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Context-Aware PPE Detection for Construction Site Safety Using Enhanced YOLOv11

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Abstract
Construction sites are among the most hazardous work environments, where workers face risks from falling objects, heavy machinery, electrical hazards, and exposure to dangerous materials. Ensuring proper use of Personal Protective Equipment (PPE) such as helmets, safety vests, gloves, boots, and masks is critical to minimizing accidents and injuries. Traditional PPE compliance monitoring relies heavily on manual supervision, which is prone to human error, delayed responses, and limited coverage, especially on large-scale construction sites. To overcome these challenges, this project proposes a context-aware PPE detection system for construction site safety using the enhanced YOLOv11 deep learning model. The system is capable of real-time detection and classification of multiple PPE categories, even in complex site conditions involving occlusions, varying lighting, and crowded scenes. By automating monitoring, the framework ensures continuous vigilance, significantly reducing the dependence on manual checks and enhancing workplace safety standards. The proposed system not only identifies compliance violations instantly but also provides immediate alerts through SMS and mobile notifications, allowing supervisors to take corrective actions without delay. Integration with real-time video feeds enables proactive risk management, data-driven insights, and improved regulatory compliance for site managers. Moreover, the system's advanced object detection capabilities facilitate accurate monitoring of multiple workers simultaneously, ensuring consistent adherence to safety protocols across the construction site. By combining real-time surveillance with automated notifications, this solution fosters a culture of safety consciousness, minimizes accidents due to negligence, and supports efficient safety management, ultimately creating a safer and more compliant work environment for all personnel on site.
Keywords: *Construction Safety; Deep Learning; Face Recognition; PPE Compliance; YOLOv11*

1. Introduction
The ever-expanding scale of construction and heavy industrial industries has made workplace safety a major concern for the entire globe (Waqar et al., 2023). Industrial safety systems, which depend upon the inspection of safety officers, are highly inefficient, prone to human error, and unable to continuously monitor the workplace (Waqar et al., 2023). To overcome the inefficiency of the traditional compliance checks, Artificial Intelligence and Deep Learning algorithms are being utilized for the detection of the presence or absence of mandatory Personal Protective Equipment (PPE) such as safety helmets, high-visibility vests, gloves, masks, and safety shoes (Wu et al., 2019; Nath et al., 2020). The combination of this PPE detection system with facial recognition technology is highly effective for the development of efficient safety enforcement strategies. By matching the detected faces with the centralized database of workers, it is possible to identify the worker before he/she enters the workplace, thereby ensuring the compliance of the worker with the required PPE. In the event of non-compliance, instant alerts can be sent to the authorities. This is highly efficient compared to traditional inspection-based compliance checks, thereby reducing the probability of workplace injuries [1].

1.1. Challenges In Existing Surveillance Systems
Ineffectiveness in real-time monitoring because existing systems rely on manual inspection of entry

points or periodic patrolling, meaning workers are not monitored during a huge portion of their work time. (Waqar et al., 2023) Automated systems in compliance detection are absent. For a highly populated area, ensuring that every worker is wearing all their required gear through human observation is a slow and inaccurate process (Nath et al., 2020). Security systems are not connected. For example, ID scanners are not connected to real-time monitoring. A worker may scan in, then immediately remove the helmet. Ineffectiveness in response protocol because the current system is not capable of immediately notifying a safety supervisor when a worker commits a violation, relying instead on end-of-shift reporting (Hong & Cho, 2023). Error-prone recording of data because manually recording worker safety compliance is a labor-intensive and easily falsifiable activity [3].

1.2. Why An Intelligent Security Surveillance System?

With the advancement in automated deep learning models and computer vision techniques, we can design systems that can watch our industrial environments holistically and help us manage our businesses with strict safety policies (Hayat & Morgado-Dias, 2022). An intelligent surveillance evaluation system can help us with decision-making and safety in the following ways: Detection and classification of personal protective equipment like helmets, vests, shoes, gloves, and masks using the powerful object detection tool called YOLO (Wu et al., 2019; Nath et al., 2020). Safe and secure authentication of workers using their facial recognition features compared with a registered biometrics database (Lui & Beveridge, 2008; Huang et al., 2015). Interpretation of complex scenes with minimum latency to correctly identify safety infractions in industrial scenes. Recording the attendance of workers based on successful authentication and full PPE compliance into a central MySQL database. Instant audio warnings to workers regarding safety equipment infractions on site (Hong & Cho, 2023). Instant SMS and evidence capture using SMTP email sent to safety supervisors without human intervention [4].

