



# Pose-Aware PPE Compliance System

Core Idea: Merge YOLO-powered PPE detection with pose-region mapping and OpenVINO edge-speed—plus live monitoring dashboard.

Date - **18<sup>th</sup> June, 2025**

- |                          |                   |
|--------------------------|-------------------|
| 1. <b>Hitarth Mehra</b>  | <b>1RV23CS100</b> |
| 2. <b>Harshit Raj</b>    | <b>1RV23CS096</b> |
| 3. <b>Kiran Kumar S</b>  | <b>1RV23CS112</b> |
| 4. <b>Aaditey Chalva</b> | <b>1RV23Al001</b> |
| 5. <b>Aniket R T</b>     | <b>1RV23Al017</b> |

# Literature Review



1. An effective deep learning approach enabling miners' protective equipment detection and tracking using improved YOLOv7	Zheng Wang et al.	2023	<i>Xi'an Univ. of Science &amp; Tech.</i>	Tailored YOLOv7-PE for miners, real-time tracking in harsh environments
2. Integrating real-time pose estimation and PPE detection with cutting-edge deep learning...	Mohamed Imam et al.	2025	<i>Neurocomputing</i>	Combines pose + PPE detection, enhanced rescue ops, low false positives
3. A Deep Learning Approach to Detect Complete Safety Equipment...	Islam et al.	2024	arXiv	Full PPE detection in construction; ~87.7% mAP
4. Real-Time Personal Protective Equipment Compliance Detection	Lo et al.	2022	<i>IEEE</i>	Techniques across YOLOv3/4/7; YOLOv7 ~97% mAP @25FPS
5. Target Detection of Safety Protective Gear Using the Improved YOLOv5	Liu & Qin	2024	<i>IEEE Trans.</i>	YOLO-EA for small objects; precision ~98.9%, recall ~94.7%
6. Edge-based pose & PPE compliance in mining (Underground)	Imam et al.	2023	<i>IEEE Access</i>	YOLO-Pose-Edge; robust under low light, occlusion
7. A Combined Detection Algorithm for PPE Based on Lightweight YOLOv4	Ma et al.	2022	<i>Sensors</i>	CLSlim YOLOv4 (pruned); size ↓ 98%, speed ↑ 1.8×
8. Helmet Detection Using Improved YOLOv5s	Chen et al.	2023	<i>Journal of Real-Time Image Processing</i>	Attention-enhanced helmet detection @100+ FPS, ~94.7% mAP

Note: Readers, year, venue, and primary contribution captured for each.



# Problem & Motivation

- PPE non-compliance causes injuries & financial loss.
- Automation demands real-time, accurate, explainable systems.
- Manual monitoring is unreliable & slow.
- Edge deployment is necessary for safety-critical sites.

