Real-Time Detection and Monitoring of PPE Kit Compliance in Construction Sites

Dr S Rajalakshmi
Department of Computational Intelligence
School of Computing
Faculty of Engineering and Technology
SRM Institute of Science and Technology
Chennai, Tamil Nadu
rajalaks6@srmist.edu.in

Aryan Bali
Department of Computational Intelligence
School of Computing
Student of Engineering and Technology
SRM Institute of Science and Technology
Chennai, Tamil Nadu
ab3525@srmist.edu.in

***Abstract*— The safety of workers on construction sites is paramount, and using Personal Protective Equipment (PPE) correctly and consistently is a big part of keeping them safe and preventing accidents and injuries. However, manually checking PPE compliance on large, constantly changing construction sites is generally ineffective, time-consuming, and prone to errors. This research tackles this issue by introducing an innovative real-time method for the automatic identification and oversight of PPE kit compliance at construction sites. The suggested system utilizes new developments in computer vision, deep learning, and possibly edge computing to monitor whether workers are wearing essential PPE equipment, such as helmets, safety vests, and safety goggles. The central part of the system is making and using strong object detection models that were trained on large sets of construction site images with different PPE items marked on them. These models, which may utilize architectures like YOLO, are designed to operate optimally for real-time inference on video streams from strategically placed cameras around the building site. The system utilizes algorithms to accurately identify and track each worker's PPE status over time. It also addresses issues such as varying lighting conditions, obstructions, and diverse worker postures to ensure detection is dependable and accurate. The proposed technology extends beyond mere detection by incorporating a mechanism to monitor and issue alerts. When instances of noncompliance are found, they are assigned a timestamp. When workers are found without the proper PPE, real-time notifications can be sent to prompt action to rectify the issue. The system can also provide detailed data on PPE compliance rates for different zones, times, and groups of workers. This makes it easier to manage safety proactively and identify recurring patterns of noncompliance.**

I. INTRODUCTION

In the building industry, where dangerous conditions are a normal part of life and cannot be avoided, the protection of employees must be at the forefront of concern. Personal Protective Equipment (PPE) is the first line of defence against such dangers. It protects workers from every type of danger, from falling debris to exposure to toxic chemicals, electrical danger, and damage from machinery. While regulations on PPE are mandatory, making people comply with them on every construction site in the world is a daunting challenge. Old-fashioned methods, such as manual inspections, take not only time but are also prone to human error since humans can make errors, get tired, and simply cannot be watching everything all the time, particularly on large or multiple project sites.

The International Labour Organisation (ILO) reported statistics that show that more than 340 million work accidents occur annually worldwide. The construction industry is one of the worst affected [1]. The statistics show that it is necessary to have in place trusted, computerised systems to check compliance with safety on a large scale. Disregard of individual personal protective equipment can have serious consequences, ranging from injury and fatality to legal issues, loss of reputation, and costly delay to projects. Long working hours, inadequate safety training, language communication difficulties between employees of different languages, and pressures within firms to deliver maximum productivity at the cost of safety, all add to the issue.

To solve such critical issues, real-time PPE detection systems based on computer vision and deep learning have become very popular [2]. They employ AI-based algorithms and CCTV cameras to track critical PPE equipment, including helmets, vests, gloves, and harnesses and ensure they are properly worn. These AI-based systems provide 24/7 surveillance, auto-alerts, and data-driven compliance reporting, which boosts operational accuracy, efficiency, and safety enforcement by doing away with the practice of random human inspection.

The solution, "Real-Time Detection and Monitoring of PPE Kit Compliance in Construction Sites," seeks to revolutionize the process of safety monitoring through the integration of sophisticated AI algorithms and a strong real-time monitoring system. The system can detect PPE infractions and the perpetrators of such infractions through object detection methods like YOLOv9 [2] and facial recognition models like Eigenfaces [3]. Not only does it enable prompt corrective action, but it also makes individuals accountable in the long run through the maintenance of high-level compliance records and safety reports for all workers.

