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Design of intelligent embedded system for personal protective equipment detection and face recognition access control

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ABSTRACT

This paper presents an artificial intelligence (AI)-powered automated access control system that aims to reduce delays and improve safety. The primary problem addressed is effective monitoring of compliance with personal protective equipment (PPE) and secure access control for personnel entering sites. This study represents the design and development of an access control system that includes accurate detection of essential PPE items (e.g., safety helmets, gloves, goggles, and gas detectors), integration of facial recognition for identity verification, real-time monitoring of video feeds, and an intuitive user interface for security personnel to manage access and compliance efficiently. The software part uses you only look once (YOLO) version 8 for real-time object detection, classification, and drawing the bounding boxes around the detected object in a single forward pass. The hardware platform consists of NVIDIA Jetson AGX Orin 64 GB as an edge computing device. The developed AI-based embedded system is tested and validated with real-world scenarios and achieved a mean average precision (mAP) of 98.4% for PPE detection and 99.38% accuracy for face recognition.

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1. INTRODUCTION

In an increasingly high-risk industrial setting, accidents caused by non-adherence to safety regulations at the workplace are becoming a serious concern. The prevention of accidents depends on making sure that personnel do not breach the proper personal protective equipment (PPE) protocols, such as wearing helmets, gloves, and goggles. At the same time, it is necessary to control access to restricted areas to ensure security. Traditional systems, which are not fully automated but rely on human observation and manual checks, are prone to human error and inefficiency. An automated and smart system that can recognize the correct use of PPE and authenticate personnel at the same time is needed, ensuring better safety and security in the industrial working environment. The present work uses artificial intelligence (AI)-based image processing techniques and facial recognition technology to address these requirements. AI-powered PPE detection and facial recognition technologies have emerged as transformative tools to improve workplace safety. These technologies leverage deep learning models to automate compliance monitoring and restrict unauthorized access to high-risk zones.

Real-time detection of PPE compliance, including helmets, gloves, and vests, has been shown to significantly reduce workplace accidents [1].

The advent of AI applications during the last decade has resulted in many interesting use cases in the field of industrial safety, where AI-based monitoring systems have shown high potential in preventing accidents in various domains such as industrial operations, healthcare, and transportation [2], [3]. Researchers demonstrated various AI techniques and tools to enhance the industrial safety within different applications utilizing the you only look once (YOLO) algorithm [4]. Deep learning-based PPE detection system using the YOLOv8 architecture, tailored for industrial environments requiring high accuracy, non-destructive monitoring, and real-time performance. A custom dataset was developed and used for training, validation, and testing to ensure robustness. The model consistently achieved high detection accuracy, validating its effectiveness for workplace safety applications. YOLOv8 has been shown to effectively meet stringent industrial PPE detection requirements [5]. For industrial compliance, YOLOv8-based detection of missing helmets and jackets improved mean average precision (mAP) compared to earlier systems, strengthening safety standard adherence [6].

A YOLOv5 system for head-mounted PPE reported 0.857 precision, addressing enforcement challenges in strict-regulation workplaces [7]. MARA-YOLO, enhanced YOLOv8 variant with MobileOne-S0, attentional space-to-depth block (AS-Block), R-C2F, and a module built upon R-C2F and adaptively spatial feature fusion (RASFF) modules, achieved 74.7% mAP on the KSE-PPE dataset, outperforming other lightweight detectors [8]. Finally, a few-shot graph neural network (GNN) approach for substations identified eight PPE types with 79–100% similarity, emphasizing efficiency, robustness, and privacy in low-data environments [9]. Recent advances in PPE detection extend beyond single-modal YOLO-based systems by integrating multi-modal architectures and novel datasets.

Pei *et al.* [10] combined YOLOv4 with high-resolution net (HRNet) keypoint detection using generalized intersection over union (GIoU) to not only detect medical personal protective equipment (MPPE) but also verify its correct usage, significantly improving compliance monitoring. Zhang *et al.* [11] proposed a Conv-Transformer model that integrates convolutional features with transformer attention, supported by a denoising diffusion probability model (DDPM), achieving robust anomaly detection in data-limited industrial environments. To address dataset scarcity, Yipeng and Junwu [12] introduced a diverse PPE dataset and an enhanced YOLOv5, which achieved a 0.9 average precision gain in underrepresented categories, highlighting the role of comprehensive datasets in model development. Real-world studies further underscore practical impact: Önal and Dandıl [13] reported that industrial deployments reduced manual inspection times by up to 75% while maintaining $> 99.5\%$ system uptime, confirming both efficiency and reliability in safety-critical applications.