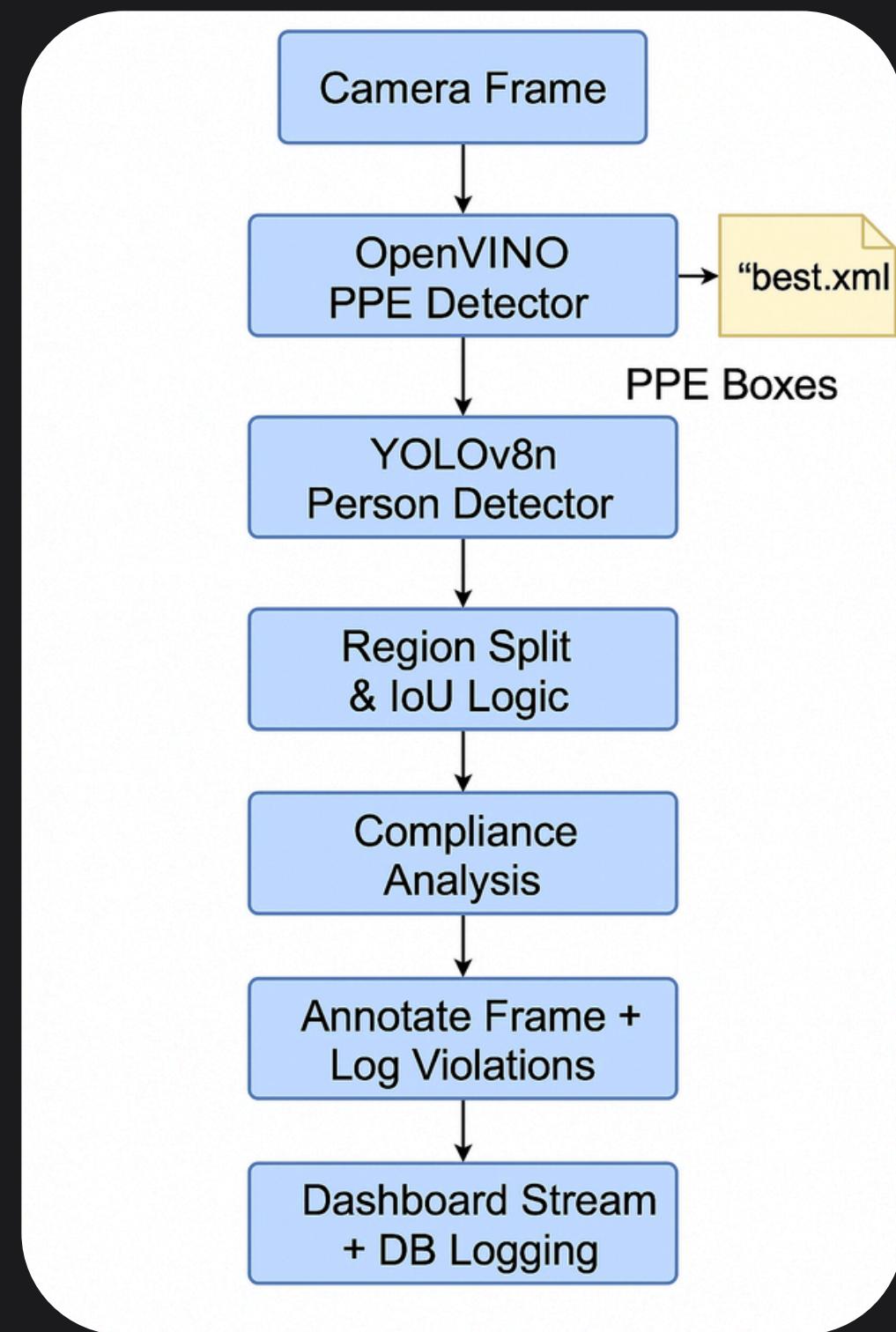


# Objectives

- Real-time PPE detection per body-region (head, torso, limbs).
- Pose-guided logical checks for misplaced gear.
- Utilize OpenVINO for fast inference on-device.
- Provide live alerting & employee dashboard logging.



# System Architecture

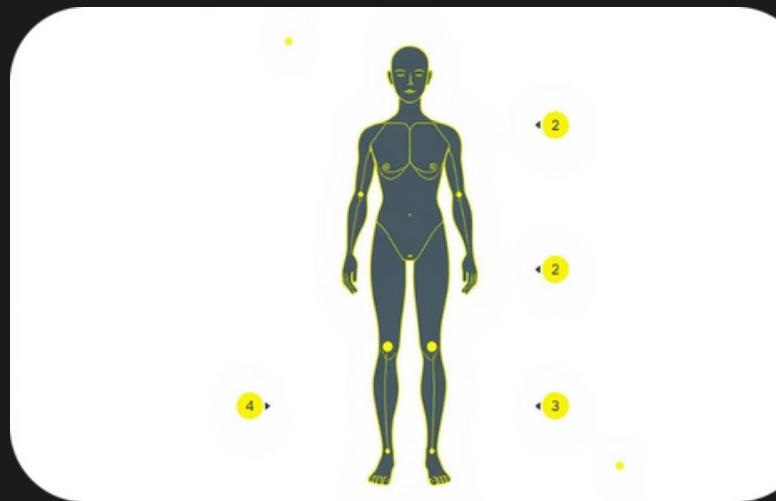


This pipeline performs real-time PPE compliance checks:

