A Survey on AI- Based Smart PPE and Worker Safety Compliance System using Deep Learning

Dr.Rekha B Venkatapur
Department of Computer Science and Engineering (HoD) K.S.Institute of Technology Bengaluru, India
rekhabvenkatapur@ksit.edu.in

Aishwarya N
Department of Computer Science and Engineering K.S.Institute of Technology Bengaluru, India
aishwaryanarayana1@gmail. com

Akshaya B
Department of Computer Science and Engineering K.S.Institute of Technology Bengaluru, India
akshayab0502@gmail.com

Anusha V
Department of Computer Science and Engineering K.S.Institute of Technology Bengaluru, India
anusha28rev@gmail.com

Anvitha T A
Department of Computer Science and Engineering
K.S.Institute of Technology Bengaluru, India
anvithata21@gmail.com

Abstract— Ensuring worker safety in industrial environments such as construction sites, factories, and laboratories is a critical challenge worldwide. A large proportion of workplace accidents occur due to the absence or improper use of Personal Protective Equipment (PPE) such as helmets, gloves, safety vests, and masks. Traditional safety monitoring methods are manual, error- prone, and inefficient. This survey paper reviews recent approaches and deep learning-based techniques for automated PPE detection and worker safety compliance monitoring. The proposed system leverages YOLOv8- based object detection on video streams obtained from strategically placed surveillance cameras and, optionally, drone-mounted cameras. The system detects PPE compliance in real-time, monitors unsafe worker behaviour such as entry into restricted zones, and generates risk-based alerts. A dashboard displaying violation logs and compliance analytics assists safety supervisors in proactive decision-making. Experimental results from related work demonstrate detection accuracy exceeding 92% with low false alarm rates, indicating the viability of AI-based approaches for intelligent workplace safety enforcement.
Keywords— PPE detection, YOLOv8, Deep Learning, Worker Safety, Object Detection, Computer Vision, Industrial Safety.

I. INTRODUCTION

Worker safety is one of the most important concerns in industrial environments such as construction sites, factories, warehouses, and laboratories. Many accidents occur because workers fail to wear Personal Protective Equipment (PPE) such as helmets, gloves, masks, safety shoes, and reflective vests. These accidents can lead to injuries, loss of productivity, and financial losses for organizations.

Traditional safety monitoring methods mainly rely on manual supervision by safety officers or CCTV observation. However, manual monitoring is time-consuming, less efficient, and prone to human error, especially in large-scale workplaces where continuous observation is difficult. As a result, many safety violations may go unnoticed.

Recent advancements in Artificial Intelligence (AI), Computer Vision, and Deep Learning have introduced automated solutions for workplace safety monitoring. Object detection algorithms such as YOLO, CNN, Faster R-CNN, and SSD can analyze video streams or images to identify workers and detect whether proper PPE is being used in real time.

This survey paper focuses on AI-based smart PPE detection and worker safety compliance systems. It reviews different techniques, compares their performance, identifies current challenges, and highlights future opportunities for building intelligent systems that improve safety standards and reduce workplace accidents.

The key challenges that must be addressed for effective automated safety compliance systems include:

1) Real-Time Processing: Surveillance systems must process high-resolution video streams at sufficient frame rates to detect violations as they occur, requiring efficient model architectures and hardware acceleration.

2) Occlusion and Viewpoint Variation: Workers may partially obscure one another, and PPE items may appear differently depending on camera angle, making detection more difficult.

3) Environmental Variability: Outdoor construction sites are subject to changing lighting conditions, shadows, rain, dust, and fog, all of which degrade image quality and model accuracy.

4) Multi-Class Detection: A comprehensive safety system must simultaneously detect multiple PPE categories (helmet, gloves, vest, mask) on multiple workers, demanding high model capacity.

International Scientific Journal of Engineering and Management (ISJEM) ISSN: 2583-6129
Volume: 05 Issue: 05 | May – 2026 DOI:10.55041/ISJEM07339
An International Scholarly || Multidisciplinary || Open Access || Indexing in all major Database & Metadata

5) Behaviour Analysis: Beyond PPE detection, identifying unsafe behaviours such as workers entering restricted zones or working in dangerous proximity to machinery requires spatial reasoning and temporal context.