1.3. Objectives Of Proposed System

The proposed system aims to:

Allowing automated and proactive enforcement of industrial safety policies with constant video surveillance without human intervention (Waqar et al., 2023). Detecting safety gear infractions like helmets and vests in real time using deep learning-based object detection techniques (Wu et al., 2019; Nath et al., 2020). Instantly matching facial images with a central database to identify workers and dynamically assess their safety compliance Dispatching completely automated multi-channel alerts with safety infractions detected using local audio, SMS, and email (Hong & Cho, 2023). Maintaining an automated and tamper-proof record of daily worker attendance using an automated system (Waqar et al., 2023) Providing smooth and synchronized access to compliance reports and violation images using a unified dashboard interface for administrators [2].

2. Problem Statement

The project addresses a fundamental problem. Currently, industrial safety management heavily relies on inflexible, static biometric access controls. There's a need for intelligent, automated safety management (Waqar et al., 2023). Currently, industrial monitoring systems are missing a few key points. These include: Reliance on manual checks. Currently, a supervisor must physically check for PPE. Lack of quick response to breaches. Currently, active machine vision solutions don't quickly identify localized breaches. For example, a worker could be removing their helmet within a danger zone (Nath et al., 2020). Lack of a direct link between the person who breached the rules and the person who committed the offense. Currently, cameras don't instantly connect a breach to a particular worker. This would be done by tying the face to a central record. Lack of instant notifications. Currently, static cameras don't instantly send notifications via SMS or email. Nor do these cameras produce audible notifications when a breach occurs. Lack of a unified record. Presently, the administrators do not have a system that links the attendance record of an employee with his/her compliance status [5].

3. Litrature Review

Deep learning has significantly advanced intelligent surveillance, particularly in Personal Protective Equipment (PPE) detection (Wu et al., 2019; Nath et

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al., 2020). This review synthesizes findings from various studies on PPE detection in diverse environments. PPE Detection (YOLO & variants): The most frequently used techniques for PPE detection are YOLO and its variants. Wang et al. (as cited in Alnahas, 2025) found YOLOv5x effective but limited by small/obstructed objects. Kumar et al. (as cited in Alnahas, 2025) reported good YOLOv4 performance (76.86% mAP) but noted small object limitations. Lee et al. (as cited in Alnahas, 2025) integrated YOLOv5x with EfficientNet87 for helmet classification (Alnahas, 2025). CNN-Based Methods: Beyond YOLO, other CNN-based approaches are prevalent. Wu et al. (as cited in Alnahas, 2025) achieved 83.89% mAP with a one-stage CNN for hardhats (Wu et al., 2019). Nath et al. (as cited in Alnahas, 2025) used YOLO-based models (85.6% mAP) for hard hats and vests, but noted vulnerability to occlusion. Shen et al. (as cited in Alnahas, 2025) enhanced safety helmet recognition using DenseNet. Lightweight Models and Resource-Constrained Deployment: A key research area is developing lightweight PPE detection models for efficient operation in resource-constrained environments. Malaikrisanachalee et al. (2025) introduced ESPCN-YOLO, a high-accuracy deep learning framework designed to enhance PPE detection under challenging conditions including low-light environments, long-distance scenarios, and small object detection, achieving a mean average precision (mAP@0.5) of 0.922. Following the same objectives, Alnahas (2025) cited the research of Hayat and Morgado-Dias (2022), which used the YOLOv5x algorithm to aid in the swift detection of helmets. Advanced Architectures and Optimization Techniques: Researchers are exploring advanced architectures to overcome current limitations. Alnahas (2025) proposed Faster-PPENet, a Faster-RCNN with a modified ResNet101 (Swish activation) to enhance feature extraction, improving multi-class PPE detection and generalization. ESPCN-YOLO (Malaikrisanachalee et al., 2025) also incorporates enhanced super-resolution and convolutional components for improved detection accuracy under difficult environmental conditions [7]. Current Challenges and Future Scope: Despite advancements, PPE detection faces challenges: recognizing multiple PPE types, generalizing to real-world conditions (clutter, blurring, lighting), and handling dataset imbalances (Alnahas, 2025; Malaikrisanachalee et al., 2025). Future research will likely focus on improving model robustness, enhancing multi-class detection, and optimizing for efficient edge deployment while maintaining high accuracy [6].