Hao *et al.* [14] addressed critical limitations in helmet detection systems under adverse weather conditions through their improved YOLOv5s-based approach. Azizi *et al.* [15] employed faster region-based convolutional neural network (Faster R-CNN) architecture with ResNet-50 backbone and compared it with few-shot object detection (FsDet) to address dataset compilation challenges in object recognition training. This work focuses solely on PPE detection without integrating identity verification through face recognition.

Sandru *et al.* [16] proposed a novel deep learning method combining person detection, body pose estimation, and classification with spatial attention mechanism for PPE detection, using pose estimator supervision only during training. While innovative in its use of pose estimation for PPE detection, this system lacks face recognition capabilities for identity verification. It cannot provide access control functionality or link PPE compliance to specific individuals, making it unsuitable for comprehensive industrial security applications.

Lee *et al.* [17] developed a multi-function facial recognition access control system combining principal component analysis (PCA)/linear discriminant analysis (LDA)-based recognition, radio frequency identification (RFID) authentication, and password verification. While effective for identity verification, it lacks PPE detection, making it unsuitable for safety-critical industrial contexts. Rashidi *et al.* [18] introduced a sensor-based PPE monitoring system that integrates safety gear with real-time location, temperature, and pressure sensing. However, this approach does not incorporate computer vision or access control, limiting its ability to verify identity or enforce restricted entry.

These studies illustrate a critical gap: current systems typically address either safety compliance or access control independently. Traditional PPE detection cannot link violations to specific individuals, while access control systems ignore PPE compliance, leading to vulnerabilities where unauthorized or improperly equipped personnel can enter hazardous areas. This fragmentation increases accident risks and fails to meet modern safety and security demands.

The motivation for the proposed system lies in addressing these challenges through an integrated dual-authentication framework that simultaneously verifies identity and PPE compliance. The prior PPE-only and identity-only systems leave an enforcement gap, and the proposed dual-authentication machine learning pipeline closes this gap by fusing both decisions into a single conjunctive access policy executed on edge hardware. The contributions of this work are as follows: i) YOLOv8-based PPE detector trained on a custom dataset of 4,351 images across six classes; ii) Dlib-based face recognition module with 128-D embeddings; iii) dual-authentication pipeline that gates access only when both checks pass; and iv) edge deployment on the Jetson AGX Orin with TensorRT acceleration.

The paper is structured as follows. Section 2 describes the proposed integrated system architecture combining YOLOv8-based PPE detection with facial recognition technology. Section 3.1. provides detailed software design with YOLO variants for industrial applications. Section 3.2. presents the experimental methodology and implementation details of intelligent embedded system-based hardware design. Section 4 discusses the results and performance evaluation of the integrated system. Finally, conclusions are drawn in section 5.

2. DESIGN OF AI-BASED PERSONAL PROTECTION EQUIPMENT DETECTION AND FACE RECOGNITION

The hardware architecture of the proposed system is centered around the Jetson AGX Orin 64 GB, which serves as the primary edge computing device. The system is designed as a standalone embedded unit capable of real-time monitoring and access control decision-making at industrial entry points. The NVIDIA Jetson AGX Orin serves as the core processor, performing real-time inference of both PPE detection and facial recognition tasks. A logitech USB webcam provides live video input, while an Arduino Uno controls peripheral devices such as a DS3225MG servo motor for door actuation. The system is designed to ensure that only authorized personnel wearing required PPE are granted access to restricted industrial areas. The Jetson AGX Orin processes live video feed from the webcam and runs deep learning models to detect safety gear such as helmets, gloves, safety glasses, and gas detectors. Moreover, it performs facial recognition to authenticate individuals attempting to gain access. The system workflow is summarized in Figure 1, presented as a flowchart for clarity. This figure shows the sequence from video input to decision-making and gate actuation.

System integration involves coordination between the webcam, Jetson AGX Orin, and Arduino Uno to ensure seamless communication. When both PPE compliance and facial match are confirmed, a general-purpose input/output (GPIO) signal is sent to the Arduino to open the access gate. A custom dataset was curated and annotated for training the PPE detection model. It was split into 90% training set and 10% validation set. Transfer learning techniques were applied to fine-tune the pre-trained model for detecting specific PPE classes relevant to this application. Rigorous testing was conducted under various lighting conditions and environmental settings. Performance metrics such as precision, recall, and mAP were used to evaluate system effectiveness. This design ensures high reliability, low latency, and edge-based processing, making it suitable for deployment in remote or high-risk environments where cloud dependency is not feasible.