- Camera Frame: Captures live video input
- OpenVINO PPE Detector: Detects gear like helmets, gloves using an optimized model
- YOLOv8n Person Detector: Identifies people in the frame
- Region Split + IoU Logic: Matches PPE items to body parts (head, torso, legs)
- Compliance Analysis: Flags missing gear as violations
- Annotate & Log: Displays results and logs violations
- Dashboard & DB: Streams output and updates violation records

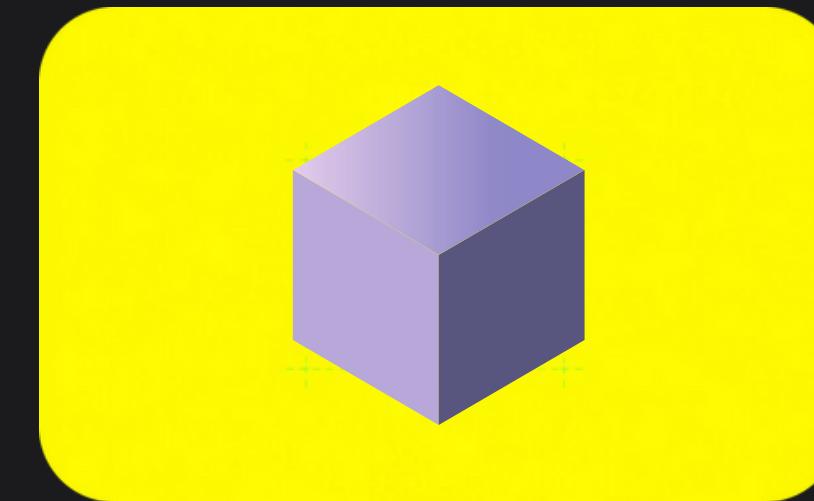
(Diagram visually illustrating the above pipeline)

# Core Algorithms & Logic



## Region Partitioning

Dividing the detected person into distinct body regions: head, torso, and legs.



## Box-IoU Checks

Utilizing Intersection over Union (IoU) to assess the overlap between detected PPE items and their corresponding body regions.



## Thresholding

A 0.25 IoU threshold determines successful PPE detection within each region, ensuring adequate coverage.

