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A Modular, Extensible AI-Based PPE Compliance Framework for Engineering Technology Labs

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Abstract

Ensuring consistent compliance with personal protective equipment (PPE) requirements in engineering technology laboratories is a persistent instructional and safety challenge. In many laboratory settings, PPE enforcement relies primarily on instructor observation, which can be difficult to maintain when multiple students are engaged in hands-on activities. As class sizes grow and laboratory tasks become more complex, opportunities for missed or delayed safety interventions increase. This paper presents a modular, extensible, AI-based PPE compliance framework designed to augment instructor oversight in instructional laboratories without replacing human instruction. The proposed system integrates an Intel RealSense camera with lightweight computer vision models to automatically assess PPE compliance at the individual student level. The current implementation focuses on two critical PPE elements—face masks and safety glasses—selected because they are commonly required across manufacturing, mechatronics, robotics, and electromechanical laboratories. A face detection module first identifies individuals in the scene. Dedicated deep learning models are then applied to each detected face region to determine mask usage and the presence of safety glasses. The system operates in real-time on standard laboratory computers and provides immediate visual feedback, allowing students to correct unsafe conditions as they occur. While the present work emphasizes mask and eye protection, the framework is intentionally designed to support incremental expansion to additional PPE categories, gesture recognition, and depth-based safety zone monitoring. Experimental observations demonstrate reliable real-time performance under typical laboratory conditions while also identifying practical limitations related to lighting, viewing angle, and PPE appearance. These findings suggest that AI-assisted PPE monitoring can serve as a practical instructional aid for reinforcing safe practices in engineering technology education.

Introduction

Hands-on laboratory instruction is an essential component of engineering technology education. Manufacturing, mechatronics, robotics, and electromechanical engineering laboratories provide students with meaningful experiential learning opportunities, but they also introduce inherent safety risks associated with machinery, electrical systems, and human–machine interaction. To mitigate these risks, institutions mandate the use of personal protective equipment (PPE), including face masks, safety glasses, gloves, and protective clothing. Despite clearly established policies, ensuring consistent PPE compliance remains challenging, particularly in laboratory environments where multiple students perform tasks simultaneously.

Instructors are often required to divide their attention among technical instruction, equipment supervision, and safety monitoring. As a result, PPE violations may go unnoticed or be addressed only after an unsafe condition has already occurred. Automated safety monitoring systems offer a potential solution by supporting instructor oversight with continuous, objective observation. Because manual PPE monitoring is labor-intensive and prone to human error, automated real-time detection has been proposed as a practical alternative for improving safety compliance [1].

Recent research demonstrates strong interest in automated PPE compliance monitoring; however, real-world deployment continues to face practical barriers, including environmental variability, computational constraints, identity and privacy considerations, and the difficulty of maintaining robust real-time performance [2]. These challenges are especially relevant in educational settings, where laboratory layouts, lighting conditions, and user behavior vary significantly.

In manufacturing teaching laboratories, hazards often mirror those found in industrial environments, and PPE requirements commonly include masks, gloves, and safety glasses [3]. University instructors must therefore enforce safety compliance while simultaneously supporting learning outcomes. Lightweight, real-time monitoring systems can reduce reliance on constant manual supervision and provide immediate feedback to both instructors and students during laboratory activities. Prior laboratory-focused studies emphasize the potential role of visual monitoring systems in improving PPE compliance within manufacturing education contexts [3].

Recent advances in computer vision and embedded artificial intelligence have made real-time visual analysis feasible on relatively modest hardware platforms available in instructional laboratories. Rather than replacing instructors, such systems can support and strengthen safety expectations, provide immediate visual feedback, and allow instructors to focus more fully on pedagogy.

This paper introduces a modular, extensible AI-based PPE compliance framework designed specifically for instructional laboratory environments. The proposed framework builds upon prior experience with lab-centered instructional environments in engineering technology education, where hands-on activities and real-time feedback have been shown to enhance student engagement and learning outcomes [4]. By integrating real-time computer vision with a flexible system architecture, the approach is intended to support instructors in promoting safe laboratory practices without disrupting instructional flow.

