Institute of Professional Studies

AUTOMATED CLEANROOM
SAFETY MONITORING SYSTEM

Submitted By:

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UNDER THE SUPERVISION OF: DR. SURENDER DHIMAN (HOD - ECE)

INTRODUCTION

- India’s electronics manufacturing is rapidly growing, emphasizing yield, contamination control, and cleanroom safety to meet global competitiveness.
- This project develops a Deep Learning-based PPE compliance system using CNN and object detectors (YOLO, SSD) trained on annotated cleanroom images.
- The system detects essential PPE items and triggers real-time alerts for non-compliance, improving automated monitoring and reducing human error.
- By automating compliance, it enhances product quality, worker safety, and operational efficiency, supporting India’s scalable electronics ecosystem.

OBJECTIVES

A deep learning-based PPE compliance system automates cleanroom safety checks, reducing contamination risks and manual errors while improving efficiency and regulatory compliance.

1. Deliver explainable and measurable performance through clear validation protocols: class-wise precision/recall, confusion matrices, and stress tests (occlusion, PPE color/texture variations).
2. Ensure privacy, security, and compliance by implementing privacy-preserving modes (face blurring, minimal metadata storage), secure data transport, and role-based access controls.
3. Minimize false passes for safety-critical items via class-specific threshold tuning and decision logic, keeping the miss rate for critical PPE classes below 10%.

OBJECTIVES

A deep learning-based PPE compliance system automates cleanroom safety checks, reducing contamination risks and manual errors while improving efficiency and regulatory compliance.

4. Detect PPE compliance in cleanroom environments with high accuracy using deep learning (CNN-based detectors such as YOLO/SSD) on image-and-label datasets, targeting ≥90% precision and ≥85% recall for critical PPE classes (hood, coverall, mask/respirator, goggles, gloves, shoe covers).

5. Build a robust training pipeline with backpropagation over multi-epoch schedules, effective augmentations (lighting, occlusion, motion blur), and strategies for class imbalance (focal loss/class weights) to sustain performance across varied camera views.

METHODOLOGY

Our methodology builds a reliable PPE compliance system by converting labeled cleanroom images into accurate detections using practical steps like data preparation, augmentation, clear pass/fail rules, validation with standard metrics, and iterative threshold tuning.

Data and Labeling

01

- Define PPE classes (coverall, hood, mask, goggles, gloves, shoe covers) and simple pass/fail rules.
- Collect diverse images from relevant areas; annotate images with bounding boxes in a labeling tool (e.g., CVAT).
- Split data into train/validation/test; apply basic augmentations.

Model Development & Training

02

- Use standard CNN-based object detectors (e.g., YOLO/SSD) to detect PPE items and persons.
- Train models with backpropagation over multiple epochs; tune basic hyperparameters (learning rate, image size).

Compliance Logic

03

- For each detected person, check if required PPE items are present.
- Apply simple, configurable rules to decide “compliant” or “non-compliant.”

Evaluation & Validation 04

- Measure accuracy with common metrics (precision, recall, mAP) on the validation/test sets.
- Review errors visually; adjust thresholds and augmentation if needed.

Preparation for Deployment 05

- Optimize the selected model for speed and stability.
- Package a simple service that takes images/frames, runs detection, and outputs compliance results.

Monitoring and Improvement 06

- Track performance over time; collect difficult cases.
- Periodically update labels and retrain to handle new conditions (lighting, PPE variations).