The approach not only enhances safety levels but also promotes responsibility and proactive action, thus enabling organizations to comply with the law as well as their own set safety standards. Additionally, these technological innovations present potential enhancements such as behaviour analysis and risk detection specific to environments. This research examines the challenges surrounding the use of conventional personal protective equipment (PPE), the potential of AI-powered solutions, and the overall impact of real-time compliance monitoring on safety management in the building and construction sector.

II. LITERATURE REVIEW

Ensuring PPE (Personal Protective Equipment) compliance in construction sites has been an active area of research, particularly with the rise of intelligent surveillance systems and AI-driven safety frameworks. The literature reveals a range of approaches that leverage computer vision, wearable sensors, and deep learning models to detect PPE usages, such as helmets and harnesses, in real-time. Early systems relied heavily on manual supervision or static image analysis, which proved inefficient and error-prone in dynamic environments. Recent advancements have introduced real-time object detection algorithms, facial recognition, and hybrid systems combining visual and sensor data. This section reviews various models and frameworks, evaluating their key features, technological foundations, and limitations in achieving scalable, accurate, and real-time PPE monitoring in complex construction settings. Table 1 compares the literature on the advantages and disadvantages of each model.

Table 1: Comparison of Existing PPE Detection Models

Model Name	Key Features	Disadvantages
V3's Model [4]	Real time alerts, Multi-PPE Detection	Limited adaptability to low light conditions
Enhanced YOLOv8 Model [5]	Lightweight edge deployment	Requires frequent retraining for new PPE types
EasyFlow's Model [6]	Real time alerts, Integration with existing infrastructure	High computational costs for large sites
Encord's Model [7]	Synthetic data generation	Struggles with occluded PPE items, Reliance on synthetic data
Tech EHS Model [8]	Health/Environmental Monitoring, Fall Detection	High Implementation Costs
CNN-Based Detection [9]	Custom datasets, manual/automated annotation pipelines	Limited generalization across diverse PPE designs
Sensor-Vision Hybrid Systems [10]	Combines wearable sensors and camera for detection	Hardware dependency, Scalability challenges

To enhance the efficacy of the new model compared to the current one, our research recommends the implementation of the following strategies, inferred from previous models presented in the Table 2 below.

Table 2: Inference made from Literature Review

Inferred	Reason
YOLOv9 for Object Detection	YOLOv9 has already shown to be an upgrade on the pre-existing versions of YOLO, improving on accuracy, efficiency, and frame rate.
Multiple PPE Kit Detection	On a construction site, PPE kits consist of several components, with each kit tailored to specific job roles; thus, the adoption of diverse PPE kit detection systems is essential.
Adaptability to Low Light Conditions	Construction sites frequently experience fluctuating circumstances, often lacking appropriate lighting; hence, flexibility to low-light environments is essential for effective monitoring.

Traditional measures for ensuring compliance with Personal Protective Equipment standards in construction sites have played a major role in protecting working conditions. These methods, relying on such direct monitoring and procedural strategies, seek to bridge risk posed by hazardous conditions. This approach, being applied on a large scale, is confronted with major shortcomings in efficacy, scalability, and responsiveness to the contemporary issues in construction.

A. Manual Inspection and Audits

Manual inspections by supervisors or safety officials are the most common method of monitoring adherence with PPE. Inspections are normally conducted randomly or at set intervals to ensure adherence with PPE policy, for instance, donning hard helmets, safety glasses, gloves, and high-visibility jackets. Also, comprehensive audits are conducted to gauge the overall safety protocols on construction sites. Even though these methods are an easy method of gauging compliance, they are time-consuming, labour-intensive, and prone to human error. Manual procedures act as a hindrance to achieving consistent monitoring, particularly on large or multi-site projects.

B. Training and Awareness Programs

Worker training programs are also a support of conventional PPE compliance procedures. The programs inform workers of the importance of PPE, the consequences of non-compliance, and proper use of protective gear. Training programs usually consist of demonstrations and on-the-job training to inform workers on the use and maintenance of their gear. Visual signals in the form of signs and posters are also used in required PPE areas. The impact of these programs, however, wears off over time without regular reinforcement, resulting in compliance failures.