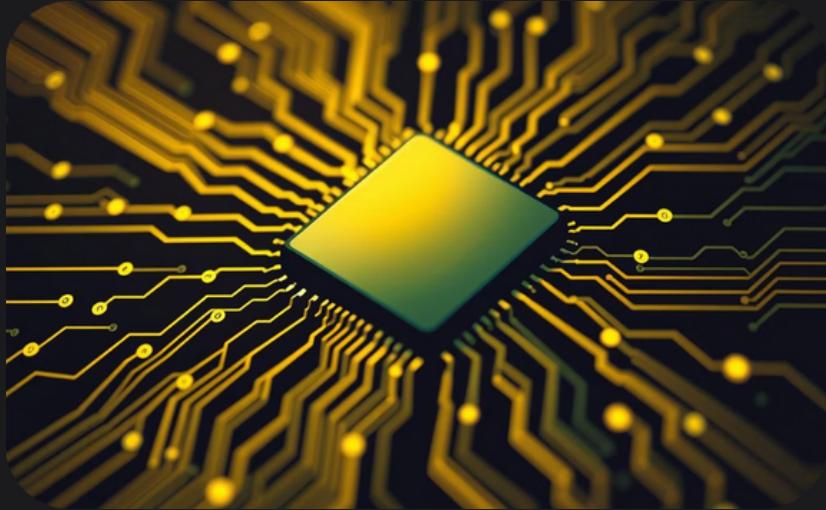


## Compliance Checklist

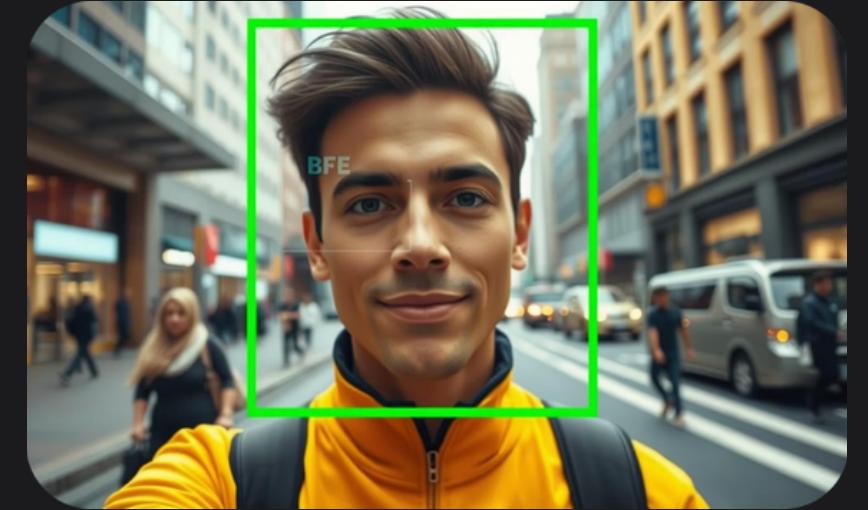
A dynamic checklist evaluates PPE status for each body part, resulting in a final "Safe" or "Unsafe" compliance label.

These algorithms are scripted and implemented using OpenCV for image processing, Ultralytics YOLO for object detection, and OpenVINO for optimized inference.

# Implementation Details



**OpenVINO:** PPE inference  
(best.xml) @ ~2.4 ms/frame.



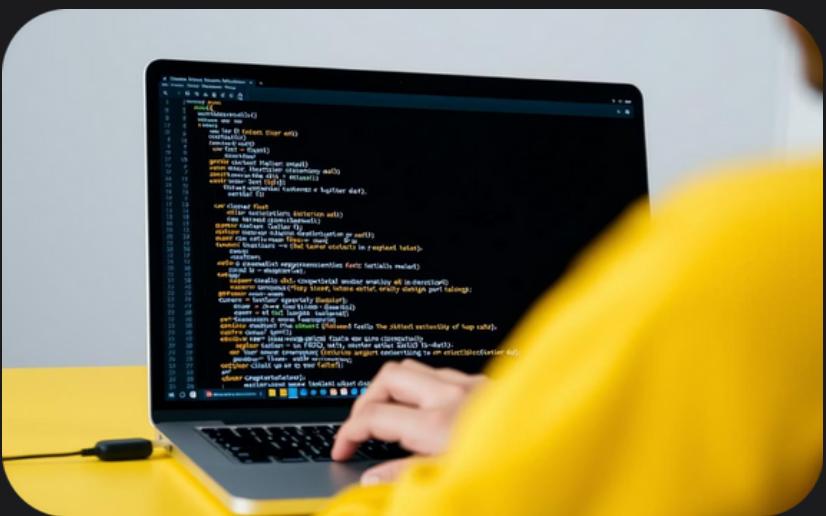
**YOLOv8n:** Person detection @  
~30 FPS.



Webcam demo includes  
bounding boxes, safety labels.