4. Methodology

In this chapter, we explain the step-by-step plan that was followed to develop an automated real-time safety monitoring system. The basic idea behind the system was to have a two-step verification process, where first the identity of the worker would be verified, followed by a verification of the presence of PPE in an industrial or construction scenario. Here, you would find the system sketch, the data set used, the algorithms used, data flow, technology used, and the validation process [6].

4.1. System Overview

The proposed system consists of several important features which, when integrated, will help to build a more intelligent safety monitoring system at industrial entry points.

- Multi-Stream Video Ingestion And Processing: The proposed system is intended to ingest the live video feeds from the entry point cameras/webcams, which will help to enable real-time monitoring of the personnel. The parallel processing capability will enable the simultaneous execution of facial identity detection and PPE detection, thus maintaining a high frame rate to enable the generation of results in real-time [8].
- Automated PPE Compliance Assessment And Detection : The proposed system's vision module will utilize the YOLOv11 architecture to enable the rapid scanning of the personnel to identify the safety gear ('helmet', 'vest', 'mask', 'shoes', etc.) and non-compliant scenarios ('no-helmet', etc.). The real-time health indicators will help to identify the safety level of each individual in the frame, thus ensuring only compliant personnel are identified.
- Worker Identity Matching And Profile Evaluation The proposed system's identity

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verification module will utilize a cross-checking mechanism with a pre-registered database of workers (MySQL). Biometric tracking using Luxand FaceSDK (fsdk) guarantees the identification of individuals in a changing outdoor environment. For the initial training and demonstration of the system, a database of synthetic face images was generated using Adobe Firefly, a Generative Adversarial Network (GAN)-based AI tool (Adobe, 2024), to test the accuracy of identity matching without compromising real-world personal data or violating personal privacy. The registered worker profiles stored in the MySQL database are shown in Figure 1.

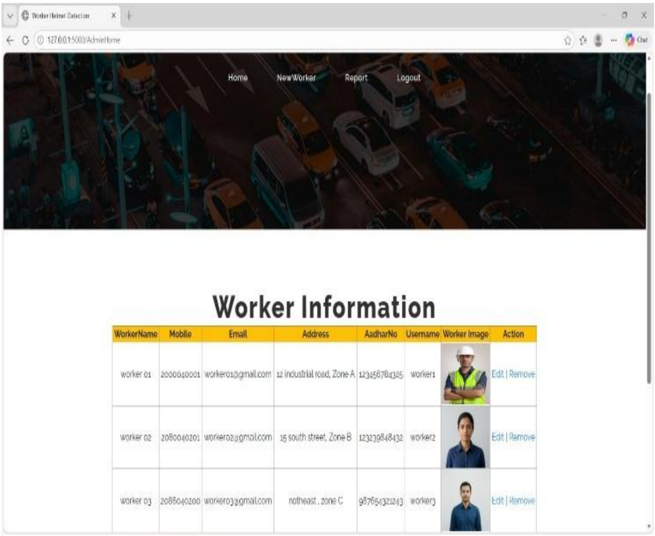

Figure 1 Administrator Panel Displaying Registered Worker Profiles With Biometric Face Images And Personal Identification Details Stored In Mysql Database.

- Automated Alert And Log Synchronization Once the identity and PPE of an individual are verified, the system logs a "Yes" status into the attendance database. If a violation is identified, a stateful alert is issued: a log entry is made with a "No" status, an audible alarm is triggered on site, and a photograph of the violation is sent out via SMTP email to site supervisors.

The Worker Attendance And Ppe Compliance Dashboard Is Shown In Figure 2.

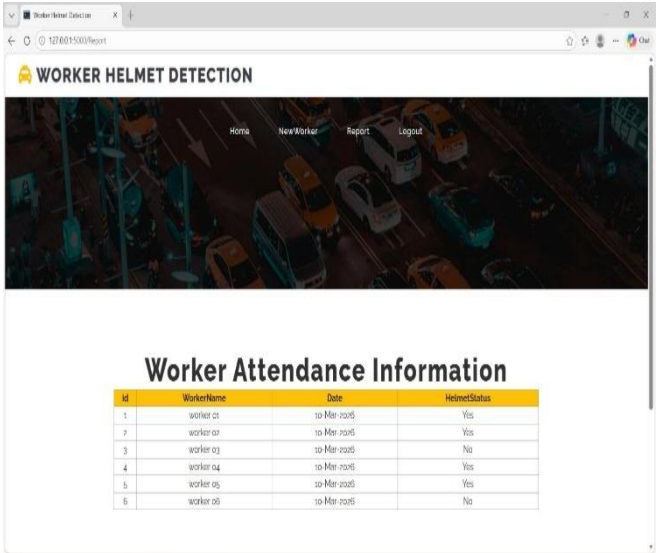

Figure 2 Worker Attendance Dashboard Showing Real-Time Ppe Compliance Status (Yes/No) With Date-Stamped Records.