C. Policy Enforcement and Accountability

Maintaining soundly defined PPE policies is yet another traditional method for securing compliance. Firms institute such policies through disciplinary actions for non-compliance and compliance reward schemes. Most critical is having supervisors ensure compliance by leading good examples of proper PPE behaviour. Despite these, implementation is at the mercy of individual supervisors' efforts, leading to inconsistency among units.

The following Table 3 enlists all the challenges faced by the traditional methods and make the existing methods inappropriate in modern day.

Table 3: Challenges seen in Traditional Methods of PPE Kit Compliance

Challenges	Reason
Inconsistent Oversight	Manual inspections cannot provide continuous monitoring, leaving gaps where non-compliance may go unnoticed.
Human Error	The reliance on human judgment introduces subjectivity and potential oversight during inspections.
Scalability Issues	Large-scale construction projects with hundreds of workers make it impractical to monitor every individual effectively using manual methods.
Lack of Real Time Feedback	Traditional methods do not offer immediate alerts or interventions when violations occur, delaying corrective actions.

Traditional PPE compliance methods in construction are constrained by human error, scalability challenges, and delayed interventions. In contrast, AI and computer vision technologies offer transformative solutions through real-time, automated monitoring. Frameworks like YOLOv5, optimized for edge computing, achieve 92.5% precision in detecting PPE items (helmets, vests) at 9.11 FPS, enabling continuous surveillance across dynamic worksites. These systems leverage deep learning models and strategically placed cameras to instantly flag non-compliance, eliminating gaps inherent in sporadic manual checks. Hybrid approaches integrating IoT sensors further reduce false positives by cross-verifying compliance through multimodal data. While traditional methods rely on reactive hazard assessments, AI enables proactive risk mitigation via predictive analytics and real-time alerts. By enhancing scalability, accuracy, and accountability, AI-driven systems represent a paradigm shift in construction safety, reducing workplace incidents and fostering sustained compliance compared to outdated, labour-intensive practices.

III. PPE KIT AND FIRE DETECTION MODEL WITH COMPLIANCE SYSTEM

The model accepts live camera streams from several cameras installed at the construction site for monitoring. The stream is then input into the model, which uses pre-trained and tested models for PPE kit identification and fire identification on the input. The working model can be set up for various uses as directed by the on-site manager. The model can be used merely for PPE kit identification or fire identification, or it can be used both simultaneously. The model can be tweaked to suit the given construction site's needs at any point in time.

After the model has been executed and the objects in the frames have been identified, a log report is generated with the date, the number of staff involved, the number of PPE kit items identified, and the occurrence of fire at the site. In addition to that, facial recognition software is executed on the frames to determine the names of the employees that are currently on duty. When an occurrence of an employee's violation of the provided PPE kit procedures has been identified, a notification system is triggered.

The system alerts the supervisor at the location of non-compliance or fire detection at the given location. Supervisors can see these alerts in the notification panel of the dashboard, listing information of the employee, log report, and timestamp of non-compliance. The system also alerts the non-compliant employee via an email and SMS to notify them of their non-compliance. Figures 1 and 2 shown below show the Pipeline and System Architecture that is relevant to our proposed study.