Data and labeling

Define ppe classes and collect/annotate images

Model Development & Training

Use CNN-based object detectors and train models

Compliance Logic

Check if required PPE items are present

Evaluation & Validation

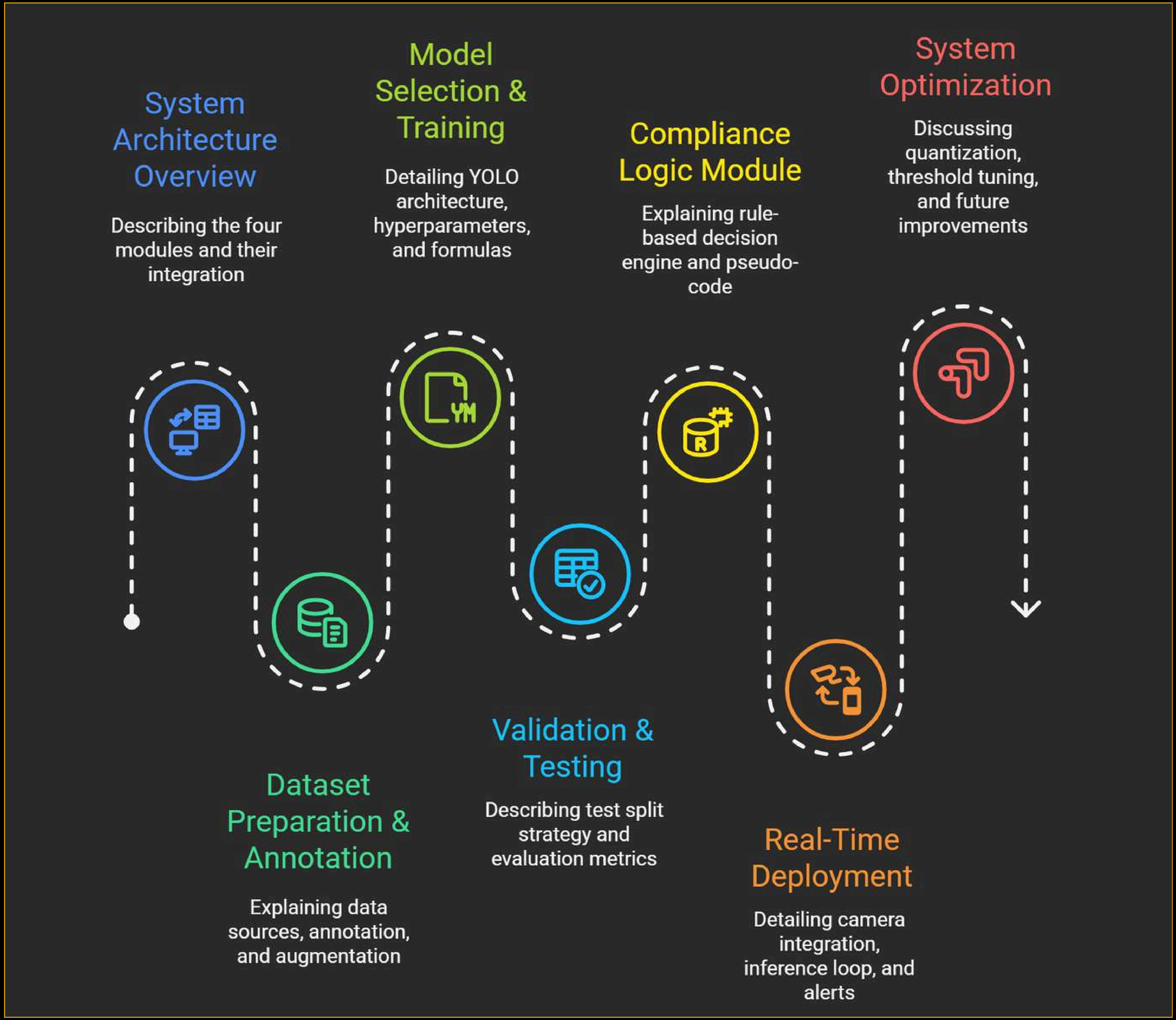
Measure accuracy with common metrics

Preparation for Deployment

Optimize model for speed and package model

Monitoring and improvement

Track performance and difficult cases


System Architecture Overview
Describing the four modules and their integration
Dataset Preparation & Annotation
Explaining data sources, annotation, and augmentation
Model Selection & Training
Detailing YOLO architecture, hyperparameters, and formulas
Validation & Testing
Describing test split strategy and evaluation metrics
Compliance Logic Module
Explaining rule-based decision engine and pseudo-code
Real-Time Deployment
Detailing camera integration, inference loop, and alerts
System Optimization
Discussing quantization, threshold tuning, and future improvements

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TOOLS USED

DATA AND LABELING

Roboflow (dataset management), Python, Pandas, NumPy

COMPUTER VISION AND MODELING

PyTorch, Ultralytics YOLO (v5/v8), OpenCV, Albumentations, Pillow

EVALUATION AND ANALYTICS

scikit-learn (precision/recall/F1, pycocotools (mAP), Matplotlib/Seaborn; Power BI for dashboards.

LOGIC BUILDING

numpy/scipy.spatial for IoU/association, shapely for geometry, pydantic/YAML for rules/config

PRODUCTIVITY

Git/GitHub, Jupyter Notebooks, MLflow

ADVANTAGES

Contamination Prevention

Ensures workers are always wearing cleanroom suits, gloves, masks, goggles, and shoe covers, minimizing the risk of dust, hair, microbes, or particles contaminating sensitive environments.

Quality Assurance

Reduces chances of defective products in semiconductor, pharma, and electronics manufacturing.

Protects sterile environments needed for experiments and production.

Worker & Product Safety

Prevents workers from being exposed to hazardous chemicals, biohazards, or static electricity.

Protects products from human-induced contamination.

Scalability

Can be deployed in multiple cleanroom zones with varying PPE requirements.

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DISADVANTAGES

Visual Reliability

Susceptible to occlusion, glare, motion blur, and low light; small or partially covered PPE (e.g., gloves, goggles) can be missed or misclassified.
Domain shift requires ongoing data refresh when cameras, lighting, or PPE styles change, or accuracy degrades over time.

Data and Labeling Dependence

Performance hinges on high-quality, diverse annotations; label errors and class imbalance can bias results and hurt mAP/precision/recall
Limited public PPE datasets; custom data collection is needed to cover site-specific edge cases and partial occlusions.

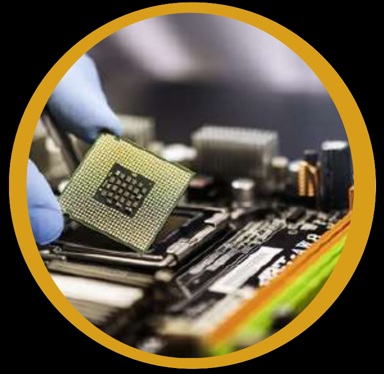
Real-Time and Hardware Constraints

Achieving low latency on edge devices requires careful model choice and optimization; speed–accuracy trade-offs are unavoidable on constrained GPUs/CPUs
High-resolution streams and multi-camera setups increase compute/memory demands and can bottleneck pre/post-processing (e.g., NMS)

Operational and Policy Limits

Vision-only rules can misjudge compliance in ambiguous cases (improperly worn items, partial visibility); sometimes needs human review or additional sensors.
Privacy, governance, and change management add constraints to video retention, alerting policies, and integration with safety workflows

APPLICATIONS



SEMICONDUCTOR INDUSTRY

Detects full-body cleanroom suits, masks, gloves, and anti-static PPE compliance during chip fabrication.