Related Work

A recent systematic review provides a comprehensive overview of computer vision–based PPE compliance monitoring, summarizing commonly used algorithms, datasets, and deployment strategies while emphasizing persistent challenges such as environmental variability, computational constraints, and ethical considerations related to identity management and privacy [2]. Early efforts in automated PPE detection focused primarily on object recognition for safety glasses compliance in industrial environments, reflecting the importance of eye protection in hazardous workplaces [5].

More recent PPE monitoring systems increasingly rely on YOLO-family object detectors due to their strong real-time detection performance. Laboratory-focused studies evaluate multiple YOLO variants (e.g., YOLOv4, YOLOv5, and YOLOv6) for detecting PPE items and report competitive performance metrics such as mean average precision and F1 score, while also identifying practical failure cases including occlusion, small-object visibility, and variations in pose [3]. Other YOLO-based approaches similarly highlight performance advantages and recommend expanding datasets and detection classes—such as gloves and protective eyewear—to broaden PPE coverage [6][7].

A key challenge in realistic scenes is reliably associating detected PPE items with the correct individual, particularly in crowded environments or under partial occlusion. Recent industrial studies address this problem by proposing modular pipelines that combine worker detection, pose estimation, and PPE recognition, along with duplicate removal and association mechanisms to improve PPE-to-person matching accuracy [8].

The availability of large, annotated datasets has further accelerated research in this area. Recent work has released comprehensive PPE datasets that support benchmarking and comparative evaluation of modern object detection models across diverse environments and PPE categories [9].

While automated safety monitoring has been widely explored in industrial contexts—where systems prioritize robustness and scalability in large, controlled environments—educational laboratories present distinct challenges. These include diverse PPE styles, frequent occlusions, and rapidly changing user poses. In addition, instructional laboratories often involve close student interaction with equipment and frequent movement within shared workspaces, further complicating reliable visual monitoring. Within academic settings, prior work has examined vision-based systems for attendance tracking, behavioral monitoring, and gesture recognition; however, relatively few studies focus specifically on PPE compliance in instructional laboratories using low-cost RGB or depth-capable cameras.

This work contributes to the literature by adapting proven industrial PPE detection techniques to the constraints and pedagogical goals of engineering technology education, with an emphasis on real-time operation, modular and extensible system design, and practical deployment within instructional laboratory environments where safety and learning objectives must be addressed simultaneously.

System Architecture

The proposed framework follows a modular pipeline architecture that allows individual components to be developed, evaluated, and extended independently. This design supports incremental deployment in instructional settings, where safety requirements and sensing needs may evolve over time in response to changing laboratory practices.

Figure 1 illustrates the overall system architecture. An RGB video stream from an Intel RealSense camera serves as the primary input. Each video frame is processed by a face detection module, which identifies all visible faces and defines regions of interest (ROIs). These ROIs are then passed in parallel to specialized PPE analysis modules. In the current implementation, separate models are used for mask classification and safety glasses detection. The outputs of these models are combined by a decision layer to determine overall PPE compliance for each individual, and visual feedback is displayed on the live video stream to indicate compliance status. This processing flow enables real-time assessment of multiple individuals while maintaining responsiveness suitable for active laboratory environments, with end-to-end latency on the order of tens of milliseconds on standard laboratory computers.

By structuring PPE analysis as parallel, face-centered modules, the architecture reduces unnecessary computation on background regions while enabling consistent per-person compliance assessment in multi-user laboratory scenarios. This approach also facilitates straightforward extension of the system to additional PPE categories or safety-related analyses without requiring modification of the core processing pipeline.

The vision pipeline processes camera frames in real-time to detect faces and classify PPE compliance using lightweight convolutional neural networks deployed on embedded hardware. The system does not perform identity recognition, store personally identifying information, or rely on cloud connectivity; instead, it provides immediate visual feedback only, supporting privacy-conscious deployment in instructional environments while maintaining responsive real-time performance.