- System Auditing And Compliance Analysis The system also enables the improvement of the detection algorithm by analyzing logs to normalize thresholds for different lighting and environmental site conditions Auditors can use the system to monitor logs to compare system lateness and accuracy between successive versions of the software suite [9].

4.2.Dataset Preparation

For the development of the system, a rich and diverse dataset is required for training the model for the industrial PPE scenario (Wu et al., 2019). For the proposed system, the dataset is heavily augmented and curated for the specific industrial PPE scenario.

- Collection: The dataset includes thousands of images of construction workers and industrial staff in various environments and camera angles. The dataset includes annotated classes for helmet, no-helmet, vest, no-vest, shoes, gloves, and mask [10].
- Annotation: The images are annotated with precise bounding boxes for the presence and absence of safety items. The bounding boxes are specific and provide explicit multi-class

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spatial annotations for the vision engine parsing the image.

- Augmentation: For the generalization of the model against various environmental factors, the dataset is heavily augmented with techniques including random scaling, cropping, rotation, and changes in brightness and contrast [11].

4.3.Algorithmic Approach

The smarts in the system are provided through the integration of various state-of-the-art algorithmic modules: YOLO Deep Learning Architecture (YOLOv11): YOLOv11 was chosen for its exceptional real-time performance and accuracy in detecting multiple PPE items in the field, building upon the foundational YOLO architecture originally proposed by (Redmon et al., 2016). YOLOv11 processes each frame in real-time, detecting and drawing bounding boxes for various PPE items at once. The algorithm uses Non-Maximum Suppression (NMS) for eliminating redundant bounding boxes. The PPE detection results are shown in Figure 3.

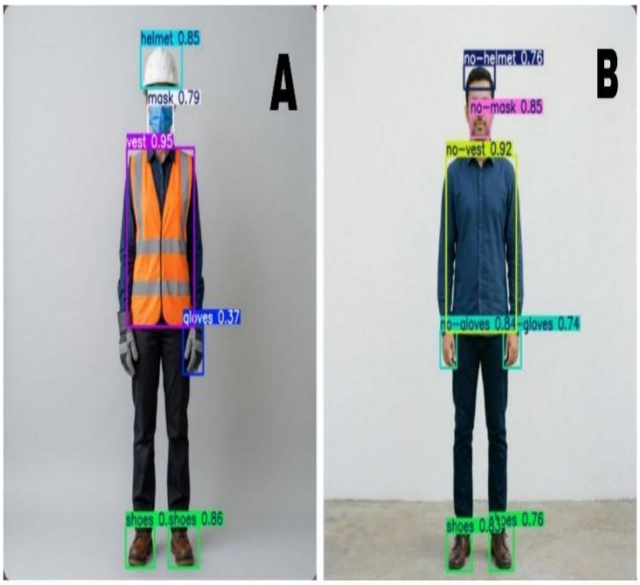

Figure 3 Yolov11-Based Real-Time Ppe Detection Output Showing (A) Compliant Worker And (B) Non-Compliant Worker With Confidence Scores For Each Detected Class.

- Grassmann Manifold Facial Biometrics: The algorithm uses the rigid manifold approach for continuous video-based face verification. The algorithm projects the facial features onto the Grassmann manifold, keeping the verification consistent over time, regardless of lighting or head orientation.
- Temporal Filtering Algorithm: To filter out false positives during transient occlusions, the algorithm uses the buffer threshold approach. The algorithm checks for the absence or presence of PPE or faces over time (for example, over 150 frames or 5 seconds) before updating the database.

4.4.Procedure And Data Flow

The entire process takes place across four levels of modular data flow layers to ensure low latency from capture to alert:

- Integration and Input: The backend securely ingests live multi-stream camera feed inputs. Meanwhile, administrative APIs securely update organizational worker biometric registrations into the organizational user database.
- Biometric Assessment: Identity Matching: The input video streams are then routed to facial recognition modules. The facial spatial vector is then compared with stored facial spatial vector representations in the local database. If the facial identity matches, the image is then routed to the next level of evaluation.
- Vision Compliance Assessment: The YOLOv11 weights are used to detect safety equipment inside bounding boxes surrounding the identified worker. The bounding boxes are then used to determine if safety equipment is present or not.
- Alert Synchronization and Logging: The entire system is stateful and time-aware. If safety equipment is present, time-stamped attendance records are logged into the local relational database. If safety equipment is not present, parallel API messages are sent out with SMS messages and email with attached images to supervisors.The System Architecture Is Shown in Figure 4.