PHARMACEUTICALS & BIOTECHNOLOGY

Ensures sterile gowning (lab coats, masks, caps, gloves, goggles) before entering drug manufacturing areas.

MEDICAL DEVICE MANUFACTURING

Protects sensitive devices (implants, surgical tools) from contamination.

FOOD & BEVERAGE INDUSTRY (STERILE PACKAGING)

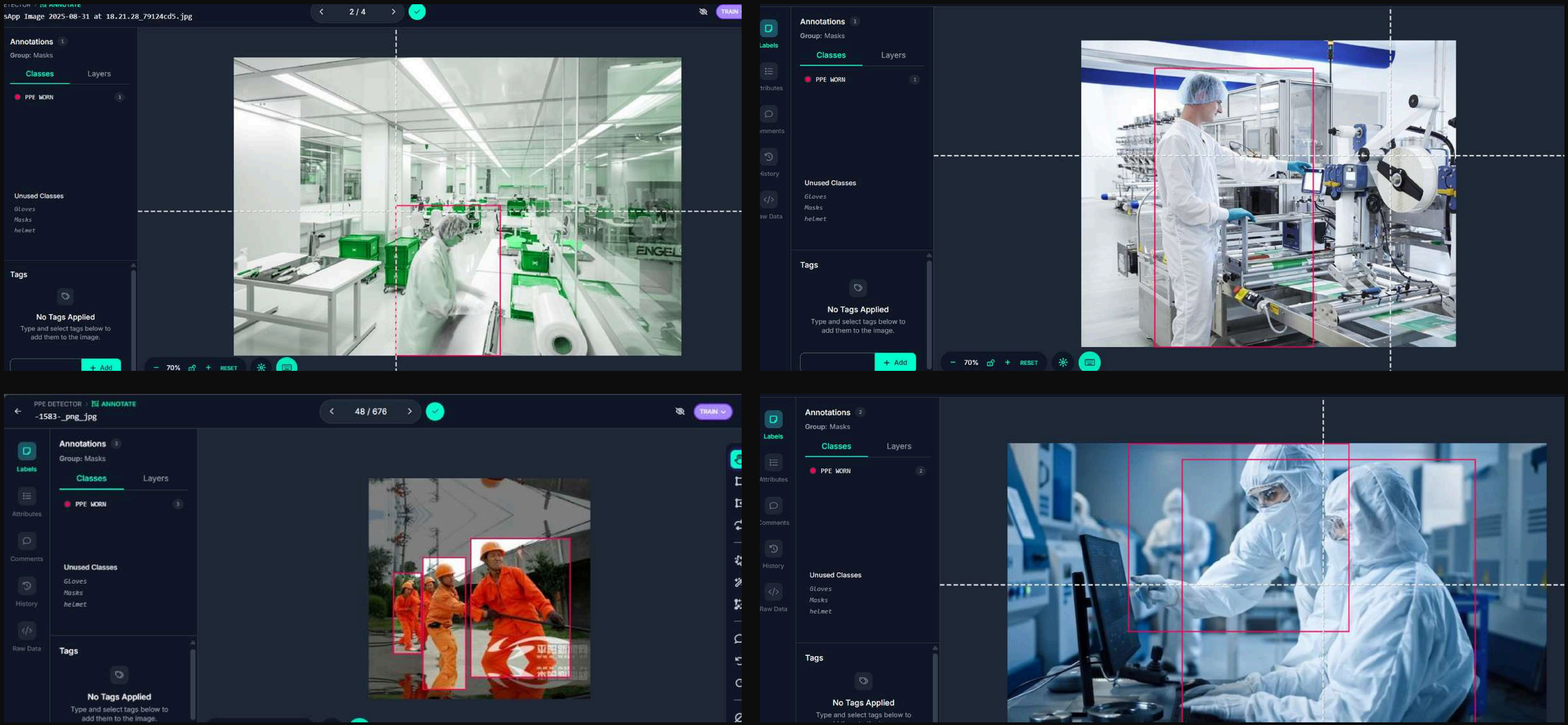
Ensures workers wear proper PPE to maintain hygiene during sterile packaging and processing.

AEROSPACE & PRECISION ENGINEERING

Prevents contamination in cleanroom environments for spacecraft, satellite, and high-precision part assembly.

RESEARCH LABORATORIES

Ensures compliance in microbiology, nanotechnology, and genetic research cleanrooms.