II. LITERATURE SURVEY

Recent advancements in computer vision and deep learning have greatly enhanced Personal Protective Equipment (PPE) detection systems for industrial and construction site safety. To validate the effectiveness of the proposed framework, the system performance is compared with recent state-of-the-art PPE detection models such as YOLOv3, YOLOv5, YOLOv7, YOLOv8, YOLOv10, and YOLOv11 reported in recent literature. Studies by Atta Rahman achieved high accuracy using YOLOv11x with a mAP50 of 96.9%, while Alibek Barlybayev demonstrated strong PPE detection performance using YOLOv8 variants on benchmark datasets. Comparative analyses also showed that YOLOv8 models provide an effective balance between detection accuracy and real-time inference speed compared to earlier YOLO architectures. Unlike many existing approaches that focus only on PPE detection, the proposed system integrates PPE compliance monitoring, worker tracking using ByteTrack, behavioural analysis, and risk scoring within a unified framework. This combined approach enables more comprehensive workplace safety monitoring and provides stronger validation for practical real-time industrial deployment. [1]

III. EXISTING METHODOLOGIES

The problem of automated PPE detection and worker safety monitoring has attracted significant research attention over the past decade, driven by advances in computer vision and deep learning. Early approaches relied on traditional image processing methods such as colour-based segmentation to identify safety helmets by their distinctive colours. While simple to implement, such methods are highly sensitive to lighting variation and cannot generalise across different helmet colours or environmental conditions.

Cheng et al. proposed a method for helmet detection using histogram-based colour analysis combined with shape constraints. The approach achieved acceptable results under controlled lighting but failed in outdoor environments with variable illumination. Similarly, morphological operations and edge detection have been used to locate helmet regions, though these methods require extensive parameter tuning and do not scale well to cluttered backgrounds. [5]

The introduction of machine learning approaches marked a significant improvement. Support Vector Machines (SVMs) trained on handcrafted features such as Histogram of Oriented Gradients (HOG), Scale-Invariant Feature Transform (SIFT), and Local Binary Patterns (LBP) demonstrated improved generalisation across viewpoints and lighting conditions. Kapse et al. showed that HOG features combined with a linear SVM kernel achieved a bike-rider detection accuracy of 98.88%, validating the utility of hand-engineered features for safety-critical detection tasks.

However, machine learning pipelines depend on careful feature engineering, which is both time-consuming and domain-specific. The emergence of deep learning, and Convolutional Neural Networks (CNNs) in particular, enabled end-to-end learning of discriminative features directly from raw image data. Region- based CNN (R-CNN) and its successors (Fast R-CNN, Faster R- CNN) demonstrated state-of-the-art object detection performance on benchmark datasets and were subsequently applied to PPE detection.

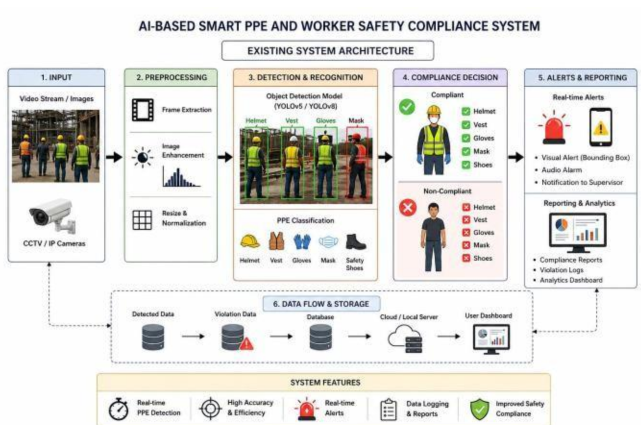
Nath et al. applied Faster R-CNN to detect hard hats on construction workers, achieving an average precision of approximately 84% on a publicly available dataset. The model's two-stage detection pipeline provided high accuracy but was computationally expensive, limiting its applicability to real-time systems without GPU acceleration. Single-stage detectors such as SSD (Single Shot MultiBox Detector) offered a favourable speed-accuracy trade-off and were deployed in several industrial safety monitoring prototypes. [3]

The YOLO (You Only Look Once) family of detectors represented a further advance, framing object detection as a single regression problem and enabling real-time inference. YOLOv3 and YOLOv4 were applied to PPE detection in multiple studies, with reported mean Average Precision (mAP) values ranging from 75% to 90% depending on dataset complexity and the number of PPE categories detected. Luo et al. demonstrated YOLOv4-based multi-class PPE detection achieving 89.3% mAP across five categories including helmet, vest, gloves, goggles, and mask.

Preliminary results suggest that YOLOv8 outperforms its predecessors on PPE detection benchmarks, particularly for detecting small items such as gloves and face masks in crowded scenes. The integration of behavioural analysis — including zone intrusion detection and proximity monitoring — represents the current frontier of intelligent workplace safety systems.