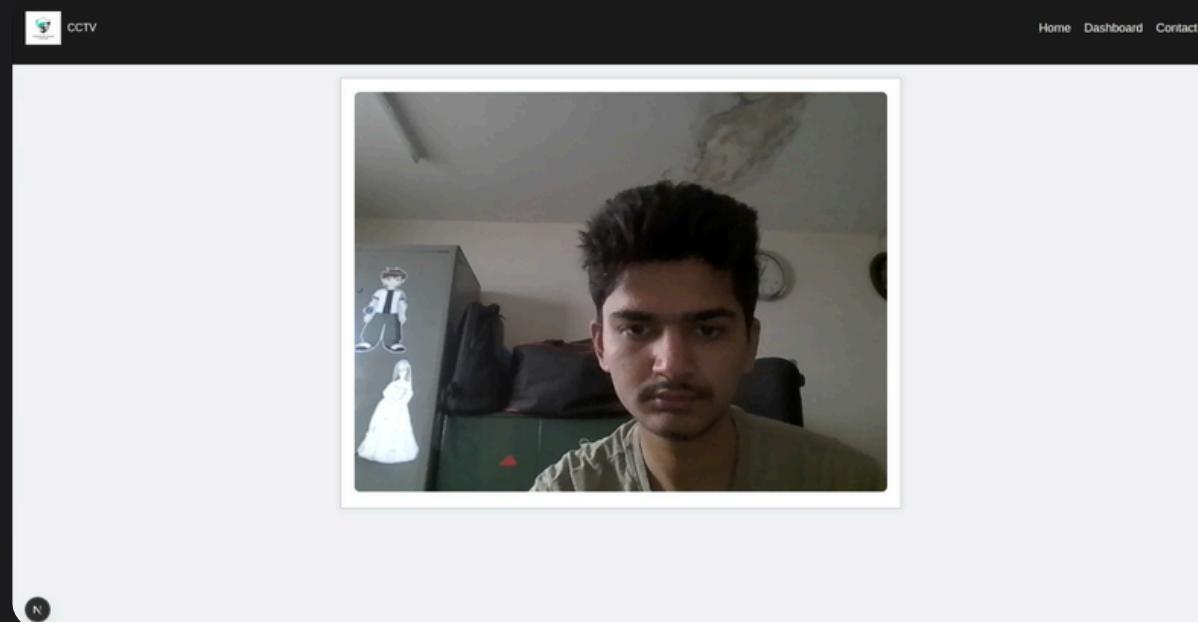


Modular for extension: violations,  
alerts, API-chaining.

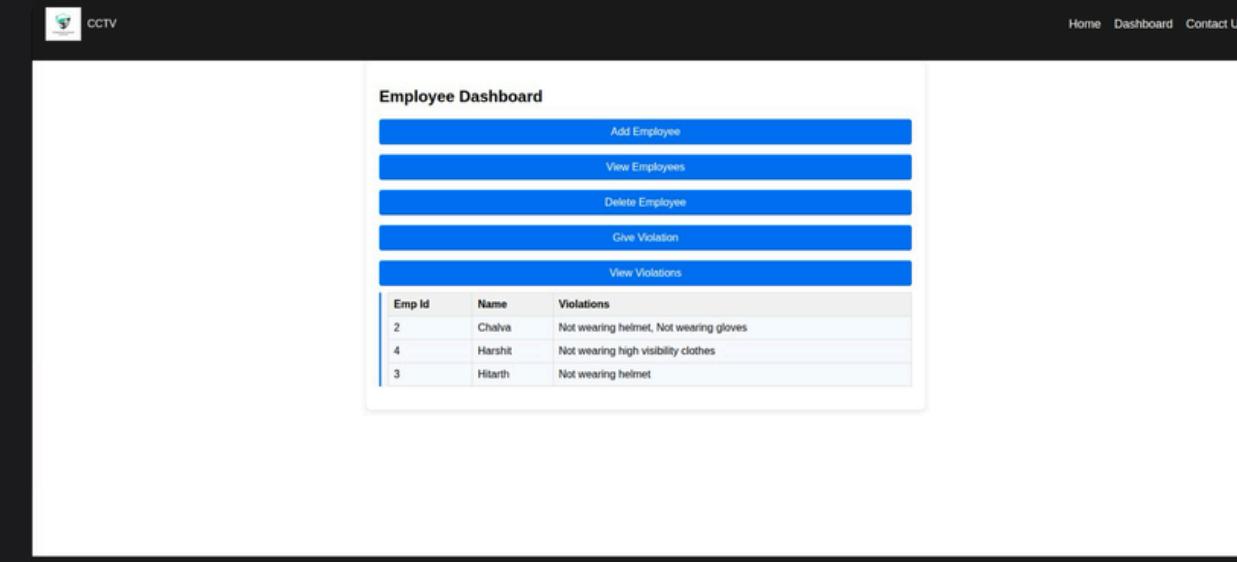


Integrated in Python  
(Jupyter/Script).