sApp Image 2025-08-31 at 18.21.28_79124cd5.jpg
2 / 4
TRAIN
Annotations 1
Group: Masks
Classes
Layers
PPE WORN 1
Unused Classes
Gloves
Masks
helmet
Tags
No Tags Applied
Type and select tags below to add them to the image.
+ Add
70%
RESET
Labels
Annotations 1
Group: Masks
Classes
Layers
PPE WORN 1
Unused Classes
Gloves
Masks
helmet
Tags
No Tags Applied
Type and select tags below to add them to the image.
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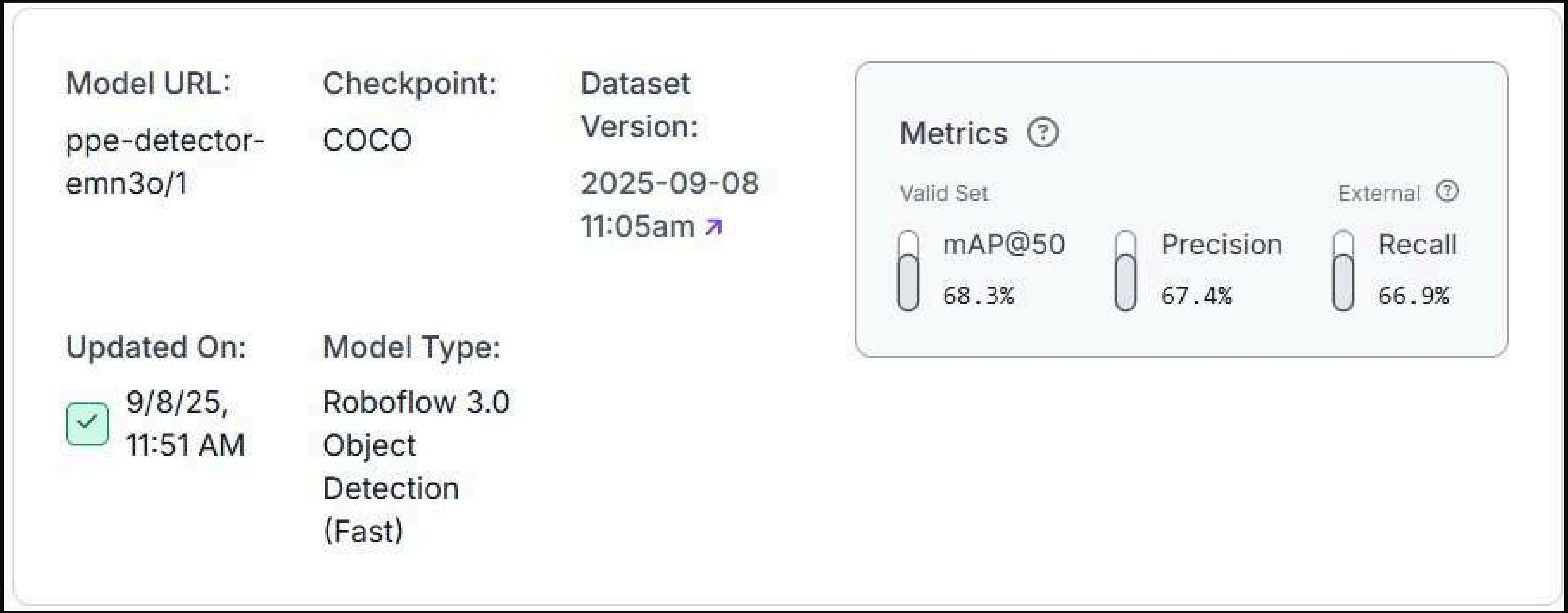
PPE DETECTOR
ANNOTATE
-1583-_png_jpg
48 / 676
TRAIN
Labels
Attributes
Comments
History
Raw Data
Annotations 3
Group: Masks
Classes
Layers
PPE WORN 3
Unused Classes
Gloves
Masks
helmet
Tags
No Tags Applied
Type and select tags below to add them to the image.
Labels
Attributes
Comments
History
Raw Data
Annotations 2
Group: Masks
Classes
Layers
PPE WORN 2
Unused Classes
Gloves
Masks
helmet
Tags
No Tags Applied
Type and select tags below to

(fig.-1)



(fig.-2)

Fig.-2 shows the performance summary of a object detection model (ppe-detector-emn3o/1), trained on a COCO-style dataset and updated on September 29, 2025. Key metrics are displayed: mAP@50 of 68.3%, precision of 67.4%, and recall of 66.9% for PPE detection tasks.

