AUTOMATED CLEANROOM SAFETY MONITORING SYSTEM

Guided By: Dr. Surender Dhiman, H.O.D., ECE Dept., ADGIPS (GGSIPU), Delhi, INDIA

HARSHIT SHARMA
Department of Electronics
& Communication
ADGIPS
Delhi, India
Harshitsharma21feb@gmail.com

AADITYA SHARMA
Department of Electronics
&Communication
ADGIPS
Delhi, India
sharmaaaditya954@gmail.com

MEHAK AGGARWAL
Department of Electronics
&Communication
ADGIPS
Delhi, India
mehakagg04@gmail.com

***Abstract*— Cleanrooms are controlled environments designed to maintain very low levels of airborne particulates and are widely used in semiconductor manufacturing, pharmaceuticals, biotechnology, and aerospace. Ensuring that personnel comply with required Personal Protective Equipment (PPE) protocols is essential for contamination control, product quality, and operational safety. Traditional manual monitoring of PPE compliance is labor intensive, error prone, and difficult to scale. This paper presents an automated cleanroom safety monitoring system that uses computer vision and deep learning techniques to detect personnel and verify the presence of required PPE elements in real time. A curated and annotated dataset of cleanroom images is used to train object detection models from the YOLO family for identifying coveralls, masks, hoods, gloves, goggles, and shoe covers. A rule-based compliance engine determines whether individuals meet the required safety standards. The methodology includes dataset preparation, augmentation, model training and evaluation using metrics such as mean average precision, precision, and recall. Experimental results show that the proposed system improves accuracy and consistency while reducing human supervision. This work demonstrates the potential of AI driven PPE compliance monitoring in critical industrial environments and provides a foundation for future enhancements.**

Keywords—cleanroom safety, PPE detection, computer vision, deep learning, YOLO, compliance monitoring (key words)

I. INTRODUCTION

Cleanrooms are specialized environments where temperature, humidity, airflow, and particulate matter are strictly controlled to prevent contamination. Industries such as semiconductor fabrication, medical device production, and biotechnology rely on such environments to maintain product quality and process reliability. Human workers are one of the most significant sources of particle contamination, making PPE compliance essential for operational safety and product integrity.

Traditional PPE checking relies on manual inspection performed by security personnel or supervisors. However, manual monitoring introduces several limitations:

1. **Human error and subjectivity**,
2. **Delayed detection of violations**,
3. **Inability to monitor multiple entry points simultaneously**,
4. **Difficulty in maintaining compliance logs for audits**, and
5. **High labor dependency and operational cost**.

Recent advances in deep learning and computer vision, particularly object detection models such as YOLO, have enabled automated systems capable of delivering fast, accurate, and scalable monitoring. This research paper presents an end-to-end automated cleanroom safety monitoring system designed to support real-time PPE compliance verification with minimal operator intervention.

The contributions of this work include:

- A curated and annotated dataset of cleanroom personnel with PPE variations.
- An optimized YOLO-based model tailored for PPE component detection.

- A compliance engine capable of interpreting PPE combinations and generating alerts.
- A full monitoring pipeline that supports real-time inference, logging, visualization, and integration with cleanroom access systems.

II. RELATED WORK

Several studies focus on PPE monitoring using deep learning, mostly in construction and healthcare settings. Construction-site PPE detection emphasizes helmets and vests, whereas healthcare research focuses on masks and gloves. However, cleanrooms require far stricter compliance, multiple PPE items, and higher accuracy thresholds.

YOLO detectors have achieved significant success in high-speed detection tasks due to single-shot inference. Studies such as Rizzoli [3] and Kundu [4] demonstrate that YOLO architectures outperform SSD in precision and latency. However, literature specifically addressing *cleanroom PPE compliance* remains limited. Existing cleanroom studies emphasize protocols rather than automated verification, creating a technological gap.