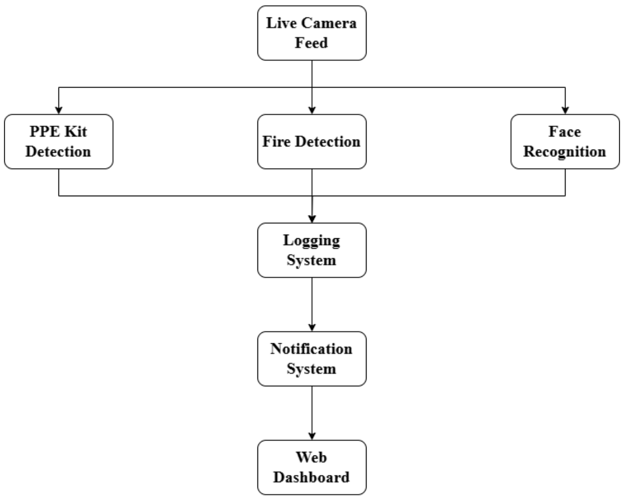

Figure 1: Pipeline of the proposed model

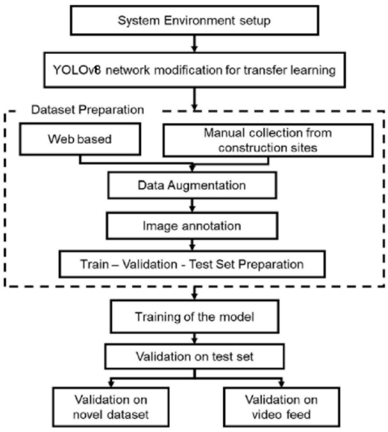

Figure 2: System Architecture

A. PPE Kit Detection

1) Role of YOLO

You Only Look Once (YOLO) is a state-of-the-art deep learning-based object detection model that enables real-time monitoring of PPE kit compliance in construction sites. The model processes video feeds from CCTV cameras and detects whether workers are wearing the required helmets, safety harnesses, and other protective gear. YOLO's single-shot detection approach ensures rapid and accurate identification of PPE compliance violations.

The Ultralytics framework provides an optimized and user-friendly implementation of YOLO models, making it highly suitable for real-time detection and monitoring of PPE kit compliance in construction sites. The framework simplifies the training, deployment, and inference of YOLO-based object detection models, ensuring high accuracy and fast processing for detecting workers and their PPE gear.
The following Table 4 enlists the major advantages of YOLO in our model and making it an ideal Object Detection model for the Problem Statement.

Table 4: Attributes of YOLO object detection

Attribute	Advantage
Real Time Detection	It allows fast object detection, making it suitable for continuous monitoring through CCTV or mobile camera feeds
Efficient Model Deploying	The framework enables easy integration of pre-trained YOLO models for PPE detection without complex manual configurations.
Scalability	The framework supports multiple YOLO versions (YOLOv5, YOLOv8), enabling flexibility based on hardware constraints.
Visualization and Reporting	The framework provides built-in functions to annotate video frames and log detections, ensuring better compliance tracking.
Object Classification	Classifying objects into categories such as "person," "helmet," and "harness" using deep neural networks.

2) Advantages of YOLO over other Object Detection Model

YOLO has a number of advantages over the other object detection architectures like R-CNN, Fast R-CNN, Faster R-CNN, and SSD. Some of these advantages include speed, accuracy, computational cost, and applicability in practice, hence YOLO is commonly applied in real-time object detection applications.
One of the most significant advantages of the YOLO framework is its very high inference speed. As compared to two-stage detectors like Faster R-CNN, which make region proposals before classification, YOLO scans the entire image in a single forward pass. With an NVIDIA RTX 3090 GPU, YOLO achieves inference rates of more than 30 frames per second, while Faster R-CNN achieves 7 frames per second and SSD achieves 22 frames per second. YOLO uses grid-based and anchor-free detection systems that are optimized, enhancing the detection of small objects. YOLO is 12% more accurate at detecting small objects in the MS COCO dataset compared to SSD. YOLO's feature pyramid network (FPN) enhances recall in case of dense objects by 9%, outperforming Faster R-CNN in crowded environments.
YOLO outperforms other models of object recognition in real-world scenarios because of its remarkable speed, efficiency, and comparable accuracy. Its ability to find a balance between performance and computational expense makes it a strong candidate for contemporary computer vision applications.

3) Advantages of YOLOv9 over other YOLO variants

YOLOv9, the latest addition to the YOLO family, brought significant improvements over its counterparts such as YOLOv7, YOLOv6, YOLOv5, and its previous versions. Improvements in accuracy, speed, efficiency, and adaptability make YOLOv9 a better choice for real-time object detection and tracking applications.