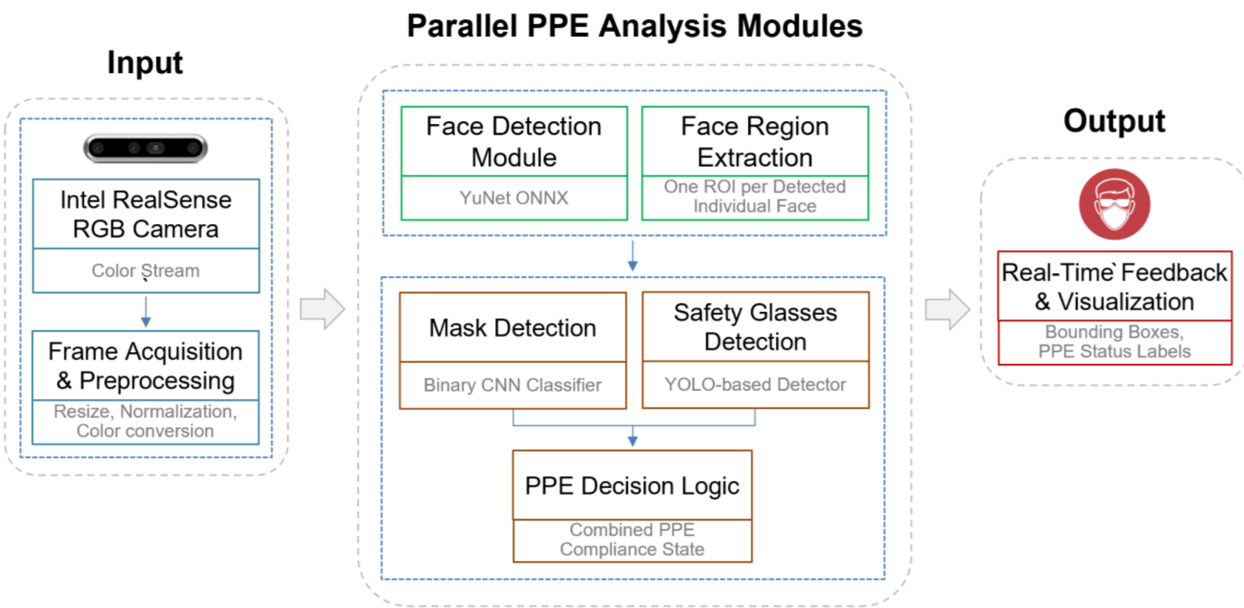


Figure 1. System architecture for the AI-based PPE compliance framework

- **Hardware Platform**

An Intel RealSense camera provides synchronized RGB data for visual analysis. While depth data is not required in the current implementation, the hardware selection allows for future integration of spatial reasoning and restricted-zone monitoring. The Intel RealSense camera was selected due to its reliable RGB imaging, ease of integration with standard laboratory computers, and widespread availability in academic environments. This capability provides a clear upgrade path for future spatial safety monitoring applications, such as proximity-based alerts and spatial awareness–based safety functions.

All video processing and inference are performed on standard laboratory desktop computers without the use of dedicated GPU hardware, supporting scalable deployment in teaching environments.

- **Face Detection Module**

A lightweight neural face detector identifies all visible faces in the scene. Each detected face defines a region of interest (ROI) that serves as the input for subsequent PPE analysis. Using a dedicated face detector reduces computational cost and improves PPE detection accuracy by focusing analysis on relevant image regions.

The face detection module operates on each video frame and returns bounding boxes for all visible individuals, enabling simultaneous PPE assessment for multiple students. By restricting subsequent analysis to face regions, the system reduces computational load while improving detection robustness under cluttered laboratory backgrounds.

In the current implementation, face detection is performed using a compact Open Neural Network Exchange (ONNX)-based neural model designed for efficient face localization, selected for real-time performance and robustness to pose variation in classroom and laboratory settings.

- **Mask Detection Module**

Mask compliance is evaluated using a lightweight two-class convolutional neural network that classifies each face ROI as either “mask” or “no mask.” A classification-based approach was selected due to its low computational overhead and strong performance when mask placement is constrained to the facial region, making it well suited for reliable real-time deployment in educational laboratory environments under typical lighting conditions.