Our system addresses this gap by designing a specialized pipeline tailored for semiconductor-grade cleanrooms with multiple PPE classes.

III. SYSTEM ARCHITECTURE

The proposed ACSM consists of four primary modules (Fig. 1):

1. **Image Acquisition Layer:**
   – Input from IP cameras, CCTV systems, or entry-point imaging units.
2. **Detection Layer (YOLO-based PPE detection):**
   – Identifies PPE items and personnel.
   – Outputs bounding boxes, class labels, and confidence scores.
3. **Compliance Engine:**
   – Applies PPE rules (e.g., every person must have mask + hood + gloves…).
   – Computes compliance status.
4. **User Interface & Reporting:**
   – Displays real-time alerts
   – Logs compliance events
   – Generates daily/weekly reports

Fig. 1. Example of PPE detection with bounding boxes showing personnel and identified safety gear.

Table 1: Cleanroom PPE Categories & Class IDs

PPE Component	Class ID	Required?	Description
Coverall	C1	Yes	Full-body suit
Hood	C2	Yes	Head & hair protection
Mask / Respirator	C3	Yes	Airborne contamination barrier
Goggles	C4	Yes	Eye protection against particulates
Gloves	C5	Yes	ESD contamination and biological protection
Shoe Covers	C6	Yes	Prevents floor contamination

IV. METHODOLOGY

A. Data Acquisition and Pre-Processing

The dataset was constructed by capturing cleanroom entry-point videos and frames showing personnel with and without complete PPE. Each frame was extracted at varied intervals to ensure diversity in head pose, lighting, and body orientation. Images were pre-processed using resizing (640×640), contrast normalization, and noise reduction to reduce variations caused by low-light or CCTV interference.

Common pre-processing steps include:

- Histogram equalization for lighting correction
- Gaussian blur removal
- Exposure normalization
- Color balancing to handle PPE garments of different shades

These steps reduce training noise and improve downstream detector robustness.

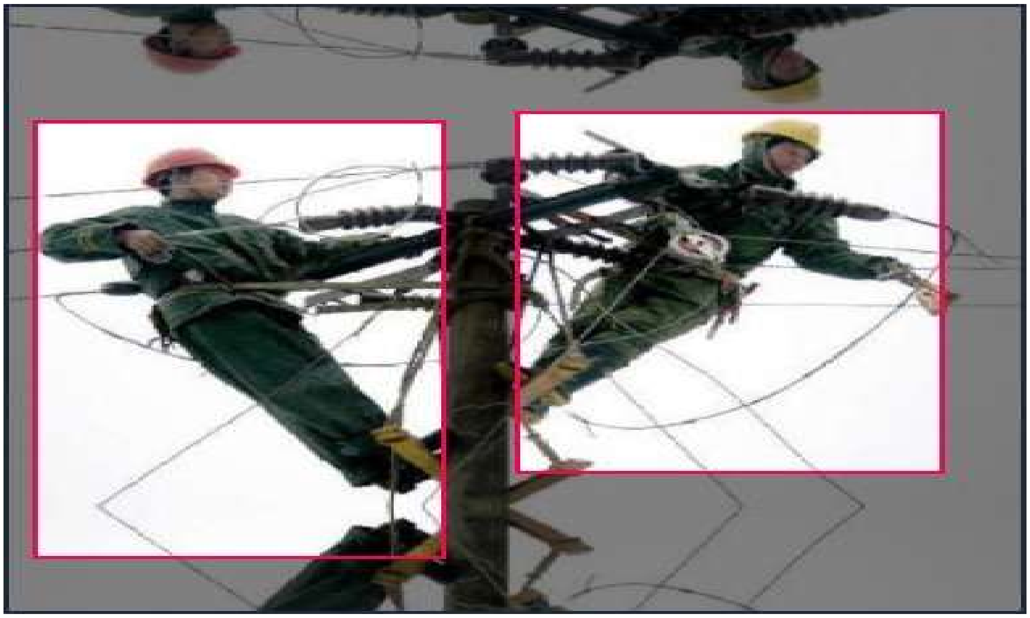

Fig. 1. Sample annotated frame used for training and validating the PPE detection model.