The flowchart as shown in Figure 1, outlines a systematic process for automated access control using facial recognition and PPE detection. The sequence begins with system initialization and real-time video input from a webcam. Facial recognition algorithms are applied to identify human subjects. If no face is detected, the system loops back to await new input. Upon successful face detection, the YOLOv8 algorithm is employed to verify the presence of the required PPE. If PPE is missing, access is denied, and the system reinitiates the input cycle. When both facial recognition and PPE detection are successful, a Jetson device signals an Arduino microcontroller by setting the GPIO Pin 8 to LOW. This triggers the Arduino to open a door using a servo motor and activate a bulb as a visual indicator of access approval. After a five-second delay, the door is closed and the bulb is turned off, completing the access cycle. This integrated approach ensures that only authorized individuals wearing appropriate safety gear are granted entry, enhancing both security and compliance in controlled environments.

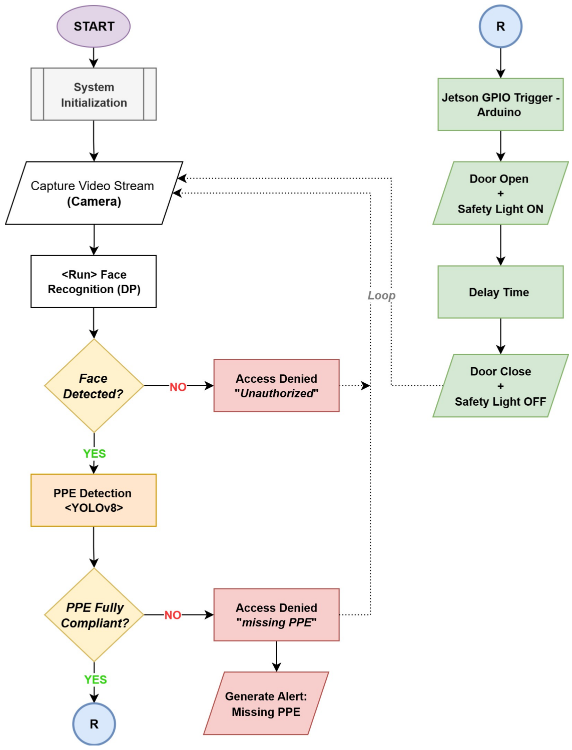

Figure 1. The system workflow for PPE detection, facial recognition, and access control

3. METHOD

The methodology consists of software and hardware components. The software component covers dataset preparation, training of a YOLOv8n-based PPE detector on a custom six-class dataset, and integration of a Dlib-based face recognition module using 128-D facial embeddings. The hardware component covers the deployment of the trained models on an NVIDIA Jetson AGX Orin edge device, TensorRT-based inference optimization, and Arduino Uno-controlled actuation of the access gate. Together, these components form the dual-authentication pipeline described in the following subsections.

3.1. Deep learning-based software system design

Python 3.10 and YOLOv8 was used for the design of the AI-based PPE detection and face recognition system. YOLOv8 is one of the latest in the series of YOLO object detection algorithms, known for its speed, accuracy, and scalability on different hardware platforms [19]. YOLOv8 was selected due to its robust performance in real-world conditions and its ability to detect multiple objects simultaneously, making it ideal for industrial safety monitoring applications. The system also integrates the face recognition Python library for facial verification, enabling secure access control by comparing detected faces with a database of registered personnel.

3.1.1. Data collection and preparation

A custom dataset was created to detect PPE, including helmets, gloves, glasses, vest, boots, and gas detectors. A total of 4,351 images were collected and annotated with bounding boxes, resulting in 9,051 annotations across six PPE classes. The dataset was prepared using Roboflow, a platform for managing and preprocessing vision datasets. The images were uploaded to a Roboflow workspace, where they were annotated either manually or using autolabeling tools followed by manual refinement. To improve model robustness, data augmentation techniques such as brightness adjustment, flipping, rotation, and blurring were applied. The dataset was split into: (90% training set and 10% validation set).

Then it was exported in the YOLOv8 format and integrated into the local training environment. In addition, a small set of facial images was collected to support auxiliary tasks such as mask detection, including variations in lighting, pose, and expression. Using Roboflow streamlined annotation, augmentation, and formatting, significantly reducing data preparation time.

