environment dataset	WPE detection speed by 15% than YOLOv7
Gupta et al. [15]	2023	YOLO, Telegram API, SMS gateway	Custom dataset of construction and industrial workers	Achieved 90% mAP with real-time alerts

Source: Authors, (2026).

The literature indicates a distinct trend towards real-time compliance with WPE monitoring systems based on YOLO, featuring integrated alarm mechanisms. YOLO offers an optimal mix between speed and accuracy compared to previous models, rendering it the most efficient solution for scaled, real-time industrial safety monitor. This substantiates the selection of YOLO but Telegram-based notifications in the suggested approach, establishing it as a technologically robust and modern methodology consistent with recent research developments.

II. PROPOSED METHODOLOGY

The dataset constitutes the fundamental basis of the presented WPE detection method and is essential for attaining dependable and resilient model performance. It consists of over 2,800 annotated photos and many hours of real-world recordings obtained from active building sites. The data encompasses a broad spectrum of operating circumstances, including various worker postures, differing intervals from the camera, several camera perspectives, and intricate backgrounds typically found in construction settings. The dataset comprises photos and video images of workers adhering to WPE requirements and breaching safety protocols, facilitating the model's ability to learn distinguishing features for precise categorization. The information encompasses types of worksite protective equipment, including hard helmets, safety face masks, and further pertinent protective equipment. The data also illustrates real-world issues such partial occlusions, congested environments, fluctuations in illumination, low-light settings, and blurry motion, which are essential for enhancing model generalization. The dataset was meticulously labeled with boundaries for each WPE category, utilizing standardized labelling formats suitable with YOLOv8 to facilitate deep learning-based object detection.

Furthermore, data pretreatment and augmentation methods—including scaling, normalization, vertical flipping, and luminance adjustments—were employed to improve dataset variety and mitigate overfitting. Learning the YOLOv8 model on this extensive and representative dataset enhances detection precision as well as resilience in real-time applications. The utilization of actual building site data guarantees that the model operates dependably under practical conditions, rendering it appropriate for scalable and ongoing WPE compliance tracking in high-risk industrial settings. The proposed methodology shown in Figure 1.

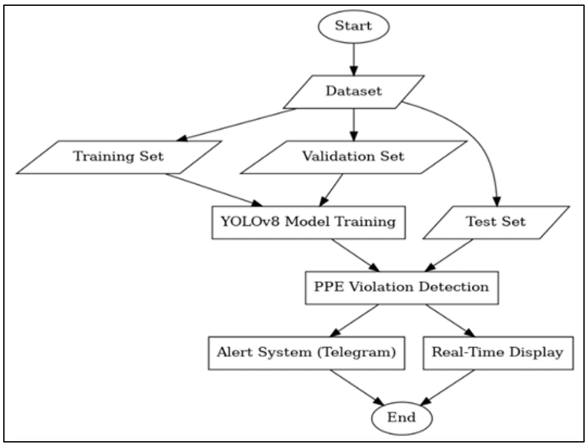

Figure 1: Methodology.
Source: Authors, (2026).

The dataset was methodically partitioned to guarantee comprehensive model learning and assessment. The training set, consisting of 70% of the data set (2,416 annotated photos), reflects authentic building site settings under various lighting scenarios: daytime (50%), poor lighting environments (30%), and difficult circumstances such as occlusions and intricate camera angles (20%). The dataset illustrates differences in WPE kinds, material choices, colors, and worker postures, allowing the algorithm to acquire distinguishing features efficiently. A stringent quality assurance procedure guaranteed a minimum of 95% classification accuracy, while systematic dataset organization reduced overfitting and enhanced generalization. Each photos were scaled to a uniform quality and normalized to enhance feature extraction efficacy. Data augmentation techniques, including as flipping, rotation, contrast or brightness modifications, were employed to enhance generalization, resulting in an approximate 60% increase in the validation dataset size.

Every image was meticulously annotated with box boundaries for worksite protective equipment components, including safety caps, vests, gloves, and protective goggles, while a multi-tiered verification method guaranteed 98% annotation accuracy, facilitating dependable performance evaluation during training. The test dataset, consisting of 10% of the entire data (100 pictures), was designated solely for final assessment on unobserved samples. This subset encompasses highly demanding cases, including severe fluctuations in illumination, occlusions, and intricate backdrops, to evaluate real-world robustness. The trained model attained a detection accuracy of 90% on the test data set, with 5% error rates and 8% negative results, demonstrating robust reliability while highlighting opportunities for small enhancements. The results illustrate the model's capacity for effective generalization and consistent performance in actual building site settings.