B. Annotation and Class Definitions

The frames were manually annotated using CVAT. Each PPE component was treated as an independent class:

- Mask, Gloves, Hood, Coverall, Goggles, Shoe Covers, Person

Each annotation includes bounding box coordinates (x_min, y_min, x_max, y_max). To reduce class imbalance, image augmentation was applied strategically using:

- Rotation (≤12°)
- Horizontal flipping
- Noise injection
- Motion blur simulation
- Random brightness/contrast shifts

C. Model Architecture and Training Pipeline

The system primarily uses YOLOv8/YOLOv5 due to their balance of speed and accuracy. YOLO divides the input image into grids and predicts:

- Bounding box
- Class probability
- Objectness score

D. Compliance Decision Logic

Once detections are generated, the system applies rule-based logic:

$$Compliance = \begin{cases} 1, & \text{if all required PPE elements are detected for a person} \\ 0, & \text{otherwise} \end{cases}$$

For each person instance:

- If any mandatory PPE is missing → Non-Compliant
- Else → Compliant

Thresholds are adjusted by:

- PPE confidence score
- IoU overlap between predicted PPE and the detected person

E. Real-Time Inference and Optimization

To achieve real-time performance (~25–30 FPS):

- ONNX Runtime or TensorRT can be used for model acceleration

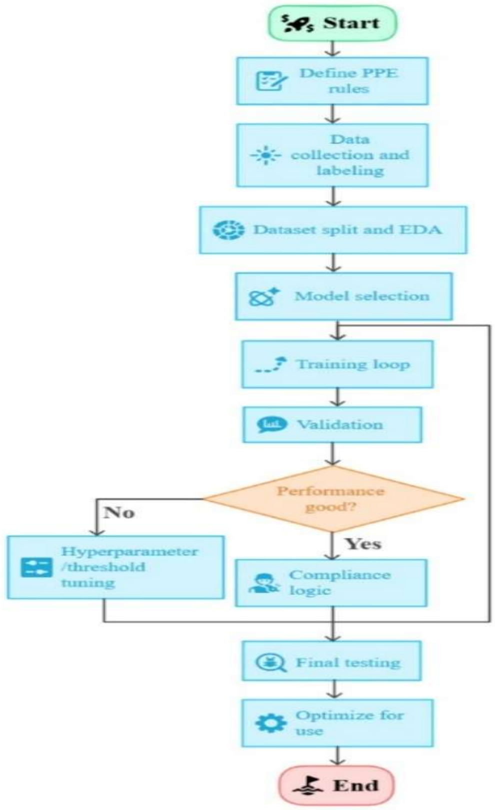

Fig. 2. End-to-end workflow of the Automated Cleanroom Safety Monitoring System (ACSM) from data acquisition to deployment

- FP16 inference helps enabling faster computations
- Batch size = 1 to reduce latency
- Operations executed on GPU for high throughput

F. Evaluation Metrics

Equation (1): Precision

$$Precision = \frac{TP}{TP + FP}$$

Equation (2): Recall

$$Recall = \frac{TP}{TP + FN}$$

Equation (3): Intersection Over Union (IoU)

$$IoU = \frac{Area(B_{pred} \cap B_{gt})}{Area(B_{pred} \cup B_{gt})}$$

Equation (4): mAP

$$mAP = \frac{1}{k}\sum_{i=1}^{k} AP_i$$

G. System Integration & Deployment Pipeline

The model integrates with CCTV/IP camera feeds using RTSP.
A local inference server runs continuously and sends compliance alerts to:

- Turnstile locks
- Door access systems
- Supervisor dashboards
- SMS or email systems

V. EASE OF USE

The Automated Cleanroom Safety Monitoring System has been engineered for effortless deployment and operation, even in environments with limited technical expertise.