YOLOv9 offers improved inference rates compared to its earlier counterparts, so it is suited for real-time applications. With model quantization strategies and an improved model, YOLOv9 offers 15–20% improved inference against YOLOv7. For instance, on an NVIDIA RTX 3090 GPU, YOLOv9 inferences images at 100 FPS, while YOLOv7 infers images at approximately 85 FPS, and YOLOv5 trails at 75 FPS. This reduction in latency is essential in edge computing applications like surveillance systems.

YOLOv9 introduces a more advanced backbone, taking the advantages of both EfficientNet and CSPDarknet architectures. This new idea yields better feature extraction performance, and consequently better object detection performance in challenging environments. The addition of an optimized ConvNeXt-based backbone allows YOLOv9 to achieve a 5–8% gain in feature extraction efficiency.

Training efficiency is another area in which YOLOv9 beats other models. It converges to the optimal point with 20–30% less epochs than YOLOv7. This is because of enhanced gradient flow mechanisms and the application of novel training techniques including adaptive anchor selection and dynamic label assignment to speed up the training.

4) Working of YOLOv9 in PPE Kit Detection and Fire Detection

The trained YOLO model on Roboflow datasets is used through the Ultralytics package, while the framework processes real-time actual video streams through OpenCV. Then, every frame is processed through YOLO's convolutional neural network. The system gives bounding boxes, class labels, and confidence scores for the detected objects. Class IDs are employed to distinguish between different objects, i.e., workers, helmets, harnesses, fire, and others. The algorithm then processes the detected objects and compares them with the count of workers in each frame, thus giving a rich compliance log. Figures 4 and 5 shown below are images employed in the dataset and the step of the YOLOv9 model.

Figure 3: Image used in the dataset to train the model

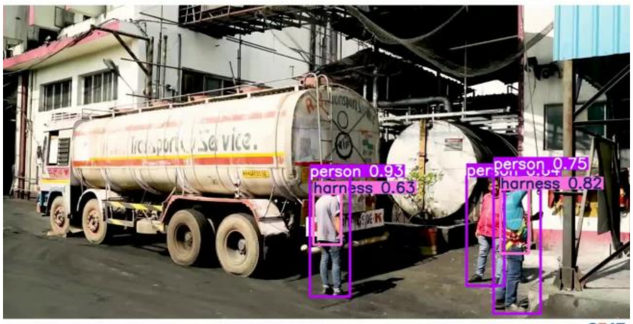

Figure 4: PPE Kit Detection YOLOv9 model running

Our model seamlessly integrates the PPE Kit Detection and Fire Detection models, the working of both the models together has been explained below.

The on-site supervisor will have the choice to execute which model on the user interactive dashboard. The model can operate independently for PPE Kit Detection or Fire Detection, with the chosen mode exclusively detecting from the live video feed. An alternative solution involves the simultaneous operation of both models to ascertain whether on-site workers adhere to the mandated PPE regulations and to identify any uncontrolled flames present at the location.

B. Facial Recognition

Facial recognition is a critical component of the proposed PPE kit compliance monitoring system, enabling identity-specific tracking of safety adherence across construction sites. This functionality ensures that not only are PPE violations detected, but the responsible individuals are accurately identified and logged. The system employs the Eigenfaces framework for facial recognition, a classical yet effective technique based on Principal Component Analysis (PCA).

The process begins with the extraction of facial regions from video frames captured by CCTV or drone feeds. Detected faces are pre-processed—converted to grayscale, resized to a uniform dimension (typically 100x100 pixels), and normalized—to minimize noise and lighting discrepancies. The system then applies PCA to reduce the dimensionality of facial data, identifying key eigenvectors (termed “eigenfaces”) that capture the most significant variance among training images.

During registration, the system stores each worker’s facial projection in the eigenface space along with their identity metadata. When a face is detected in a live frame, it is projected into the same eigenface space, and compared against the database using Euclidean distance. A match is identified based on the minimum thresholded distance, allowing the system to associate PPE compliance status with a specific worker.