The mask detection model is deployed in ONNX format and executed using CPU-based inference, enabling consistent real-time performance across heterogeneous laboratory computers.

- **Safety Glasses Detection Module**

Safety glasses detection is implemented using an object detection model trained specifically for protective eyewear. Unlike simple classification approaches, object detection enables the system to localize glasses within each face ROI, improving robustness to partial occlusions, variations in eyewear shape, and changes in head pose.

A YOLO-based object detection framework is used for safety glasses detection, selected for its ability to accurately localize small wearable items in real-time under unconstrained viewing conditions. Localization-based detection is particularly effective when safety glasses occupy only a small portion of the face or are viewed at oblique angles, conditions commonly encountered in instructional laboratory settings.

- **Decision Logic and Feedback**

For each detected individual, the system aggregates the outputs of the mask and safety glasses detection modules to determine overall PPE compliance. This decision process is implemented using rule-based logic that evaluates detector outputs on a per-face basis, allowing laboratory-specific compliance requirements to be defined clearly and transparently.

Visual indicators are displayed on the live video stream to provide immediate feedback to both students and instructors during laboratory activities. Because the compliance logic operates independently of the underlying detection models, PPE requirements can be adjusted or extended without retraining existing neural networks.

Implementation Details

This section describes practical implementation considerations for deploying the proposed PPE compliance framework in instructional laboratories. The system is implemented in Python using OpenCV for image processing and ONNX Runtime for neural network inference. All models are deployed in Open Neural Network Exchange (ONNX) format to support framework-independent execution and straightforward integration across heterogeneous laboratory computing platforms. Models are executed on the CPU, demonstrating that real-time performance can be achieved without the use of dedicated GPU hardware.

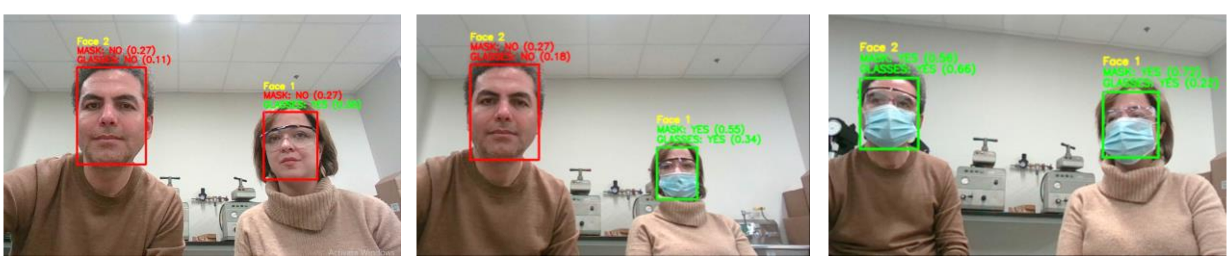
To support multi-user scenarios, the framework processes multiple face ROIs per video frame. Performance optimizations, including limiting the number of faces analyzed and adjusting inference frequency, are applied to maintain interactive frame rates during active laboratory sessions. The modular software design allows additional PPE detectors or behavioral analysis modules to be incorporated with minimal modification to the existing codebase, supporting future expansion as laboratory safety requirements evolve.

Representative qualitative results illustrating system behavior under common PPE conditions are shown in Figure 2. From left to right: no mask/no glasses, improperly worn mask (below mouth), properly worn mask, safety glasses only, and combined mask and safety glasses. Green bounding boxes indicate compliant PPE states, while red bounding boxes indicate non-compliance. Confidence scores are shown for each detection.

For visualization purposes, the system displays per-face confidence scores associated with each detection. For mask detection, the reported value corresponds to the classifier output probability for the predicted class. For safety glasses detection, the displayed value represents the peak confidence score among detected eyewear candidates within the face region. These values are used internally for thresholding and decision logic and are shown to support qualitative interpretation of system behavior rather than as formal performance metrics.