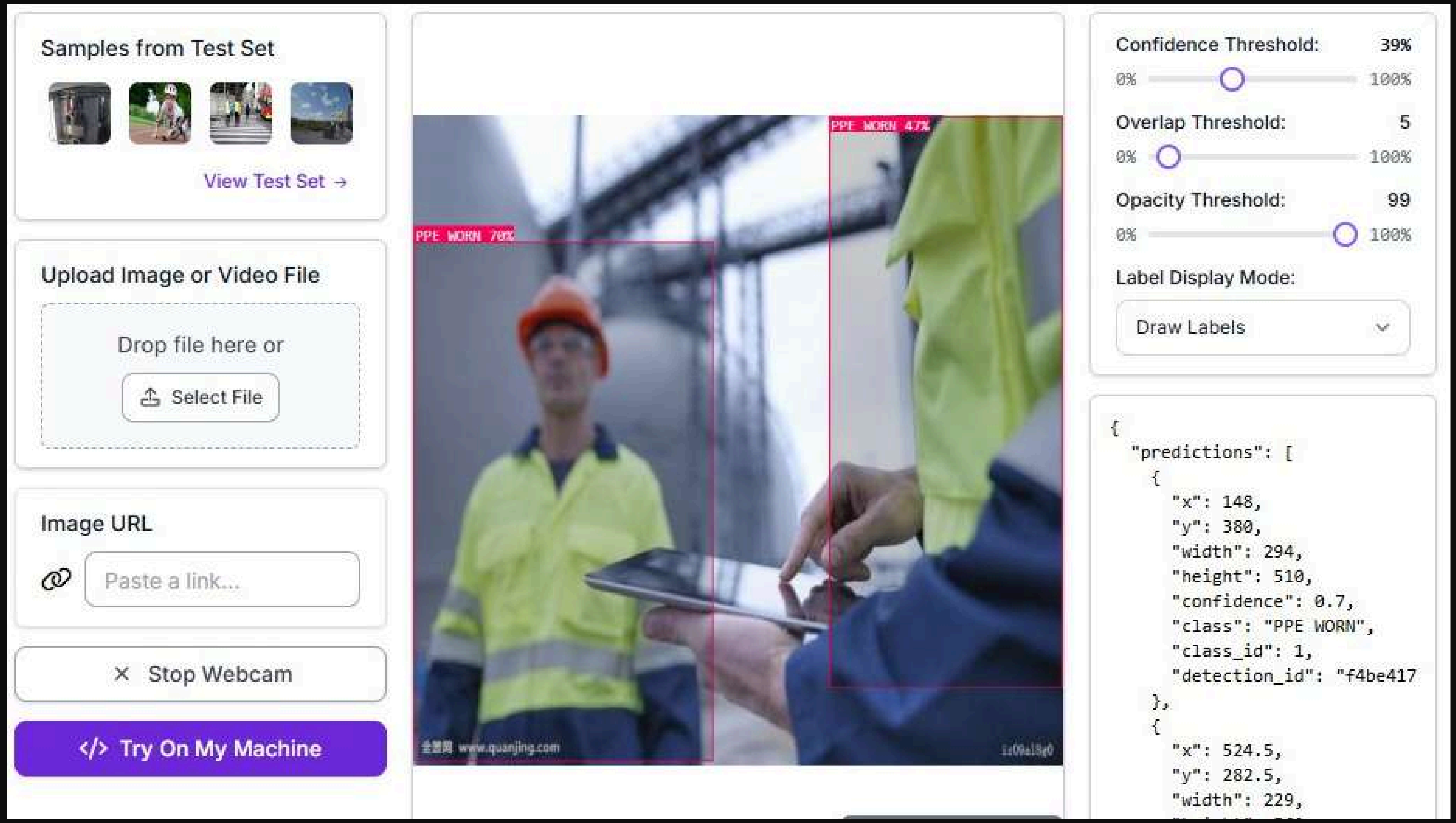
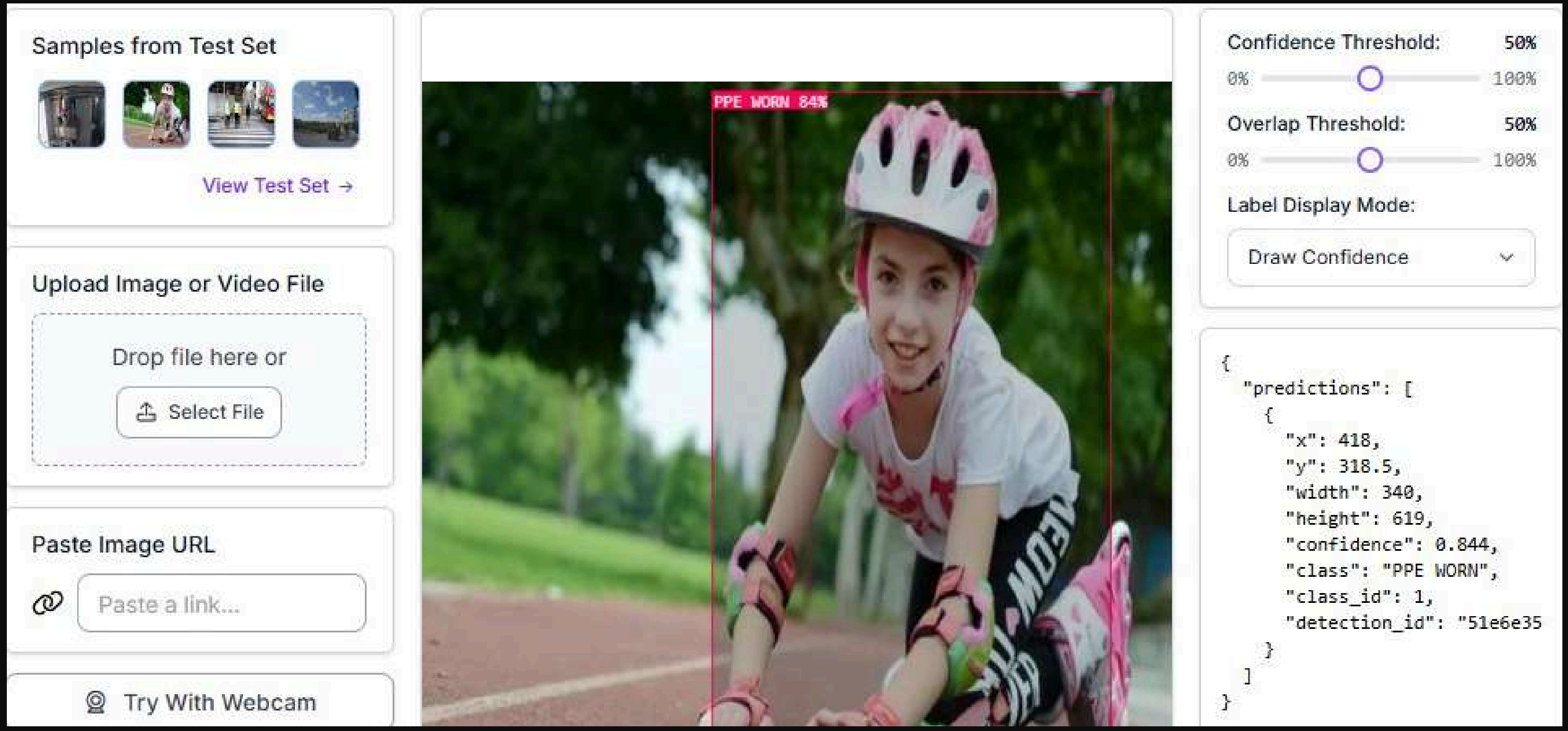


Fig.-3 shows the PPE detection model output identifying two workers wearing PPE with bounding boxes and confidence scores, alongside adjustable settings for confidence, overlap, and opacity thresholds.