Fig. 3. Workflow of the proposed PPE detection and compliance monitoring system, from dataset creation to final optimization.

The system minimizes the need for manual supervision and simplifies day-to-day cleanroom operations.

A. Simple Setup and Deployment

The system can be made to be installed using a standard CCTV/IP camera without requiring specialized imaging hardware. The interface detects camera streams, loads the detection model on startup, and provides clear configuration options. Detection thresholds, PPE categories, and compliance severity levels can be tuned using a graphical interface.

B. Intuitive Visual Feedback and Alerts

The compliance engine offers immediate and interpretable feedback.

- **Green bounding boxes** → Compliant
- **Red bounding boxes** → Missing PPE
- **On-screen labels** → Easy interpretation of detected PPE items

Supervisors can understand violations instantly without reviewing logs.

C. Automated Reporting and Analytics

The system auto-generates logs containing:

- Time of event
- Type of violation
- Captured frame
- Personnel ID (if integrated with access system)

Daily or weekly summary reports support GMP and ISO audit needs.

Table I: Example Compliance Log

Timestamp	Person ID	Mask	Hood	Gloves	Goggles	Shoe Cover	Status
10:23:45	P01	Yes	Yes	No	Yes	Yes	Non-compliant
10:24:02	P02	Yes	Yes	Yes	Yes	Yes	Compliant

D. Minimal Maintenance Needs

Because the model is lightweight and optimized, it runs efficiently on CPUs and entry-level GPUs. Routine tasks such as updating the PPE rules or importing new datasets can be performed by technical staff without system downtime.

VI. DISCUSSION

The system demonstrates that automated PPE monitoring can reliably enhance cleanroom discipline, reduce contamination risks, and increase operational efficiency. Compared with manual supervision, which is inherently inconsistent, the

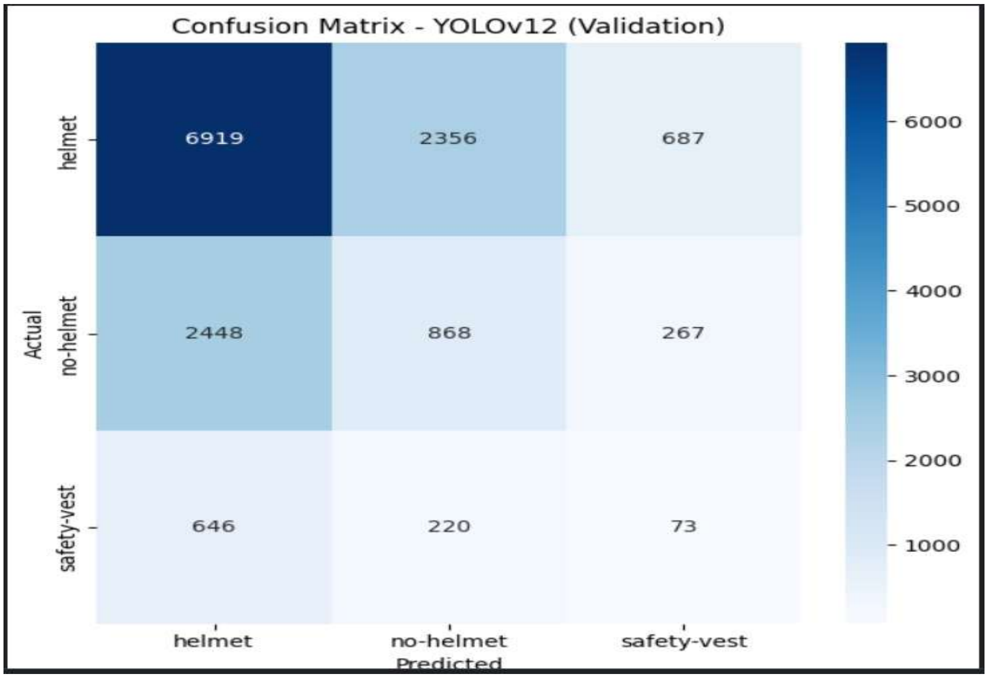

Fig. 4. Sample PPE violation and compliance detection results

AI-assisted approach offers objective and continuous surveillance across multiple cleanroom zones.