# UI & Dashboard Overview

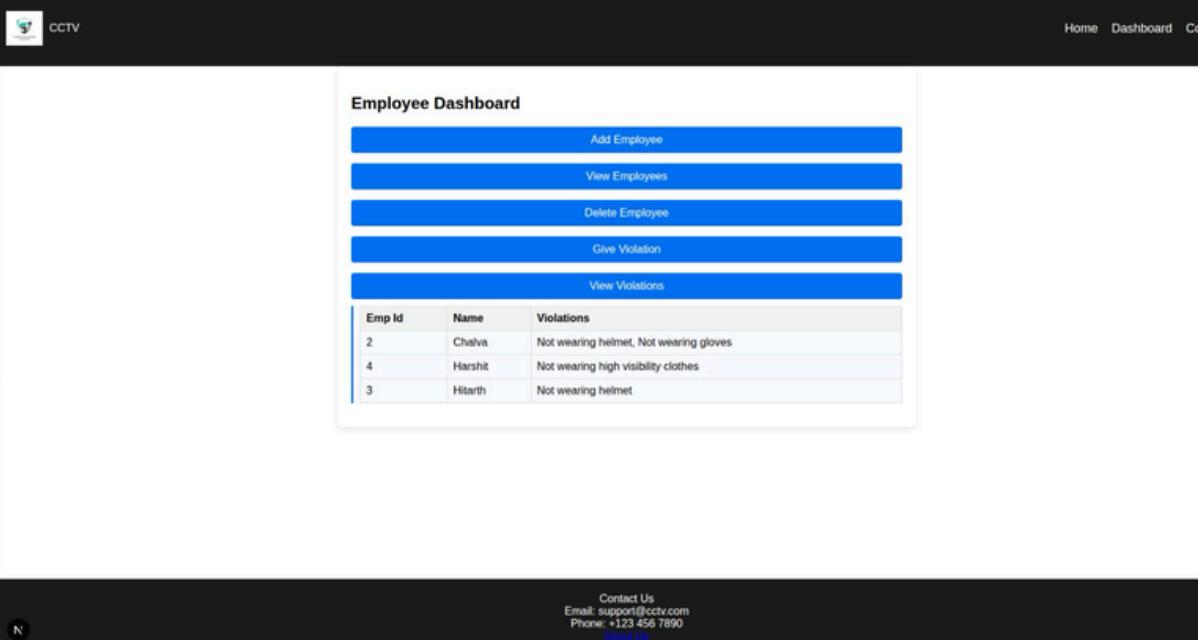


**Live webcam feed** with "Safe"/"Unsafe" overlay.



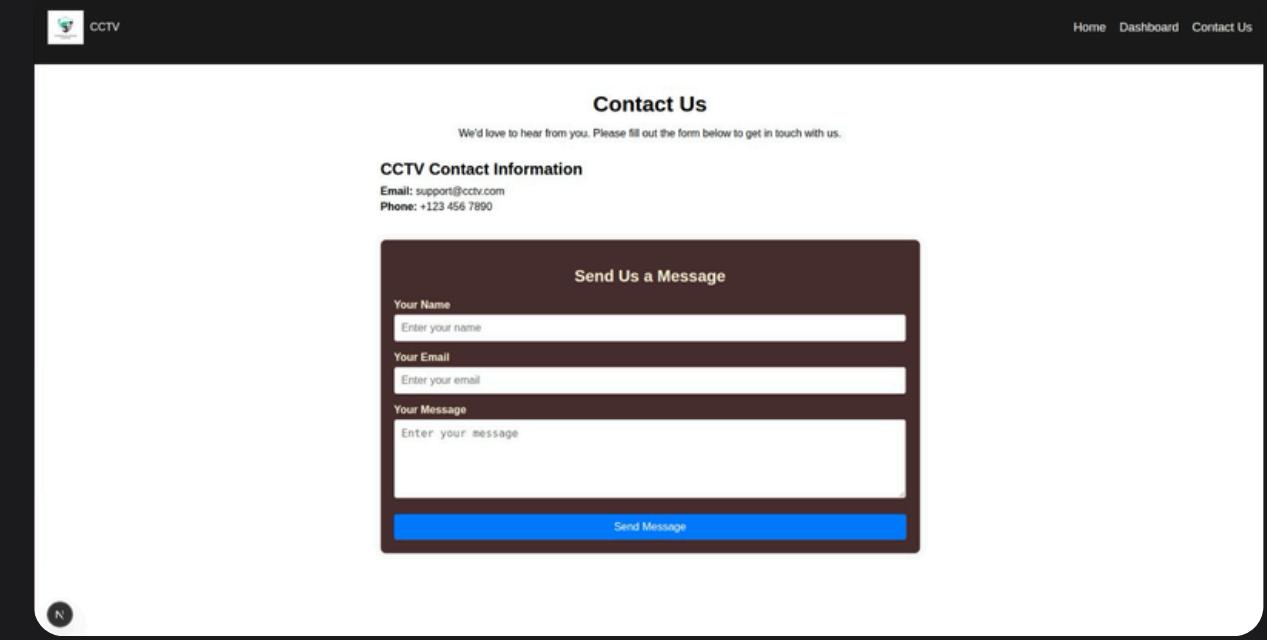
Emp Id	Name	Violations
2	Chalva	Not wearing helmet, Not wearing gloves
4	Harshit	Not wearing high visibility clothes
3	Hitarth	Not wearing helmet