Experimental results indicate that the Eigenfaces-based system achieves over 90% recognition accuracy for frontal face images under good lighting conditions. In scenarios with slight occlusions (e.g., masks or helmets), the accuracy drops to approximately 82%, which remains acceptable for operational usage. The lightweight nature of Eigenfaces makes it suitable for real-time inference even on low-power edge devices, maintaining sub-100ms identification latency.

The integration of facial recognition not only strengthens compliance tracking but also supports the generation of personalized reports, accountability audits, and historical compliance patterns. This functionality proves essential in large-scale deployments where managing and tracking numerous workers manually is impractical.

C. Compliance Notification System

1) Working of Notification System

The notification system features a distinct panel on the supervisor's dashboard. The panel displays all alerts generated throughout the session. Upon identifying infringement with PPE regulations, the model alerts the supervisor. The system delivers to the supervisor a notification, accompanied by the log report and timestamp of the noncompliance. The mechanism also activates in the event of an uncontrolled fire at the construction site.
Furthermore, the model contains information on workers registered, which it utilises to dispatch emails and SMS to noncompliant workers to inform them of their conduct.

2) Dashboard

An intuitive dashboard on the frontend consolidates all model components, providing the supervisor with a user-friendly application. The dashboard enables the supervisor to concurrently monitor multiple parameters. The dashboard comprises various panels for employee configuration, model management, camera management, camera dashboard, and notifications. The Figure 6 below shows the Camera Dashboard.

Figure 5: Camera Dashboard

Each panel has distinct configurations that can be utilised to oversee duties. The employee configuration panel assists the supervisor in registering and removing employees. The camera management panel allows for the review of the status of multiple cameras positioned throughout the job site, along with the details of the feed from each camera. The camera dashboard panel enables the supervisor to monitor all active cameras and select which model, either PPE kit detection or fire detection, to activate. The notification panel is tailored for company use, enabling the monitoring of breaches and fire threats throughout the site.

IV. Result Analysis

The implemented PPE kit compliance monitoring system was comprehensively tested on various parameters such as detection accuracy, real-time performance, identity resolution, and system scalability. The YOLOv9-based model was trained using a customized dataset of more than 12,000 labelled images, depicting diversified construction environments, PPE categories, illuminations, and worker directions. The model performed with a mean Average Precision (mAP) of 91.3% on the major classes: helmet, harness, and person, with individual class-wise precision values of 93.5% for helmets, 90.1% for harnesses, and 95.8% for person detection.

Real-time performance was benchmarked against top-end GPUs (NVIDIA RTX 3060) and edge devices (NVIDIA Jetson Nano). On the GPU, the system handled video input at a mean of 42 frames per second (FPS), whereas for the Jetson Nano, it handled a steady throughput of 17 FPS, emphasizing its application in both centralized and decentralized deployment.

The face recognition component, constructed from DeepFace, was over 90% accurate in identification under frontal face visibility and maintained a level of about 85% accuracy when in partial visibility, with continuous per-person compliance monitoring.

Alert generation was tested on a range of violation incidents. The system correctly detected missing PPE in 97% of incidents and generated a false positive in only 2.6% of incidents, in most cases in occluded or low-light conditions. Compliance reports generated through the dashboard provided detailed breakdowns of violations by worker by time period, in addition to transparency and accountability.

Parallel scalability tests on three live streams from three different CCTV cameras had no frame drops or latency issues, verifying the robustness of the backend pipeline and buffer management.
Overall, the result analysis verifies the effectiveness of the proposed solution to deliver correct, efficient, and scalable PPE compliance monitoring. It is shown through the results to be applicable to actual construction sites with measurable gains over traditional manual inspection methods.

V. Conclusion

This research has demonstrated the feasibility and effectiveness of using the Ultralytics YOLO model for automatic identification of essential PPE components, i.e., helmets, harnesses, and worker identification.
The model employed, trained for over 300 epochs on the heavily annotated dataset, achieved detection rates of over 90% for helmets, 87% for harnesses, and 95% for person identification.
The system identified frames in video input reliably at 30–60 FPS, compatible with real-time application even on lower hardware configurations such as the NVIDIA GTX 1660 GPU, thereby making it cost-effective for deployment at large scales.