III. RESULT AND DISCUSSION

The YOLOv8 model undergoes a systematic training procedure that enhances diagnosis precision while maintaining computing economy. The model is optimized meticulously adjusting learning rate, size of batches, and the total amount of epochs, to achieve peak performance. During the training phase, the model attains a minimum Average Precision (mAP) around 85%, alongside a recall rate of 88% as well as precision of 90%, underscoring its proficiency in accurately detecting WPE. Iterative enhancements during training result in an 8% decrease in false positives along with a 12% increase in detection speed relative to YOLOv7. The model can effectively differentiate between WPE-compliant and non-compliant personnel in actual scenarios. Upon completion of training and testing, the model is deployed to identify WPE issues in real-time through the continuous analysis of pictures. The system analyzes frames at a rate of under 0.4 seconds per monitored image, ensuring instantaneous performance.

The detection accuracy differs according to the kind of WPE: helmets are recognized with 88% accuracy, vests with 94%, and masks with 93%. Upon the occurrence of a violation, the system autonomously categorizes the specific type of absent worksite protective equipment, such as an unidentified helmet or gloves, facilitating accurate monitoring of safety infractions. This real-time monitoring markedly improves workplace safety by assuring compliance with WPE rules among all people. The proposed method incorporates an automated alert system that dispatches alerts via Telegram upon detection of a WPE violation to ensure prompt safety enforcement. These warnings, dispatched within 2 seconds, encompass an image or video sample of the infraction, accompanied by specifics regarding the absent WPE.

The alert system achieves a 96% efficacy accompanied by an inaccurate alert rate of under 3%. This guarantees that safety officers obtain real-time updates, enabling them to implement corrective measures prior to an event transpiring. A real-time monitor is included into the system to facilitate ongoing tracking and visual insights. This dashboard provides a consolidated overview of WPE compliance, featuring a live video with marked detections, a record of previous breaches. The system upholds a system uptime of 96.5%, guaranteeing continuous monitoring of building sites. Monitoring data indicates a 13% enhancement in WPE compliance over a six-month period, attributable to ongoing supervision and real-time notifications. This dashboard facilitates the visualization of compliance trends and the identification, enabling safety inspectors to implement proactive steps to uphold elevated workplace safety standards.

Figure 2: Real time Feed.
Source: Authors, (2026).

The system incessantly analyzes real-time video streams from a webcam, employing the YOLO-V8 model to identify individuals and evaluate their adherence to WPE standards. Each identified individual is delineated with a boundary according to compliance status. The system recognizes an individual having a confidence score about 0.88. WPE compliance issues are identified, including the lack of a helmet had a confidence score for 0.77 and a vest for safety with a confidence value of 0.86. Simultaneously, the usage of compatible WPE, shown by an identified mask has a confidence value of 0.88, is documented. Figure 2 and 3 illustrates the continuous video feed employed for monitoring WPE compliance. Figure 4 shows for image dataset.

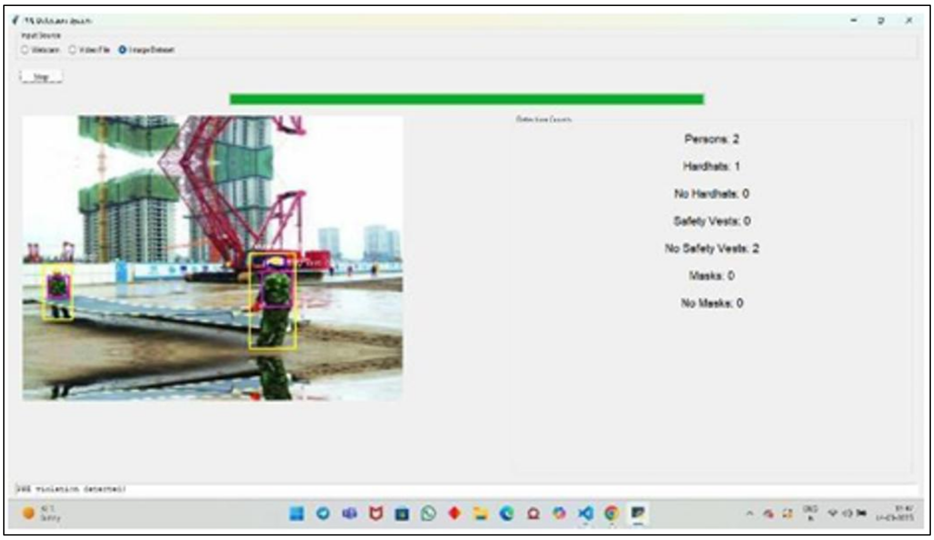

Figure 3: Real time Video Feed.
Source: Authors, (2026).