**Employee Dashboard:** add/view/delete employees.



Emp Id	Name	Violations
2	Chalva	Not wearing helmet, Not wearing gloves
4	Harshit	Not wearing high visibility clothes
3	Hitarth	Not wearing helmet

**Violation Log Table:** captures time, ID, missing PPE.



**Contact Form** for support or incident reporting.

# Results & Evaluation



PPE mAP@0.5

Detection accuracy



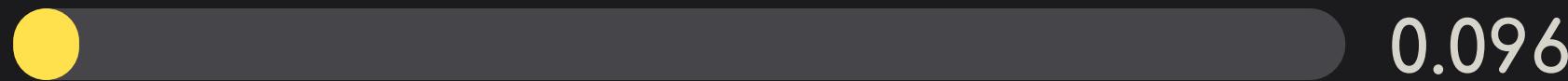
Precision

Detection accuracy



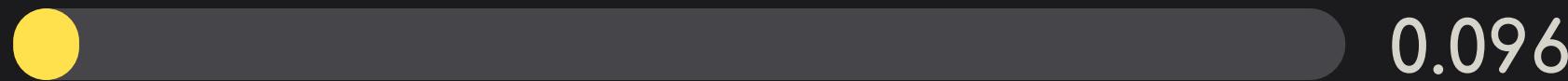
Recall

Detection accuracy



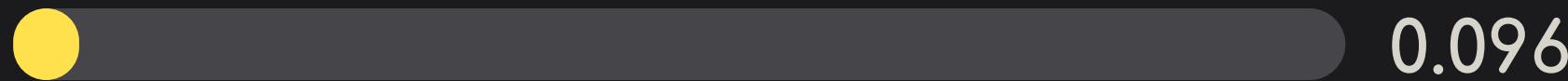
Gloves Recall

Identified as low, needs retraining



Speed

Helm detection + compliance check



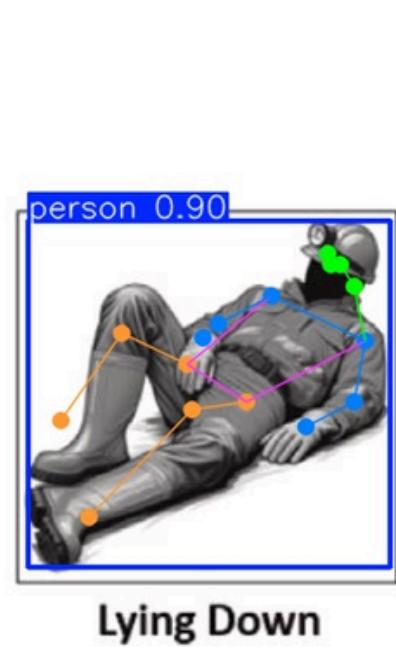
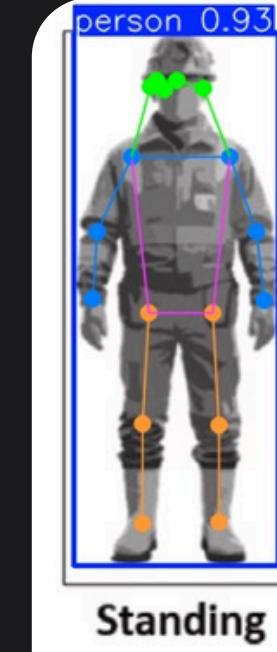
Latency