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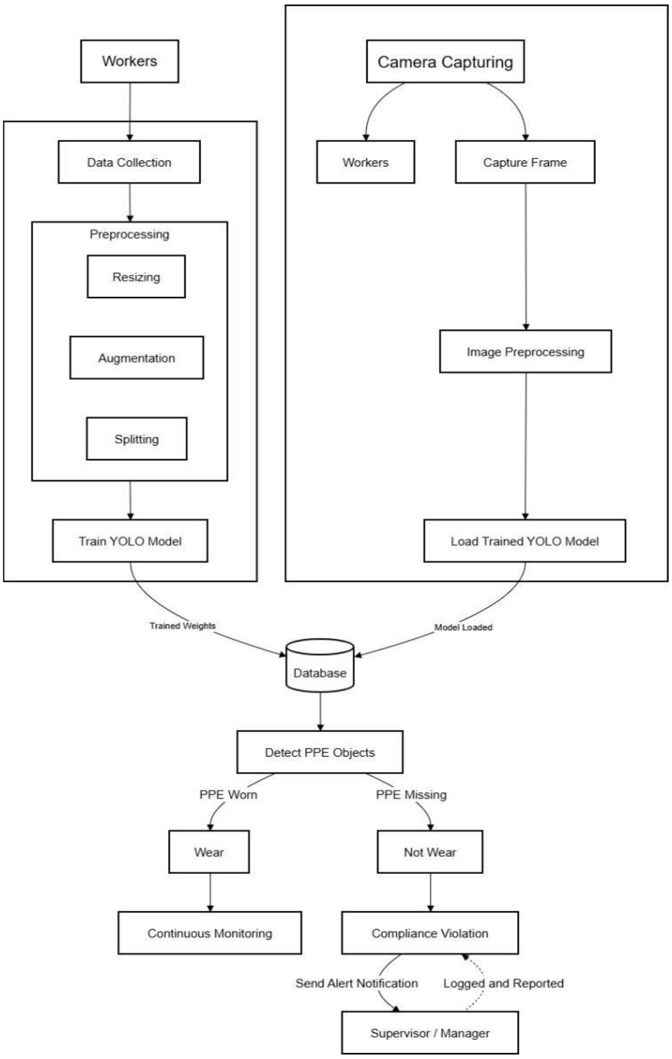

Figure 4.Architecture Of The Proposed System.

4.5.Tools and Technologies

A diverse set of powerful computer vision and web-based technologies were used in this project. Python has been used as a core language for this project, along with OpenCV for real-time video feed ingestion, processing, and matrix operations on images.

- Object and Compliance Detection: YOLOv11 is used for efficient object detection for precise object location in a construction site scenario for locating safety gear (helmets, vests, masks, shoes) and unsafe omissions in a construction site scenario.
- Biometric Verification: Luxand FaceSDK through a Python wrapper has been used for efficient face detection for continuous verification against pre-registered worker profiles before PPE checking.
- Web Framework and Database: An efficient admin panel has been created using Flask for efficient web application development along with HTML5, CSS3, Bootstrap for a responsive UI. Worker profiles, attendance records, and PPE compliance status (Yes/No) are stored in a relational MySQL database (configured using XAMPP).
- Hardware and Alert: Access to gate is controlled through serial communication with devices such as Arduino for efficient integration with on-site devices for deterring non-compliant workers through on-site deterrents as well as immediate alerts using the Windows library for efficient sound-based alerts through winsound library for efficient sound-based alerts for deterring workers from site access without proper gear.