3.1.2. PPE detection model training

For PPE detection, the YOLOv8n (Nano) variant was used, which offers an optimal balance between speed and accuracy for edge computing environments like the NVIDIA Jetson AGX Orin. Key training parameters included batch size: 16, image size: 640×640 pixels, and epochs: 100. The hardware used included high-performance workstation with Intel i9 processor, four NVIDIA RTX 2080 Ti GPUs, and 128 GB RAM. Transfer learning techniques were applied to fine-tune the pre-trained YOLOv8 model on our custom dataset. This allowed the model to be specifically adapted to the types and arrangements of PPE commonly found in industrial settings.

3.1.3. Face recognition

For facial recognition, the Dlib face recognition library was used. The Dlib face recognition library is a robust and efficient Python toolkit built on the Dlib C++ library. It is designed to implement facial recognition systems using state-of-the-art machine learning and computer vision techniques. It uses deep convolutional neural networks to encode facial features into 128-dimensional vectors, which are then compared against a database of known individuals (e.g., “Person A”, “Person B”) for authentication.

3.1.4. Integration and deployment

Once trained, the best-performing YOLOv8 model (best26.pt) was deployed to the NVIDIA Jetson AGX Orin platform for real-time inference. Using the Ultralytics API, the model was optimized with TensorRT to accelerate inference speed while maintaining high detection accuracy. A custom Python script was developed to integrate both models and run continuously on the Jetson AGX Orin. It performs the following tasks: i) captures live video from the webcam, ii) runs YOLOv8 for PPE detection, iii) runs face recognition for identity verification, iv) grants access only when all required PPE items are detected, and v) a match is found in the facial database. To enable hardware interaction, the script communicates with an Arduino Uno microcontroller via GPIO pin 8, signaling the DS3225MG servo motor to open the door if both conditions are satisfied. The complete software pipeline was tested under varied environmental conditions to ensure robustness and reliability before final deployment.

3.1.5. Software pipeline

The software pipeline integrates live video capture, PPE detection, facial recognition, and access control into a unified workflow. A Logitech USB webcam streams real-time video to the Jetson AGX Orin, where the YOLOv8 model—optimized with TensorRT for high inference speed and accuracy—detects essential PPE items such as helmets, gloves, safety glasses, gas detectors, boots, and vests. In parallel, a face recognition library processes detected faces and compares them with a database of registered personnel to verify identity. Access is granted only when both conditions are satisfied: all required PPE items are detected and the individual’s identity is confirmed. Once verified, the Jetson communicates with an Arduino Uno through a GPIO signal to activate the servo motor and open the access gate. If either condition fails, access is denied.

3.2. Intelligent embedded system-based hardware system design

The AI-based PPE detection and face recognition system was implemented using the NVIDIA Jetson AGX Orin as the core processing unit, leveraging its high computational capabilities for real-time inference. As shown in Figure 2, the system architecture integrates a Logitech USB webcam to capture live video feeds, an Arduino Uno microcontroller to control peripheral devices (e.g., servo motor for door actuation). Custom Python scripts were developed to orchestrate the entire workflow.

3.2.1. Hardware integration

The hardware integration comprises three key components working in coordination. The NVIDIA Jetson AGX Orin serves as the primary computing platform, executing both the YOLOv8-based PPE detection model and the facial recognition pipeline in real time. A Logitech USB webcam provides high-resolution video streams for continuous personnel monitoring, while an Arduino Uno acts as the interface between the Jetson and external hardware. Through GPIO signals, the Arduino controls the DS3225MG servo motor to actuate the access gate based on the system’s decision-making process. Figure 3 shows the circuit connections with hardware components (including power supplies, GPIO connections, transistor-resistor networks, and servo motor control), Jetson AGX Orin processes webcam input, sends commands to Arduino Uno via GPIO. Arduino controls the DS3225MG servo (door mechanism) via PWM on pin 9 and pin 10, with 2N2222 transistor-resistor network managing power/ground. The circuit diagram presents a comprehensive hardware integration scheme that combines high-performance computing with embedded control. At the center of the system is the Jetson AGX Orin 64 GB, which functions as the primary processing unit. It is connected to a camera via USB for real-time image acquisition and to an LCD screen through an HDMI interface for visual output. The system is powered by two distinct DC sources: a 7 V supply dedicated to powering components on the breadboard and servomotors (DS3225MG), and a 12 V supply for higher-power components. This dual-power configuration ensures stable operation in devices with varying voltage requirements. The Arduino Uno acts as an intermediary controller, interfacing with sensors and actuators mounted on a breadboard. It receives sensor inputs and controls outputs such as LEDs or relays, enabling responsive actuation based on processed data. Communication between Jetson and Arduino is established through direct wiring, allowing for synchronized operations such as triggering servo motors based on image recognition results. The use of jumper wires facilitates modular and flexible connections, making the system adaptable for prototyping and iterative development. This integrated setup supports complex tasks like PPE detection and access control by leveraging the computational power of the Jetson and the real-time control capabilities of the Arduino.