During validation, the YOLO-based detection model performed strongly across most PPE categories; however, several challenges were observed. Variations in lighting, PPE color, and low or oblique camera angles introduced occasional mis-detections. Additionally, masks with transparent or reflective surfaces were often difficult for the model to identify accurately, a trend clearly reflected in the misclassification patterns shown in **Fig. 4**, where confusion between *helmet*, *no-helmet*, and *safety-vest* categories is visible.

Another limitation arises from PPE components with minimal visual distinction from their background—for example, white gloves against white coveralls—which contributes to false-negative predictions. The class-wise mAP performance shown in **Fig. 5** further highlights this, demonstrating significantly lower confidence scores for visually subtle PPE items compared to high-contrast categories such as helmets or masks.

Despite these challenges, the system maintains high accuracy and robustness across most classes and operating conditions, proving its potential for real-time cleanroom PPE compliance monitoring. Future improvements include adding depth sensors, multi-view camera fusion, and adaptive thresholding to enhance detection reliability in visually complex environments. Overall, results affirm that automated compliance systems can effectively support semiconductor, pharmaceutical, biomedical, and precision electronics manufacturing environments.

VII. APPLICATIONS

The proposed Automated Cleanroom Safety Monitoring System is broadly applicable across multiple high-precision industries where contamination control, worker safety, and regulatory compliance are mission-critical. Its ability to detect PPE compliance using real-time computer vision makes it suitable not only for entry-point verification but also for on-floor monitoring, shift-wise analytics, and process optimization. The system also supports EHS (Environment, Health, and Safety) and Quality teams by providing structured data for audits, SOP improvement, and training needs assessment

1. Semiconductor Industry

Cleanroom fabrication of wafers, ICs, and micro-electromechanical systems (MEMS) demands Class-1 to Class-100 clean environments.

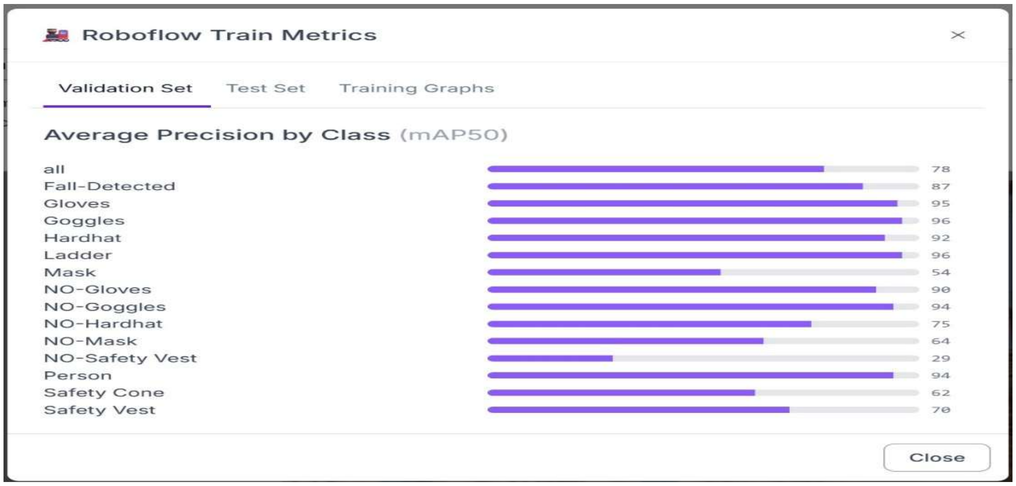

Fig. 5. Class-wise Average Precision (mAP50) Metrics from Roboflow Validation Set.