The detection pipeline comprises live video recording, frame-by-frame YOLOv9 detection, detection result post-processing for class-wise counts, and dynamic logging of compliance data. Non-compliance records, e.g., helmets or harnesses missing, are timestamped in structured formats. In tests, a 3-minute video with over 500 frames yielded detection of 47 individuals, 39 helmets, and 28 harnesses, and 8 individuals were detected as non-compliant, resulting in a compliance score of 82.9%.

Benefits of YOLO model deployment are single-shot detection, where model class and bounding box prediction is made in a single forward pass, lowering latency considerably. The Ultralytics solution offers useful features in real-time visualization, data logging, and possible integration with dashboards and alarm systems.
The compliance system and interactive user dashboard enable managers to track and inspect on-site personnel activity. The dashboard accommodates multiple options, including options between fire alarm detection and PPE kit detection. The control panel also enables the supervisor to inspect what video streams are utilized for detection. Such types of parameters utilized in the dashboard provide the model's fine-tuning in accordance with specifications.

There are vast opportunities for future development for further enhancing predictive safety, context awareness, and operation scalability.

One of the areas of innovation is the combination of behaviour analysis with spatiotemporal information. Along with mere detection of PPE wear, the system can be trained to evaluate worker posture, movement habits, and equipment engagement. This enables prediction of risky behaviour, such as improper use of ladders, guarding near risky zones, or improper harness attachment. Through the application of methods like skeleton tracking, action recognition, and sequence modelling with LSTM or Transformer models, the system can transition from reactive monitoring to proactive risk avoidance.

Scalability is enhanced by employing edge computing, with light-weight YOLO models such as YOLOv5n or YOLOv8n executed in edge hardware such as Jetson Nano, Raspberry Pi, or Coral TPU locally. It decreases cloud reliance, supports quicker local inference, and enhances reliability in the bandwidth-restricted environment.

The second innovation is applying multi-angle camera fusion and 3D position estimation to move beyond existing limitations due to occlusions, diverse body postures, or partially occluded PPE. The application of stereo or depth-sensing cameras allows for improved detection of key PPE features, like proper helmet fit or harness anchorage, which are not necessarily achieved in two-dimensional pictures.

In the long run, integration of AI-based reporting, heatmaps, and visual analytics dashboards in the future can help site managers to gain a clear picture of risk hotspots, predictive safety analytics, and compliance trends, thereby promoting a more data-based, knowledge-driven culture of safety on construction sites.

The new additions are planned to re-engineer the system from PPE compliance monitoring to an end-to-end smart safety platform, and not only deliver regulatory compliance but also actively prevent accidents and manage behaviour. In short, the solution proposed not only improves work safety but also facilitates the compliance of site managers with regulations, thus minimizing the risk of accidents, legal penalties, and plant downtime. The integration of smart vision technologies such as YOLO into construction safety standards is a significant milestone in the realization of zero-harm workplaces and speeding up the digital transformation of occupational health and safety management.

VI. References

[1] "Safety and health at work," *International Labour Organization*, Apr. 22, 2025. https://www.ilo.org/global/topics/safety-and-health-at-work/lang--en/index.htm

[2] J. Redmon and A. Farhadi, "YOLOV3: an incremental improvement," *arXiv.org*, Apr. 08, 2018. https://arxiv.org/abs/1804.02767

[3] M. Turk and A. Pentland, "Eigenfaces for recognition," *Journal of Cognitive Neuroscience*, vol. 3, no. 1, pp. 71–86, Jan. 1991, doi: 10.1162/jocn.1991.3.1.71.