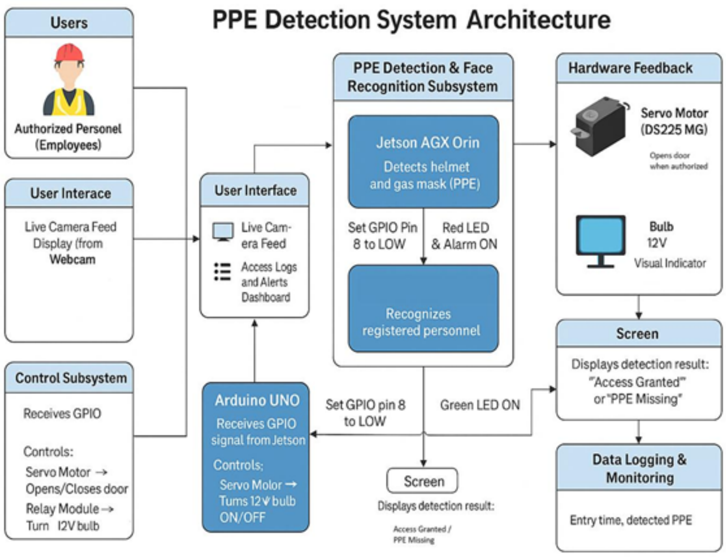

Figure 2. System architecture diagram of the AI-based PPE detection and face recognition system

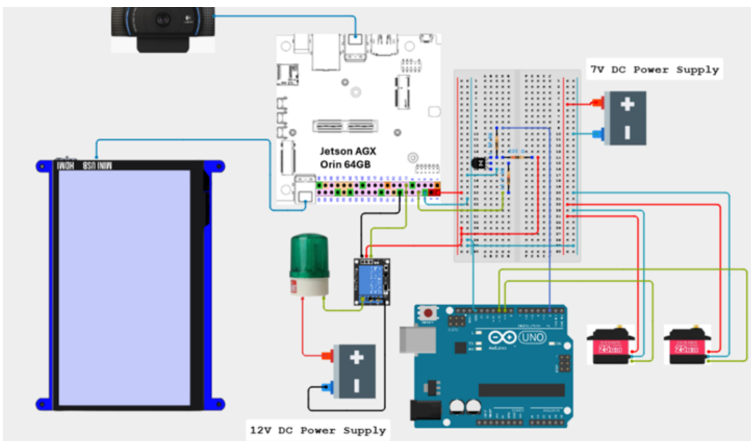

Figure 3. Complete hardware integration circuit diagram

3.2.2. Deployment and testing

The trained model was deployed in a controlled industrial environment to evaluate its performance under realistic conditions. The system was tested under varying lighting conditions, different camera angles, and various environmental scenarios to ensure robustness and reliability. Trained model deployment: the best performing YOLOv8 model (best26.pt) was deployed on the NVIDIA Jetson AGX Orin, a high-performance edge computing device ideal for real-time AI inference. The model was integrated using the Ultralytics API and TensorRT optimizations were applied to accelerate inference speed while maintaining the detection accuracy.

Hardware integration and testing: to enable real-time PPE compliance monitoring and facial recognition, the system was interfaced with the following hardware components. The hardware configuration of the system comprises several key components, each serving a specific function in the integrated PPE detection and access control workflow. At the core is the Jetson AGX Orin 64 GB, which performs real-time video processing for both PPE detection (e.g., helmets, gloves) and facial recognition, enabling rapid and accurate decision-making. A web camera captures live video input, while a monitor displays system outputs and status updates. During setup and operation, a keyboard and mouse are used to configure and control the Jetson. The Arduino Uno acts as an actuator controller, receiving signals from the Jetson and adjusting the duty cycle to operate the DS3225MG servo motors, which physically open or close a gate based on detection results. A bulb serves as a visual indicator of access authorization. To ensure safe and reliable interfacing between the Jetson (3.3 V logic) and the Arduino (5 V logic), a 2N2222 NPN transistor is used as a voltage level translator and switch, supported by resistors that limit current and stabilize signals. A relay is included to allow the Jetson to safely control the 12 V bulb, isolating high-voltage components from low-voltage logic circuitry. Power is supplied through a 12 V DC source for the bulb and relay, while the servo motors are powered by a separate 7 V DC supply. This well-isolated modular design ensures robust performance, electrical safety, and precise coordination between sensing, processing, and actuation components.