(fig.-3)

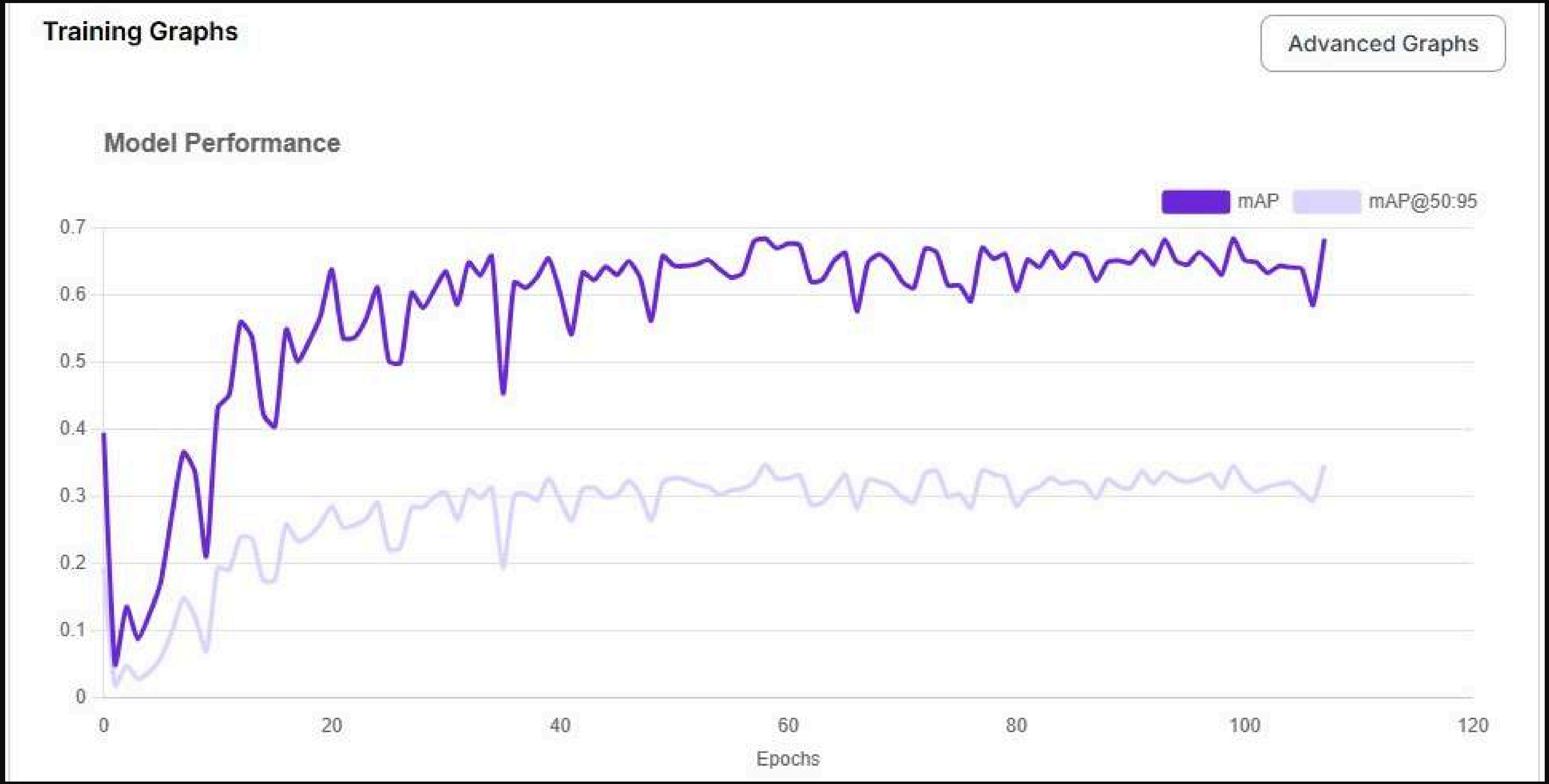
Fig.-4 displays the PPE detection model accurately identifying a child wearing safety gear, with a high confidence score shown on the bounding box overlay.