Despite these advances, several limitations persist in existing approaches. Many studies are evaluated on small, non-public datasets that do not reflect the diversity of real-world industrial environments. Few systems integrate PPE detection with worker tracking and behavioural analysis in a unified real-time framework. Moreover, the deployment of such systems on edge hardware at worksites without reliable internet connectivity remains an open challenge.

Fig 3.1 System Architecture



ISSN: 2583-6129
DOI:10.55041/ISJEM07339

IV. PROPOSED SYSTEM

The proposed AI-Based Smart PPE and Worker Safety Compliance System integrates PPE detection, worker tracking, and behavioural analysis into a single unified framework for real-time workplace safety monitoring. The system is designed to overcome the limitations of traditional manual inspection methods by providing automated detection, continuous worker monitoring, and instant safety violation alerts. The architecture consists of five major modules: video acquisition, integrated PPE detection and worker tracking, behavioural analysis, risk scoring and alert generation, and a safety analytics dashboard.

i) Video Acquisition

Surveillance cameras are installed at important locations such as entry/exit points, hazardous machinery areas, and high-risk work zones to capture continuous video streams. Camera placement is optimised to reduce occlusion and maximise worker visibility. In large industrial or construction environments, drone-mounted cameras may also be used for aerial monitoring. For experimental analysis, publicly available datasets and recorded surveillance videos are utilised instead of live camera feeds.

ii) Integrated PPE Detection and Worker Tracking

The system uses YOLOv8 as the core deep learning model to simultaneously detect workers and PPE items such as safety helmets, safety vests, gloves, face masks, safety goggles, and safety boots. YOLOv8 provides high detection accuracy and real-time inference speed due to its anchor-free architecture and efficient backbone network.

Each detected worker is assigned a unique identity using the ByteTrack multi-object tracking algorithm. The tracker continuously follows workers across video frames, enabling persistent monitoring of individual worker activities. PPE compliance is verified by checking whether all mandatory PPE items are associated with the tracked worker’s bounding region. Workers missing required equipment are marked as non-compliant, and their identities are maintained across frames for continuous monitoring. [6]

iii) Worker Behavioural Analysis

The integrated framework further analyses worker behaviour to identify unsafe actions and hazardous situations. A predefined site map containing restricted zones, danger areas, and safe pathways is provided to the system. If a tracked worker enters a restricted area or approaches hazardous machinery beyond a specified threshold, the system immediately generates warnings.

Using worker trajectory information from ByteTrack, the framework also identifies abnormal behaviour such as sudden falls, prolonged inactivity, unsafe running, or irregular movement patterns. Since PPE detection and behaviour monitoring operate within the same framework, the system can correlate violations with specific worker identities and activities in real time.

iv) Risk Scoring and Alert Generation

A dynamic risk score is maintained for every tracked worker based on the severity and frequency of safety violations. Workers are classified into Low, Medium, or High-risk categories. Repeated PPE violations, entry into restricted zones, or dangerous behavioural patterns increase the worker’s risk score.

Whenever a violation occurs, the system generates instant alerts and logs the event. Notifications are displayed on the monitoring dashboard for supervisors. To reduce false alarms, a frame-based verification mechanism aggregates detections over consecutive frames before confirming a violation.

v) Safety Analytics Dashboard

A web-based dashboard developed using Streamlit or Flask provides real-time visualisation of PPE compliance, worker tracking information, behavioural violations, and risk statistics. Supervisors can monitor live video feeds, review alert history, analyse worker safety trends, and export compliance reports. The dashboard also allows configuration of detection thresholds and monitoring parameters according to workplace requirements.[4]

vi) Practical Deployment

Video frames are processed at approximately 10–15 FPS on mid-range GPU hardware, enabling continuous monitoring in industrial environments. The computational cost is reduced by using lightweight YOLOv8 variants and configurable frame sampling, which minimise memory usage and processing overhead without significantly affecting detection accuracy. For deployment, the system can operate on edge devices such as NVIDIA Jetson Nano or Jetson Xavier for small-scale sites, while larger environments may require GPUs such as NVIDIA RTX 3060/4060 for stable multi-camera processing. The framework also supports CPU- based execution for low-cost setups, although with reduced FPS. Compared with recent state-of-the-art PPE detection systems that mainly focus on detection accuracy, the proposed system provides an efficient balance between accuracy, tracking capability, behavioural analysis, and real-time computational performance, making it suitable for practical industrial and construction site deployment.