Figure 2. PPE detection outcomes under common mask and eyewear conditions

Figure 3 demonstrates multi-person PPE compliance detection in a laboratory setting. The system simultaneously evaluates PPE status for multiple individuals, identifying compliant and non-compliant conditions for face masks and safety glasses in real time. The examples illustrate a partial compliance scenario, a mixed compliance scenario involving both compliant and non-compliant individuals, and a full compliance scenario in which all detected individuals are wearing the required PPE. Together, these cases highlight the framework's ability to operate beyond single-user scenarios typical of instructional laboratories.



(a) (b) (c)

Figure 3. Multi-person PPE compliance detection in an instructional laboratory environment:
(a) partial compliance scenario, (b) mixed compliance scenario, and (c) full compliance scenario

Table 1. Interpretation of displayed confidence values

Value	Description
Value shown after mask (e.g., 0.27)	Softmax probability of the predicted class from the two-class mask classifier
Value shown after glasses (e.g., 0.20)	Peak detection confidence score from the safety glasses detector
Different numeric ranges	Expected due to differences in model architectures and output formats
Compliance decision	Determined using predefined thresholds applied independently to each detector

Experimental Observations

The proposed framework was evaluated qualitatively under conditions representative of instructional engineering technology laboratories. Testing was conducted on a standard desktop computer without a dedicated graphics processing unit, reflecting the hardware constraints commonly found in teaching labs. The system consistently detected face masks across a range of face orientations and working distances typical of bench-level laboratory activities.

Safety glasses detection was more sensitive to viewing angles, lighting conditions, and eyewear style. Potential mitigation strategies include targeted dataset augmentation, inclusion of varied eyewear styles during retraining, and controlled camera placement to reduce glare and reflection artifacts. Clear laboratory safety glasses were detected more reliably than dark-tinted or fashion-style eyewear, particularly under uneven lighting. Despite these limitations, the system was able to identify compliant and non-compliant PPE states in real-time and provide timely visual cues to users. Table 2 summarizes representative performance characteristics observed during testing. While these values are not intended as exhaustive benchmarks, they demonstrate that real-time operation is achievable on commodity hardware suitable for instructional environments.

Table 2. Representative system performance observations

Metric	Observed Value
Input resolution	1280 × 720 RGB
Face detection rate	25–30 FPS
Mask classification latency	< 10 ms per face
Safety glasses detection latency	15–25 ms per face
End-to-end system latency	~40–60 ms

Discussion

The results indicate that even a limited set of PPE detection modules can provide meaningful safety feedback in instructional laboratories. The modular architecture enables institutions to deploy an initial system focused on high-priority PPE items and expand system capabilities incrementally as instructional needs evolve. Importantly, the proposed framework is intended to support instructional safety practices rather than replace instructor judgment or supervision. Several challenges remain, including ensuring reliable performance across diverse PPE styles and maintaining robustness under variable environmental conditions. These observations highlight the importance of iterative refinement, laboratory-specific adjustment, and continued validation when deploying AI-based safety systems in real-world educational settings.

Future Work

Planned extensions include the integration of additional PPE categories such as gloves, hard hats, and high-visibility vests. The incorporation of gesture recognition and depth-based spatial awareness is also envisioned to enhance situational understanding and support zone-based safety monitoring. At its current stage, this work represents a systems-design and feasibility study focused on real-time implementation and deployment within instructional laboratories. Future research will therefore include longitudinal studies to evaluate how real-time visual feedback influences student safety behavior, instructor workload, and overall laboratory culture, as well as comparisons with traditional human-only safety monitoring approaches.

Conclusion

This paper presents a practical and extensible AI-based framework for PPE compliance monitoring in engineering technology laboratories. By combining real-time computer vision with modular system architecture, the proposed approach enhances safety awareness while remaining adaptable to evolving instructional needs. The results suggest that AI-assisted monitoring systems can play a valuable role in supporting safe and effective hands-on engineering education. In instructional laboratories, this type of real-time feedback can reinforce PPE expectations, support consistent safety habits, and reduce reliance on continuous instructor observation.

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