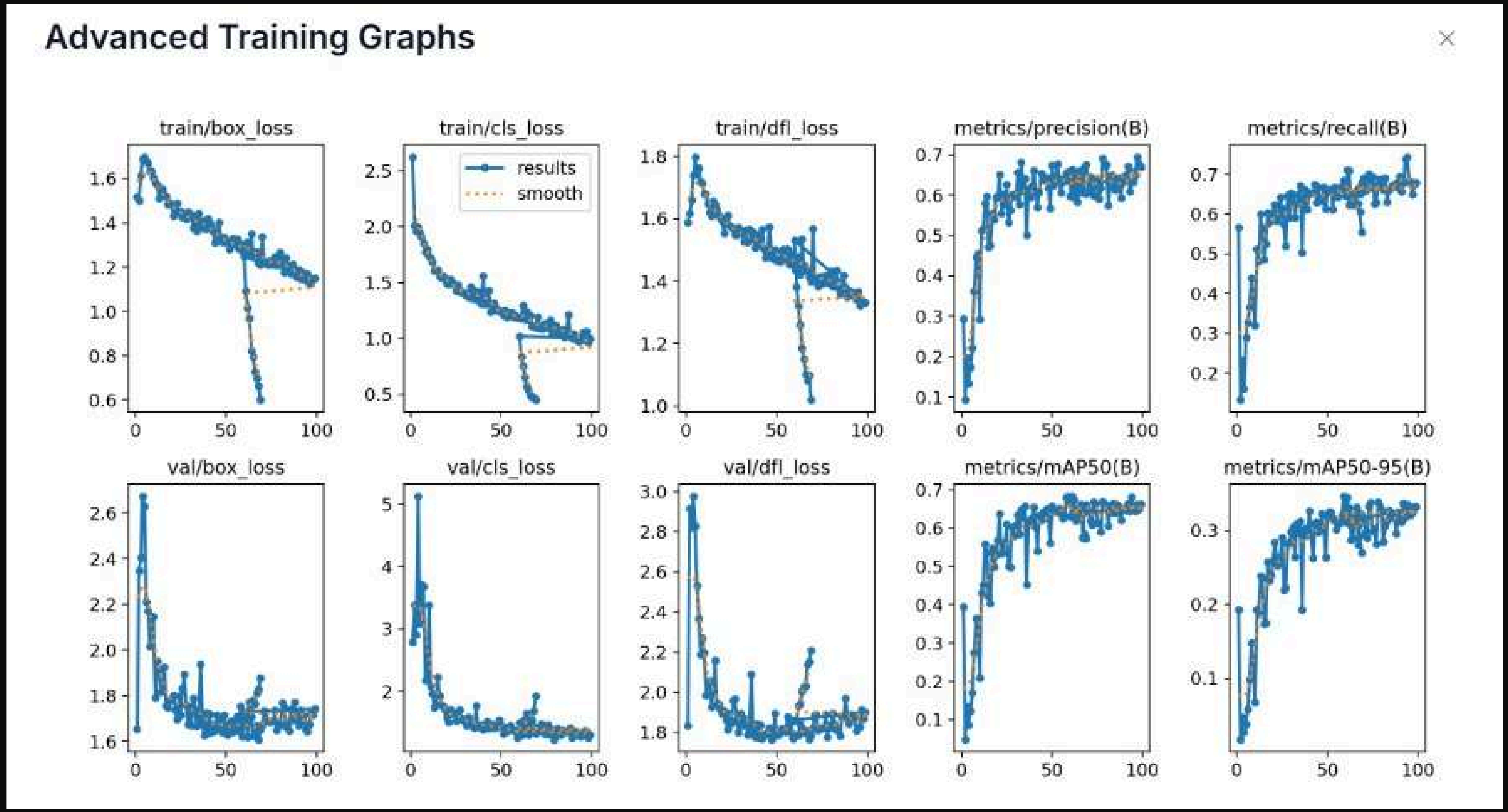
(fig.-4)


Average Precision by Class (mAP50)
Validation Set
Test Set
all 76.0%
PPE WORN 76.0%

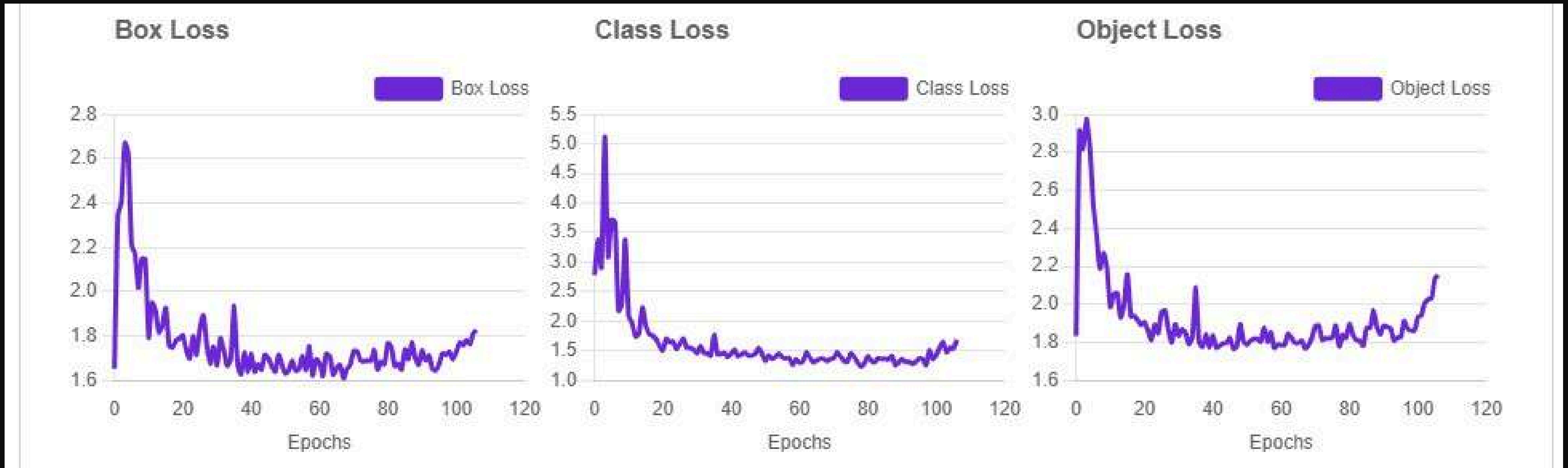
(fig.-5)