Edge-ready on CPU-only setups

```
Running validation...
val: Scanning D:\ppe_dataset\labels\valid.cache... 717 images, 0 backgrounds, 0 corrupt: 100%|████████|
val: D:\ppe_dataset\images\valid\Video2_167.jpg.rf.b7df0fd15e39d5158427deef2d4bc20f.jpg: 1 duplicate
      Class   Images  Instances    Box(P)      R     mAP50    mAP50-95): 100%|████████|
        all     717     2410    0.774    0.608    0.762    0.507
      hard_hat  717     877    0.689    0.815    0.803    0.538
      safety_vest  717     776    0.725    0.765    0.804    0.524
        gloves  717     354    0.852    0.096    0.603    0.411
        boots   717     403    0.829    0.757    0.837    0.554
Speed: 0.3ms preprocess, 2.4ms inference, 0.0ms loss, 0.7ms postprocess per image
Results saved to runs\detect\dataset_verification_run

Validation Metrics:
mAP50: 0.762
mAP50-95: 0.507
Precision: 0.774
Recall: 0.608
```

# Results & Evaluation





# References

- [1] W. Zheng, Y. Zhu, Y. Zhang, and S. Liu, "An effective deep learning approach enabling miners' protective equipment detection and tracking using improved YOLOv7 architecture," Xi'an University of Science and Technology, Xi'an, China, 2023.
- [2] M. Imam, K. Baïna, Y. Tabii, E. M. Ressami, Y. Adlaoui, S. Boufousse, I. Benzakour, and E. H. Abdelwahed, "Integrating real-time pose estimation and PPE detection with cutting-edge deep learning for enhanced safety and rescue operations in the mining industry," Neurocomputing, vol. 532, pp. 98–112, 2025.
- [3] M. S. Islam, T. Rahman, and M. M. Rahman, "A Deep Learning Approach to Detect Complete Safety Equipment for Construction Workers Based on YOLOv7," arXiv preprint arXiv:2402.04856, 2024.
- [4] C. Lo, W. Hsu, and Y. Huang, "Real-Time Personal Protective Equipment Compliance Detection," IEEE Access, vol. 10, pp. 12721–12730, 2022.
- [5] X. Liu and J. Qin, "Target Detection of Safety Protective Gear Using the Improved YOLOv5," IEEE Transactions on Industrial Informatics, vol. 20, no. 1, pp. 891–902, 2024.
- [6] M. Imam et al., "Ensuring Miners' Safety in Underground Mines through Edge Computing: Real-Time Pose Estimation and PPE Compliance Analysis," IEEE Access, vol. 11, pp. 39032–39045, 2023.
- [7] X. Ma, Z. Liu, and L. Chen, "A Combined Detection Algorithm for PPE Based on Lightweight YOLOv4," Sensors, vol. 22, no. 15, pp. 5723, 2022.
- [8] Y. Chen, H. Wang, and X. Zhao, "Helmet Detection Using Improved YOLOv5s with Attention Mechanism," Journal of Real-Time Image Processing, vol. 20, pp. 1125–1138, 2023.
- [9] K. T. Nguyen, N. P. Nguyen, and T. H. Tran, "PPE-YOLO: A Deep Learning Framework for PPE Detection on Construction Sites," Computers, Materials & Continua, vol. 71, no. 2, pp. 2589–2603, 2022.
- [10] J. Kang and S. Lee, "Construction Workers Safety Compliance Monitoring Using Deep Learning and Computer Vision," Automation in Construction, vol. 125, pp. 103599, 2021.