System integration and testing: a Python script was developed to integrate both the PPE detection and facial recognition modules. This script ran on the Jetson AGX Orin and communicated with the Arduino Uno via GPIO to control peripheral devices such as LEDs and buzzers based on detection results. The system was evaluated for its ability to: i) handle real-time camera stream, ii) maintain low-latency decision-making, and iii) trigger alerts accurately based on detected violations. Continuous monitoring confirmed that the system could operate efficiently in near real-time, with an average inference time of less than 100 ms per frame. Figures 4 and 5 show a visual representation of the deployed system. Figure 4 showing bounding boxes around detected safety gear items and facial identity verification (simultaneous detection).

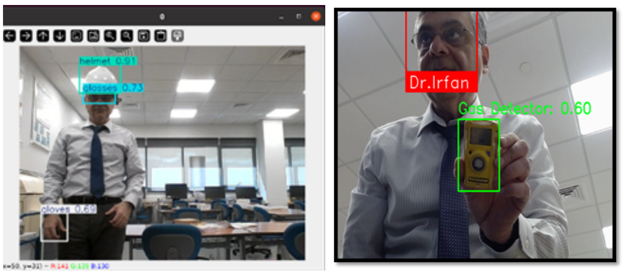

Figure 4. Real-time PPE and face recognition system in action

Figure 5. Image of the assembled and working prototype in action

4. RESULTS AND DISCUSSION

First, the performance of state-of-the-art recent work is presented to better understand the contribution of the proposed framework. Then, the performance of the AI-based PPE detection and face recognition system was evaluated using several key metrics, including precision, recall, F1-score, and mAP. The facial recognition performance evaluated against a database of 50 registered personnel. The results are presented along with visualizations of the performance curves.

4.1. Discussion in the context of prior work

The system achieved a PPE detection mAP of 98.4% and maintained near real-time operation with an average inference time of $<$100 ms per frame on the deployed edge platform and 99.38% accuracy for face recognition. These outcomes are consistent with and in several cases exceed prior YOLO-based PPE monitoring results reported in the literature. In terms of detection performance, prior studies reported YOLOv8-large average precision of 91.7% on the color helmet and vest (CHV) dataset [20], while a YOLOv4-based PPE solution achieved 79% mAP across four PPE classes [21]. More recent optimized variants have reported strong results (e.g., salp swarm assisted YOLOv8 (YOLOv8-SSA) with 98.2% accuracy and 98.9% precision) in construction monitoring deployments [22]. Within this context, the achieved 98.4% mAP indicates that the proposed model generalizes effectively to the targeted operational conditions while maintaining high detection reliability. From a real-time deployment perspective, latency is a key practical constraint. A prior PPE-safety monitoring system (SMS) system reported precision of 0.93, recall of 0.96, with 241.57 ms latency [23], demonstrating feasibility but at a higher processing delay. In comparison, the proposed system sustained $<$ 100 ms/frame decision-making in integrated testing, supporting real-time entry-point enforcement where prompt gate actuation is required.

Another YOLOv8-based framework, incorporating data cleaning, training, and deployment, achieved 94% accuracy in real-world scenarios [24]. In mining environments, combining YOLOv8 with long short-term memory (LSTM) networks enabled real-time PPE monitoring and worker behavior tracking, achieving 95.9% accuracy in detecting unsafe actions and fatigue [25]. An SSD-based system evaluated on 132 construction scenarios achieved mAP50 of 0.768, precision of 0.831, and recall of 0.693, confirming reliable but environment-sensitive performance [26]. An instance segmentation approach using Open Images V5 and DeepFashion2 datasets achieved 61.7% mAP50, enabling effective segmentation of helmets, vests, and protective gear while preserving worker anonymity [27]. A YOLOv7-based model for detecting MPPE achieved 90.93% mAP on the CPPE-5 dataset, demonstrating reliable detection across five categories of clinical protective gear [28]. Finally, while the above studies demonstrate strong PPE detection performance across industrial and construction contexts, most solutions focus on PPE compliance monitoring alone. The proposed work differs by coupling PPE compliance with identity verification and access control at the point of entry, addressing the common gap where PPE detection is not linked to authorized personnel validation.