Training Graphs
Advanced Graphs
Model Performance
mAP
mAP@50:95
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
0
20
40
60
80
100
120
Epochs

(fig.-6)


Advanced Training Graphs
train/box_loss
train/cls_loss
train/dfl_loss
metrics/precision(B)
metrics/recall(B)
results
smooth
val/box_loss
val/cls_loss
val/dfl_loss
metrics/mAP50(B)
metrics/mAP50-95(B)

(fig.-7)


Box Loss
Class Loss
Object Loss
Box Loss
Class Loss
Object Loss
Epochs
Epochs
Epochs

(fig.-8)

RESULT DISCUSSION

- This deep learning-based PPE compliance system will effectively detect all critical protective gear items in cleanroom images with high accuracy. Models like YOLO and SSD will show strong performance, achieving consistent precision and recall across different PPE classes.
- The system will minimize false passes through iterative threshold tuning, ensuring reliable identification of non-compliant cases. Real-time processing capabilities will make the system suitable for deployment at cleanroom entry points.

RESULT DISCUSSION

- Event data analytics will reveal common compliance issues, enabling targeted training and process improvements. Although some challenges may remain in handling heavy occlusion or rare PPE variants, future enhancements involving multi-angle cameras or sensor fusion will be explored.
- Overall, the results will confirm the system's capability to automate PPE monitoring, significantly reducing contamination risks and improving safety and operational efficiency in electronics manufacturing cleanrooms.

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CONCLUSION

The deep learning-based automated PPE compliance system will enhance cleanroom safety by accurately detecting critical protective gear such as masks, gloves, and coveralls. By replacing manual checks with real-time monitoring and instant alerts, it will significantly reduce contamination risks and improve operational efficiency. The system's adaptable design and IoT integration will support continuous compliance, helping industries meet stringent quality and safety standards effectively.

REFERENCES

[1] Cleanroom Industries (CLIN), “Basic Cleanroom Protocols” [Online]. Available: https://www.cleanroom-industries.com/index.php/resources/basic-cleanroom-protocols/403. [Accessed: Aug. 20, 2025].

[2] Occupational Safety and Health Administration (OSHA), “Safety in Semiconductor Manufacturing” [Online]. Available: https://www.osha.gov/sites/default/files/publications/SemiconductorFS.pdf. [Accessed: Aug. 20, 2025].

[3] Alberto Rizzoli, “The Complete Guide to CVAT - Pros & Cons [2024]” [Online].
Available: https://www.v7labs.com/blog/cvat-guide#h2. [Accessed: Aug. 20, 2025].

[4] Rohit Kundu, “YOLO: Algorithm for Object Detection Explained [+Examples]” [Online].
Available: https://www.v7labs.com/blog/yolo-object-detection. [Accessed: Aug. 20, 2025].

[5] Zoumana Keita, “YOLO Object Detection Explained” [Online].
Available: https://www.datacamp.com/blog/yolo-object-detection-explained. [Accessed: Aug. 20, 2025].

[6] Jonathan Hui, “SSD object detection: Single Shot MultiBox Detector for real-time processing” [Online]. Available: https://jonathan-hui.medium.com/ssd-object-detection-single-shot-multibox-detector-for-real-time-processing-9bd8deac0e06. [Accessed: Aug. 20, 2025].

APPENDIX

Appendix A: Data

- What we used: photos from cleanroom entry and floor areas, taken from different cameras and lighting conditions; labeled in CVAT (an image labeling tool) with classes like person, coverall, hood, mask, goggles, gloves, and shoe cover.
- How we split: training set, validation set, and test set separated by camera/time to avoid overlap; quick quality checks to fix label mistakes and keep classes balanced.

Appendix B: Model and training

- Model: YOLO (You Only Look Once), a fast object detection model built in PyTorch (a Python deep learning library) to find people and PPE in images.
- Training: used Albumentations and OpenCV (computer vision libraries) for image augmentation, then trained the model for several epochs (full passes over the data) and saved the best version using the validation results.

Appendix C: Testing and metrics

- Metrics we tracked: precision and recall (how correct and how complete the detections are), F1 score (balance of precision and recall), and mAP (mean Average Precision, a standard score for detection quality).
- Tuning: adjusted confidence thresholds and NMS (Non-Max Suppression, which removes duplicate boxes) on the validation set before running on the test set

Appendix D: Compliance rules

- Matching: linked each person to nearby PPE detections using simple geometry and overlap (IoU = Intersection over Union, a measure of how much two boxes overlap).
- Decision: set a required list (e.g., hood, mask, gloves, shoe cover). If any required item is missing or not clearly visible, mark as “not compliant” and list what’s missing.

Appendix E: Deployment and monitoring

- Running the system: set up a small service that takes images, checks for required safety gear, and returns the result quickly; also made simple tweaks so it runs faster on common computers.
- Tracking results: keep a record of each check, the pass/fail result, and how long it took; share simple charts that show overall compliance, problem areas, and trends over time.

Appendix F: Version history

- Records: maintain a simple log with the date, what was changed (like new photos added or small adjustments), and the main results so it's easy to repeat and compare progress over time.

THANK YOU