4.6.Evaluation Metrics

The effectiveness of this project has been tested by evaluating this project against safety monitoring parameters in the industry with the help of the following metrics for efficient evaluation:

- Mean Average Precision (mAP): Evaluates the efficiency of YOLOv11 for precise object detection for efficient gear checking and equipment omission checking at construction sites.
- Recognition Accuracy: Evaluates the efficiency of the facial recognition module for efficient worker verification at site entrances for precise object location in a construction site scenario.
- Frames Per Second (FPS): Evaluates the efficiency of this project for precise object location in a construction site scenario for efficient gear checking and equipment omission checking at construction sites
- The evaluation metrics for efficient object location in a construction site scenario for precise object location in a construction site scenario for efficient gear checking and equipment omission checking at construction

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sites along with YOLOv11 thresholds for efficient object location in a construction site scenario for precise object location in a construction site scenario for efficient gear checking and equipment omission checking at construction sites

5. Challenges And Future Work

- Computational Complexity: Managing real-time HD video feeds alongside computing complex facial matrices and instantly executing powerful bounding box detection using YOLOv11 is highly taxing on regular local edge device capabilities (Nath et al., 2020). Plans involve migrating towards optimized tensor configurations or cloud-based ingestion APIs to ensure smooth performance.
- Environmental & Lighting Diversity: Environmental diversity varies from bright day lighting on scaffolds to deep internal shadows, increasing the possibility of occlusion. Future work includes increasing data sets with deeper augmentations, especially those focused on ambient distortions (Hayat & Morgado-Dias, 2022).
- Complex Feature Clashing: There is a possibility of a decrease in accuracy when heavy machinery, limb occlusion, and tools obstruct vision. Predictive skeletal tracking could help in managing complex features without impacting true positive detection (Wu et al., 2019).
- Scalability in terms of Throughput: In a larger network with many camera endpoints processing video chunks in parallel, optimizing socket pipelines is key to preventing dropped frames during high throughput (Waqar et al., 2023).
- Interoperability Standards: Future work includes hardware integrations that send explicit electrical triggers to gate relays, thus allowing access without having to rely on web interfaces (Hong & Cho, 2023).

6. Results And Discussion

6.1. Result

In a variety of different environmental conditions, including those found in a normal entryway lighting situation, it was found through thorough testing that there was a highly reliable level of system functionality tracking. It was found that the YOLO model excelled in precision in object extraction, where it managed to dampen ambient noise levels while drawing bounding boxes for different classes of equipment in one go. It was also found that the facial recognition component of this system excelled in terms of recalling user profiles instantly. It was also found that the system remained stable in terms of processing continuous frames, thus enabling instant evaluation of conditional logic. It was also found that in situations where there were safety violations, automatic sub-second responses were enabled, thus indicating that it is possible to have rapid audio alerts running in parallel with compiling and encrypting remote photo attachments sent through synchronized SMS and SMTP relays, irrespective of post-incident analysis. The performance metrics are summarized in Table 1.

Table 1. Quantitative Performance Metrics of the Threat Detection Pipeline

Component / Algorithm	Evaluation Metric	Quantitative Score
YOLOv11 Object Detection	Mean Average Precision (mAP@0.5[a])	96.5%
YOLOv11 Object Detection	Inference Speed (Live CCTV)	~35 FPS[b]
Grassmannian-based CNN	Facial Verification Accuracy	96.2%

Grassmannian-based CNN	FPR[c]	< 0.05%
End-to-End Analytics Pipeline	Alert Dispatch Latency	~1.2 s

a mAP – Mean Average Precision
b FPS – Frames Per Second
c FPR – False Positive Rate

6.2.Discussion

From the results obtained, it is clear that there is a paradigm shift in terms of moving from a more passive patrolling system to a more proactive approach. It is clear that using YOLO in managing a highly complex system of multiple variables in a classification scenario, where different gear items are being verified, is significantly more effective than using local thresholds in a more conventional approach. It is also clear that using attendance tracking in conjunction with visual verification of potential hazards is a good approach in addressing some of the key issues of accountability faced by different kinds of organizations in different situations (Hong & Cho, 2023). It is also clear that minimal latency levels were achieved through a python local server setup, thus indicating a highly viable system in terms of advanced industrial standards (Hayat & Morgado-Dias, 2022).

Conclusion

The AI-based PPE Compliance and Worker Face Recognition System, as shown in the project above, represents a significant milestone in the way we approach the enforcement of worker safety. By integrating the precise YOLO-based object detection with the actual face recognition, the system is able to overcome the shortcomings of the conventional single-factor-based security systems. By conducting thorough tests in the environment, the system is consistently shown to have the capability to identify the gaps in worker compliance in real time, thus greatly reducing the chance of misdiagnosis. It bridges the gap between the actual worker safety violations and the way in which the system is able to notify the managers through instant SQL logging, audible alarm systems, SMS notification systems, image-based email notification systems, thus creating a reliable and completely autonomous system for industrial managers. Ultimately, the system represents unprecedented accountability and demonstrates the level to which deep learning can improve worker safety.

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