4.2. Personal protective equipment detection performance

The YOLOv8 model was trained and fine-tuned on a custom dataset containing 9051 annotations across 4351 images, covering six main PPE classes: boots, glasses, gloves, helmet, vest, and gas detectors. Overall, these curves and the confusion-matrix outcomes are aligned with the strong YOLO-based PPE detection performance reported in prior work, while maintaining lower end-to-end latency suitable for access-control enforcement. The model achieved high accuracy and robustness across all classes, as evidenced by the following metrics.

4.2.1. F1-confidence curve

Figure 6 shows the F1 scores for each PPE class as a function of the confidence thresholds. The F1-confidence curve analysis demonstrates optimal performance characteristics for deployment in real-world industrial environments. The overall F1-score reaches 0.94 at the optimal confidence threshold of 0.589, indicating an excellent balance between precision and recall. Most PPE classes maintain F1-scores exceeding 0.95 across the confidence range of 0.3 to 0.8, providing flexibility in threshold selection based on specific deployment requirements. The gas detector class exhibits unique behavior in the F1-confidence relationship due to limited training samples, which reflects the specialized nature of this equipment in industrial settings. This analysis provides crucial guidance for system deployment, enabling operators to select confidence thresholds that optimize performance for their specific industrial safety requirements.

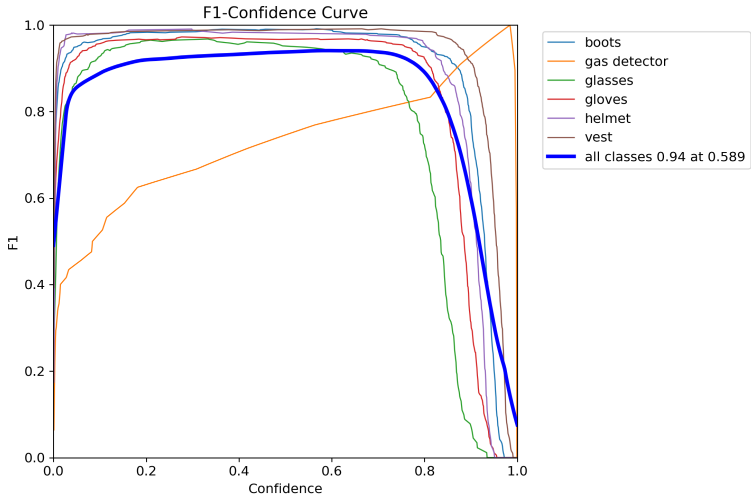

Figure 6. F1-score vs. confidence threshold curve

4.2.2. Precision-confidence curve

Figure 7 illustrates the precision versus confidence threshold curve for the trained YOLOv8 PPE detection model, providing insight into the model's ability to correctly identify PPE items across varying levels of prediction certainty. As the confidence threshold increases, the precision generally improves, indicating that the model becomes more selective and accurate in its predictions. This behavior is typical of well-trained object detection models, where higher confidence scores correlate with fewer false positives. The curve helps determine the optimal confidence threshold for deployment, balancing precision with detection coverage. In this study, the model maintained high precision across a broad range of thresholds, reinforcing its reliability for real-time industrial safety applications where accurate PPE detection is critical for access control and compliance enforcement.

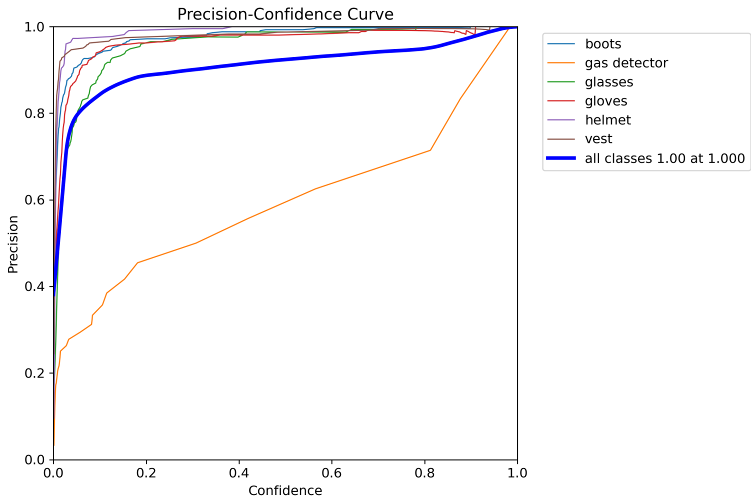

Figure 7. Precision vs. confidence threshold curve

4.2.3. Confusion matrix

To further analyze the model classification performance, a confusion matrix was generated as shown in Figure 8. The confusion matrix analysis provides detailed insights into the model's classification accuracy and error patterns. Boot detection, representing the most frequent class with approximately 1,850 instances, achieved 413 correct predictions out of 424 total instances, resulting in 97.4% classification accuracy.