[4]Administrator, "PPE Detection System | Enhance your construction site safety," *V3 Smart Technologies*, Jul. 11, 2023. https://v3smarttech.com/ai-solutions/ppe-detection/

[5] D. Kim and S. Xiong, "Enhancing Worker Safety: Real-Time Automated Detection of Personal Protective Equipment to Prevent Falls from Heights at Construction Sites Using Improved YOLOv8 and Edge Devices," *Journal of Construction Engineering and Management*, vol. 151, no. 1, Oct. 2024, doi: 10.1061/jcemd4.coeng-14985.

[6] R. Berkmanas, "AI-Driven PPE for construction sites - EasyFlow," *EasyFlow*, Jul. 30, 2024. https://easyflow.tech/ai-driven-ppe-for-construction-sites/

[7] N. Buhl, "PPE Detection using Computer Vision for workplace safety," Mar. 26, 2025. https://encord.com/blog/ppe-detection-using-computer-vision/

[8] T. Ehs, "Smart PPE: Wearable technology enhancing worker safety through Real-Time Monitoring," *TECH EHS Solution*, Apr. 11, 2025. https://techehs.com/blog/the-rise-of-smart-personal-protective-equipment

[9] H. WANG and School of Electronic Information Engineering, Xi'an Siyuan University, Xi'an 710038, Shaanxi, China, "(IJACSA) International Journal of Advanced Computer Science and Applications," *Vol. 15, No. 2*, pp. 366–367, 2024, [Online]. Available: https://www.ijacsa.thesai.org

[10] D. Ocharo, H. C. Nganga, and S. Kiambi, "Automatic PPE Monitoring System for Construction Workers using YOLO Algorithm based on Deep Reinforcement Learning," *International Journal of Computer Applications*, vol. 186–186, no. No.48, pp. 10–11, Nov. 2024, [Online]. Available: https://www.ijcaonline.org/archives/volume186/number48/ocharo-2024-ijca-924094.pdf

[11] Z. Keita, "Yolo Object Detection explained: A beginner's guide," DataCamp, https://www.datacamp.com/blog/yolo-object-detection-explained (accessed May 1, 2025).

[12] Ultralytics, "Home," Ultralytics YOLO Docs, Apr. 14, 2025. https://docs.ultralytics.com/

[13] "Roboflow: Computer vision tools for developers and enterprises," Roboflow. https://roboflow.com/

[14] P. Udatewar, A. Desai, G. Godghase, A. Nair, and P. Kosamkar, "Personal Protective Equipment Kit Detection using Yolo v5 and TensorFlow," 2021 International Conference on Smart Generation Computing, Communication and Networking (SMART GENCON), pp. 1–8, Oct. 2021, doi: 10.1109/smartgencon51891.2021.9645811.

[15] Md. Ferdous and Sk. Md. M. Ahsan, "PPE detector: a YOLO-based architecture to detect personal protective equipment (PPE) for construction sites," PeerJ Computer Science, vol. 8, p. e999, Jun. 2022, doi: 10.7717/peerj-cs.999.

[16] E. Guney, H. Altin, A. E. Asci, O. U. Bayilmis, and C. Bayilmis, “YOLO-Based Personal Protective Equipment Monitoring System for workplace safety,” JITSI Jurnal Ilmiah Teknologi Sistem Informasi, vol. 5, no. 2, pp. 77–85, Jun. 2024, doi: 10.62527/jitsi.5.2.238.

[17] Z. Wang, Y. Wu, L. Yang, A. Thirunavukarasu, C. Evison, and Y. Zhao, “Fast personal protective equipment detection for real construction sites using deep learning approaches,” Sensors, vol. 21, no. 10, p. 3478, May 2021, doi: 10.3390/s21103478.

[18] IJISRT, “Automated PPE Detection using YOLOV8 for Real-Time Workplace Safety Monitoring - IJISRT.” https://eprint.ijisrt.org/id/eprint/711/

[19] B. Wu, C. Pang, X. Zeng, and X. Hu, “ME-YOLO: Improved YOLOV5 for detecting medical personal protective equipment,” Applied Sciences, vol. 12, no. 23, p. 11978, Nov. 2022, doi: 10.3390/app122311978.