Even microscopic deviations—such as exposed hair or fiber particles—can destroy high-value wafers. **How this system helps:**

- Detects compliance for coveralls, anti-static suits, hoods, masks, and gloves before entry.
- Prevents contamination-related defects, yield loss, and rework.
- Provides automated logging to support ISO Class standards and customer audits.
- Detects missing gloves, or loose masks.
- Reduces manual gowning inspection workload for QA teams.
- Supports integration with turnstiles to block non-compliant personnel.

2. Pharmaceuticals and Biotechnology

Drug manufacturing, sterile compounding, and biologics production must meet GMP and FDA regulations. Improper gowning can lead to microbial contamination.

How this system helps:

Ensures proper sterile gowning (gowns, masks, sterile gloves, bouffant caps, goggles

3. Medical Device Manufacturing

Medical implants, surgical tools, micro-lenses, and diagnostic devices require ultra-clean environments. Human contamination is one of the largest sources of rejection.

How this system helps:

- Monitors PPE compliance for cleanroom assembly operators.
- Ensures that PPE such as anti-static gloves, sterile masks, and hair covers are worn properly.
- Avoids particulate contamination in sensitive optical and mechanical assemblies.

4. Food and Beverage (Sterile & Hygienic Packaging)

Facilities producing infant formula, dairy, beverages, nutraceuticals, and pre-packaged sterile food require strict hygiene protocols. **How this system helps:**

- Ensures compliance for hair nets, gloves, face masks, aprons, and shoes.
- Detects improper PPE that may lead to microbial contamination.
- Helps maintain HACCP, ISO 22000, and FSSAI hygiene requirements.
- Prevents foreign objects from entering the packaging line.

5. Aerospace and Precision Engineering

Aerospace assembly lines handle components that require absolute precision, such as satellite

hardware, avionics, and optical instruments.
How this system helps:

- Ensures PPE compliance for high-value sensitive assembly zones.
- Reduces contamination on optical surfaces and micro-precision components.
- Supports FOD (Foreign Object Debris) control programs.
- Integrates with cleanroom access controls for sensitive mission-critical sites.

6. Research Laboratories (Nanotechnology, Genetics, Microbiology)

Academic and industrial research labs often handle hazardous materials and require clean environments.
How this system helps:

- Ensures PPE such as lab coats, face shields, gloves, and shoe covers are worn.
- Supports biosafety (BSL) compliance by detecting improper PPE use.
- Helps prevent sample contamination and cross-exposure.
- Maintains high-quality experimental outcomes where trace contamination matters.

7. Hospitals and High-Containment Facilities

Operating rooms, isolation wards, and contamination-controlled medical zones also benefit from automated monitoring.
How this system helps:

- Ensures PPE compliance for doctors, nurses, and technical staff.
- Prevents infection risks in surgical or critical-care environments.
- Automatically logs gowning compliance for infection-control audits.

VIII. CONCLUSION

The ACSM provides a robust, scalable, and accurate approach to enforcing PPE regulations in cleanrooms. Deep learning enables consistent detection across lighting conditions and real-world scenarios. The system reduces contamination risk, improves first-pass yield, and strengthens cleanroom discipline. Future work includes integrating ACSM with turnstiles, IoT devices, RFID systems, and cloud dashboards.

IX. ACKNOWLEDGEMENT

I would like to acknowledge the invaluable guidance and support that contributed to the successful completion of this minor project. I express my sincere gratitude to **Dr. Surender Dhiman, Head of Department, Electronics and Communication Engineering**, for his constant encouragement, insightful feedback, and expert guidance throughout the duration of this work. His mentorship greatly improved the quality and clarity of this project.