Helmet detection demonstrated exceptional performance with 213 correct predictions out of 214 instances, achieving 99.5% accuracy. Gloves classification achieved 354 correct predictions from 366 total instances (96.7% accuracy), while vest detection correctly identified 228 out of 234 instances (97.4% accuracy). The analysis reveals minimal cross-class confusion, with only $1-10$ misclassifications occurring between different PPE categories, and well-controlled background false positives. Notably, no critical safety misclassifications were observed, which is essential for industrial safety applications where false negatives could compromise worker protection.

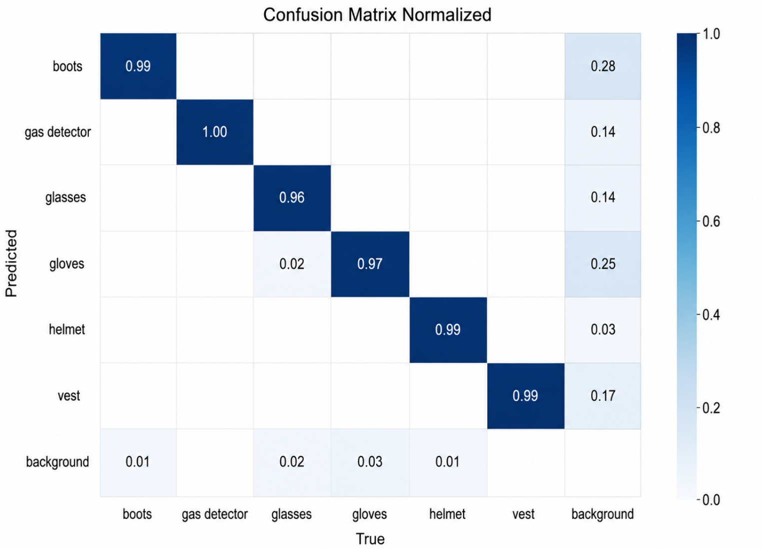

Figure 8. Normalized confusion matrix for PPE detection

4.3. Facial recognition performance

The facial recognition component, powered by the face recognition library, demonstrated high accuracy in identity verification. The system was tested against a database of 50 registered personnel under varying lighting conditions and poses. Key findings include: i) accuracy: the facial recognition module achieved an average accuracy of 99.38% in identifying authorized personnel; ii) latency: the average processing time for facial recognition was approximately 50 ms per frame, ensuring real-time performance; and iii) robustness: the system maintained consistent performance across different environmental conditions, including changes in lighting and pose variations.

5. CONCLUSION

The AI-based PPE detection and facial recognition system presented in this paper demonstrates the potential to integrate deep learning with edge computing to improve safety and access control in industrial environments. By leveraging real-time object detection using YOLOv8 and identity verification via facial recognition, the system ensures both compliance with PPE protocols and secure entry into restricted zones. The deployment on NVIDIA Jetson AGX Orin enables efficient local processing without reliance on cloud infrastructure, making it suitable for remote or high-risk locations. Future work may extend this system by incorporating additional modalities such as voice authentication or biometric sensors for multi-factor authentication. Integration with internet-of-things (IoT) platforms could allow centralized monitoring of multiple entry points across large industrial sites. Furthermore, the model can be improved to detect dynamic violations, such as improper use of equipment or unsafe behavior, using recurrent neural networks or video-based action recognition techniques.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
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R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject Administration
Fu : **Fu**nding Acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [IA], upon reasonable request.

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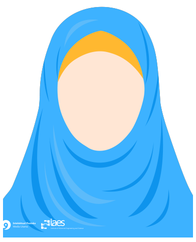

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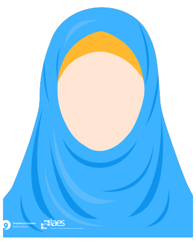

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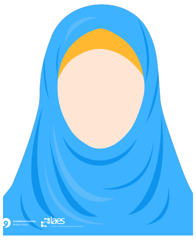

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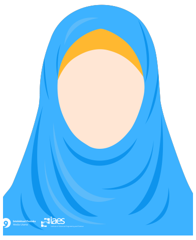

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