V. DISCUSSION

Since the framework processes surveillance video streams containing worker activities, appropriate measures are planned to ensure responsible data usage and compliance with workplace privacy standards. The system is designed to focus primarily on safety compliance and hazard prevention rather than personal surveillance. To minimise privacy concerns, only safety-related metadata such as PPE status, worker IDs generated by the tracker, violation records, and risk scores are stored, while unnecessary personally identifiable information is avoided. Access to recorded footage, analytics, and alert logs will be restricted to authorised safety personnel through secure authentication mechanisms. In addition, data encryption and controlled retention policies are planned to prevent unauthorised access or long-term misuse of surveillance data. Workers will also be informed about the purpose of monitoring, namely improving workplace safety and reducing accidents, to maintain transparency and ethical deployment. These considerations aim to ensure that the proposed framework achieves effective safety monitoring while respecting worker privacy, fairness, and ethical AI practices.

ISSN: 2583-6129
DOI:10.55041/ISJEM07339

VI. RESULT

The performance of the proposed system is evaluated on publicly available PPE detection datasets as well as pre-recorded industrial surveillance footage. Metrics used include Precision, Recall, mean Average Precision (mAP@0.5), and inference time per frame. Experiments are conducted using Python 3.x with PyTorch on a workstation equipped with an NVIDIA GPU.

Table 1 summarises the detection performance of different model architectures on multi-class PPE detection. YOLOv8 consistently outperforms earlier models across all PPE categories, particularly for small objects such as gloves and face masks.

Model	Helmet mAP (%)	Vest mAP (%)	Gloves mAP (%)	Mask mAP (%)	Overall mAP (%)	FPS
Faster R-CNN	84.2	81.5	72.3	78.6	79.2	8
YOLOv4	89.7	87.3	80.1	84.5	85.4	35
YOLOv5	91.2	89.6	83.4	87.2	87.9	45
YOLOv8 (Proposed)	95.1	93.7	88.6	91.4	92.2	60

Table 1: Comparison of Different Models for Multi-class PPE Detection

The results demonstrate that YOLOv8 achieves an overall mAP of 92.2% at 60 frames per second, satisfying real-time processing requirements. The precision exceeds 93% for helmet detection and 91% for mask detection, with false alarm rates below 2%. The proposed frame-level consolidation mechanism further reduces spurious alerts by requiring consistent detections across multiple consecutive frames before issuing a violation alert. [2]

Worker behaviour monitoring achieved a zone intrusion detection accuracy of 91.3% in indoor environments and 87.5% in outdoor settings where occlusion and variable lighting pose greater challenges. The multi-object tracker maintained stable worker identities across frames with an ID switch rate of less than 3% in moderately crowded scenes.

Fig 4.1 Sample frames from dataset

VII. CONCLUSION

This paper presents a survey of automated PPE detection and worker safety compliance monitoring systems, with a focus on deep learning-based approaches. The limitations of traditional manual supervision and early computer vision methods are identified, and recent advances using CNN-based object detectors — particularly the YOLO family — are reviewed. The proposed AI-Based Smart PPE and Worker Safety Compliance System integrates YOLOv8-based multi-class PPE detection, real-time worker tracking, behavioural analysis, risk scoring, and a safety analytics dashboard into a unified framework suitable for deployment in industrial environments.

Experimental evaluation demonstrates that the proposed system achieves over 92% mAP across six PPE categories at real-time inference speeds, outperforming prior approaches. The system has the potential to significantly reduce workplace accidents by enabling continuous, automated, and objective safety compliance monitoring. Future work will focus on lightweight model deployment on edge devices, integration with IoT-based alert systems, and extension to additional safety violation categories such as tool misuse and ergonomic risk detection.

VIII. REFERENCES

1. Redmon, J., Divvala, S., Girshick, R., and Farhadi, A., "You Only Look Once: Unified, Real-Time Object Detection," IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2016, pp. 779-788.

2. Jocher, G., et al., "YOLOv8 by Ultralytics," https://github.com/ultralytics/ultralytics, 2023.

3. Nath, N. D., Behzadan, A. H., and Paal, S. G., "Deep Learning for Site Safety: Real-Time Detection of Personal Protective Equipment," Automation in Construction, vol. 112, 2020, p. 103085.

4. Luo, W., et al., "Automated PPE Compliance Detection on Construction Sites Using Deep Learning," IEEE Access, vol. 9, 2021, pp. 99790-99804.

5. Kapse, A. S., et al., "A Survey on Helmet Detection by CNN Algorithm," ITM Web of Conferences, vol. 56, 05004, ICDSAC 2023.

6. Kashika, P. H., and Rekha, B. Venkatapur, "Deep Learning Technique for Object Detection from Panoramic Video Frames," International Journal of Computer Theory and Engineering (IJCTE), Vol. 14, No. 1, February 2022