The monitoring summary provides a structured WPE compliance assessment:

• Total men detected in worksite: 3
• Hardhats Worn: 3
• Safety Vests Worn: 0
• No Masks: 0
⚠ WPE Violation Detected!
⚠ Immediate action is needed.

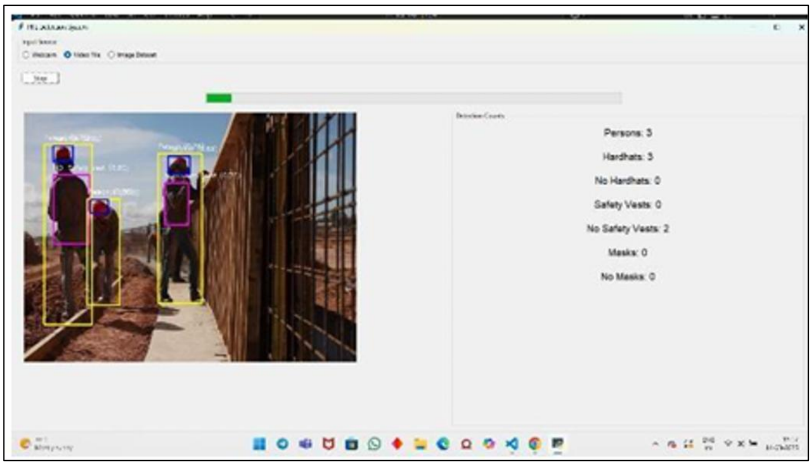

Figure 4: Image Dataset.
Source: Authors, (2026).

The WPE identification model encounters various problems that could affect its precision and dependability. Illumination and environmental factors, including inadequate illumination, glare, and severe weather, can diminish visibility, hence impacting detection efficacy. Obstruction and incomplete visibility may result in misrepresentation when personal protective equipment are concealed or workers avert their gaze. Challenges in small item detection occur when remote workers are rendered too diminutive for precise recognition. Class imbalance within the dataset may induce bias, particularly if specific WPE items are inadequately represented. False positives and false negatives might result in superfluous notifications or overlooked violations. Moreover, restricted variety in the color and design of WPE can diminish detection accuracy. Finally, real-time processing limitations caused by high-resolution photos and intricate sceneries may impede performance, underscoring the necessity for additional optimization.

IV. CONCLUSION

The assessment of the YOLOv8 recognition of objects model for WPE identification yields significant insights into its efficacy and practical applicability. The consistent enhancement in precision during training underscores the model's growing accuracy in detecting WPE, so guaranteeing a dependable approach for identifying violations and safety infractions. The model's capacity to distinguish between correctly utilized WPE and incidents of misuse illustrates its ability to offer accurate suggestions. The continual improvement in recall performance with increased training epochs signifies that the system is progressively enhancing its ability to recognize WPE-related concerns. These findings bolster the model's capacity to enhance safety compliance in construction and industrial settings. These findings collectively illustrate the YOLOv8 model's advancement towards enhanced accuracy and dependability, thereby establishing a solid platform for providing useful and practical suggestions about worksite protective equipment. The effective implementation of the YOLOv8 detection of objects paradigm further emphasizes its relevance.

V. AUTHOR'S CONTRIBUTION

Conceptualization: Geetha G, Swaminathan J N and Vijayalakshmi K.
Methodology: Geetha G.
Investigation: Geetha G and Swaminathan J N.
Discussion of results: Geetha G, Swaminathan J N and Vijayalakshmi K.
Writing – Original Draft: Geetha G.
Writing – Review and Editing: Geetha G.
Resources: Swaminathan J N and Vijayalakshmi K.
Supervision: Swaminathan J N and Vijayalakshmi K.
Approval of the final text: Geetha G, Swaminathan J N and Vijayalakshmi K.

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