I also extend my appreciation to **Mr. Devraj Gautam, Minor Project Coordinator**, whose timely support, coordination, and constructive suggestions ensured smooth progress during every stage of the project. His guidance significantly strengthened the technical direction and documentation of our work.

I am grateful to the esteemed faculty members of the **Department of Electronics and Communication Engineering, Dr. Akhilesh Das Gupta Institute of Professional Studies, New Delhi**, for their persistent support, cooperation, and encouragement throughout our academic journey. Their dedication and expertise have been a constant source of motivation.

I would also like to acknowledge the collaborative efforts of my project teammates, whose cooperation and hard work were essential in completing this project successfully.

Finally, I express my heartfelt gratitude to my **parents** and to the **Almighty** for their unwavering support, blessings, and encouragement, without which this project would not have been possible.

REFRENCES

[1] Ultralytics, "Ultralytics YOLO," GitHub, 2025. [Online]. Available: https://github.com/ultralytics/ultralytics. [Accessed: Nov. 21, 2025].

[2] Open Source Vision Foundation, "OpenCV," 2025. [Online]. Available: https://opencv.org/. [Accessed: Nov. 21, 2025].

[3] The Pandas Development Team, "pandas: Powerful Python data analysis toolkit," 2025. [Online]. Available: https://pandas.pydata.org/docs/. [Accessed: Nov. 21, 2025].

[4] The Matplotlib Development Team, "Matplotlib," 2025. [Online].

Available: https://matplotlib.org/. [Accessed: Nov. 21, 2025].

[5] K. Simonov et al., "PyYAML," 2025. [Online]. Available: https://pyyaml.org/. [Accessed: Nov. 21, 2025].

[6] Roboflow Inc., "Roboflow Python SDK," 2025. [Online]. Available: https://docs.roboflow.com/developer/python-sdk/using-the-python-sdk. [Accessed: Nov. 21, 2025].

[7] Python Software Foundation, "shutil — High-level file operations," Python Standard Library Documentation, 2025. [Online]. Available: https://docs.python.org/3/library/shutil.html. [Accessed: Nov. 21, 2025].

[8] The NumPy Development Team, "NumPy," 2025. [Online]. Available: https://numpy.org/. [Accessed: Nov. 21, 2025].

[9] F. Pedregosa et al., "scikit-learn: Machine learning in Python," 2025. [Online]. Available: https://scikit-learn.org/stable/modules/generated/sklearn.metrics.confusion_matrix.html. [Accessed: Nov. 21, 2025].

[10] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, "You Only Look Once: Unified, Real-Time Object Detection," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Las Vegas, NV, USA, 2016, pp. 779–788.

[11] A. Bochkovskiy, C.-Y. Wang, and H.-Y. M. Liao, "YOLOv4: Optimal Speed and Accuracy of Object Detection," *arXiv preprint arXiv:2004.10934*, 2020.

[12] C.-Y. Wang, A. Bochkovskiy, and H.-Y. M. Liao, "YOLOv7: Trainable Bag-of-Freebies Sets New State-of-the-Art," *arXiv preprint arXiv:2207.02696*, 2022.

[13] G. Jocher, "YOLOv5 by Ultralytics: A High-Performance Object Detector," GitHub Repository, 2020. [Online]. Available: https://github.com/ultralytics/yolov5

[14] Ultralytics, "YOLOv8 Documentation," 2023. [Online]. Available: https://docs.ultralytics.com

[15] T.-Y. Lin et al., "Microsoft COCO: Common Objects in Context," in *ECCV*, Zurich, Switzerland, 2014, pp. 740–755.

[16] R. Girshick, "Fast R-CNN," in *Proc. IEEE Int. Conf. Comput. Vis. (ICCV)*, Santiago, Chile, 2015, pp. 1440–1448.

[17] K. He, G. Gkioxari, P. Dollár, and R. Girshick, "Mask R-CNN," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 42, no. 2, pp. 386–397, 2020.