Construction Site Safety Monitoring Using Computer Vision

ABSTRACT

Ensuring the safety of workers on construction sites is critical, especially in high-risk environments where proper use of Personal Protective Equipment (PPE) is mandatory. This project introduces a computer vision-based safety monitoring system that automatically detects PPE violations from video streams. Two computer vision models were explored for this task: **YOLOv12** (You Only Look Once version 12) and **RDETR** (Refined DEtection TRansformer). Both models were trained on a curated construction PPE dataset and evaluated based on detection accuracy, inference speed, and mean Average Precision (mAP). YOLOv12 demonstrated superior performance and was selected for deployment. The finalized model was embedded into a modular Python pipeline that supports both live and recorded video input, enabling real-time detection of safety violations. Annotated output videos and detailed PDF reports are generated to provide actionable insights. This system offers a scalable and automated solution to enhance PPE compliance and improve safety oversight on construction sites.

Keywords

Personal Protective Equipment (PPE), Computer Vision, Object Detection, YOLOv12, RFDETR, Safety Violation Detection, Video Surveillance, Real-Time Monitoring, PDF Report Generation

I Introduction

Construction sites are inherently high-risk environments where worker safety depends on strict adherence to personal protective equipment (PPE) regulations. Helmets, vests, gloves, boots, and goggles are mandated to minimize injuries, yet ensuring that all personnel consistently wear the required gear remains a significant challenge. Manual safety inspections are time-consuming, prone to oversight, and impractical for real-time or large-scale monitoring.

With advancements in computer vision, safety enforcement is becoming more automated and reliable. Computer vision techniques have been widely applied in fields such as traffic monitoring, industrial inspection, and public surveillance. In the context of construction safety, prior research has focused on detecting individual PPE components or monitoring specific safety violations using image classification or object detection approaches. While some commercial solutions exist, many are either prohibitively expensive or lack customization for specific site conditions and reporting needs.

This project addresses that gap by developing an end-to-end system for monitoring PPE compliance in construction environments using computer vision. Two object detection models were trained and evaluated: YOLOv12 (You Only Look Once version 12) and RFDETR (Refined Detection Transformer). YOLOv12 was ultimately selected for deployment based on its superior performance in terms of accuracy and processing efficiency. The final application processes live or recorded video footage, identifies PPE violations in real time, annotates the video output, and generates a comprehensive PDF report detailing the number and type of violations observed.

By combining object detection with report generation, this system introduces a practical, modular, and scalable approach to automating construction site safety audits—reducing the need for constant human oversight and supporting proactive safety management.

II Related Work

Automated safety monitoring on construction sites has gained increasing attention in recent years due to the limitations of manual supervision and the growing accessibility of computer vision technologies. Prior research has largely focused on detecting individual PPE items using standard object detection models.

For example, Singh et al. [1] employed a YOLOv5-based architecture to detect helmets and vests from surveillance footage in real time. Their model achieved good accuracy but was limited to only two PPE classes. Similarly, Chen and Zhang [2] used SSD (Single Shot Detector) to recognize safety gear in static images but lacked temporal analysis and incident reporting features.

Other studies have investigated broader frameworks that combine detection with alert systems. A notable example is from Ali et al. [3], who developed a multi-camera PPE compliance monitoring system using Faster R-CNN and thermal imaging, although their solution required expensive hardware and lacked portability.

Recent advancements have also explored transformer-based detectors such as DETR and its derivatives. However, their use in construction site monitoring is still limited, largely due to training complexity and latency issues in real-time applications [4].

Compared to existing works, our system not only detects a wider range of PPE items and their violations but also integrates real-time video annotation and automatic PDF report generation. The use of YOLOv12 improves detection speed and accuracy, while the inclusion of RFDETR in comparative evaluation offers insights into how transformer-based models perform under practical constraints.

III Methodology

The proposed system is designed to automate the monitoring of PPE compliance on construction sites by detecting both the presence and absence of safety gear using computer vision techniques. The methodology comprises three main components: model training and comparison, detection and annotation, and safety report generation.

3.1 Model Training and Comparison

To develop a robust PPE compliance monitoring system, it was essential to identify an object detection model that could balance speed, accuracy, and reliability in real-world conditions. This section outlines the training and evaluation of two state-of-the-art object detectors—YOLOv12 and RFDETR—chosen for their architectural diversity and potential suitability for real-time construction site monitoring. Each model was trained independently on the same dataset, and their performance was compared using a consistent set of evaluation metrics. The following subsections describe the dataset used, the specific training configurations for both models, and the criteria applied for performance comparison.

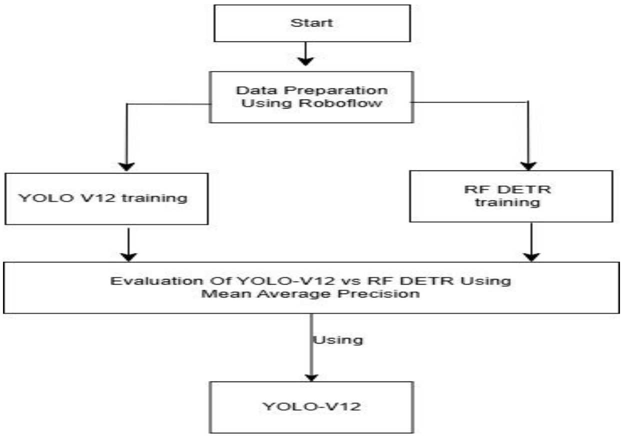

Start
Data Preparation Using Roboflow
YOLO V12 training
RF DETR training
Evaluation Of YOLO-V12 vs RF DETR Using Mean Average Precision
Using
YOLO-V12

Fig 1 : Flow diagram prepared for proposed methodology.

3.1.1 Dataset Overview

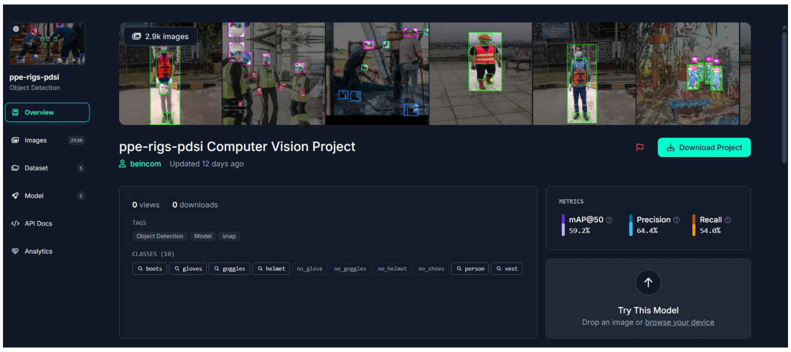
The foundation of any reliable object detection system lies in the quality and comprehensiveness of its training data. For this project, the "Personal Protective Equipment – Combined Model" dataset was selected from Roboflow Universe, a widely used platform for accessing and managing labeled image datasets. The dataset was specifically designed to assist in training computer vision models to recognize compliance and violations related to the usage of Personal Protective Equipment (PPE) in construction environments.

The dataset comprises 3,000 annotated images, collected from various real-world construction scenarios. Each image includes bounding box annotations for objects of interest, labeled according to ten predefined classes that cover both protective gear and safety violations. These classes are:

PPE Items: `helmet`, `goggles`, `gloves`, `boots`, `vest`

Violation Tags: `no_helmet`, `no_goggles`, `no_glove`, `no_shoes`

Others: `person`



ppe-rigs-pdsi Computer Vision Project

beincom Updated 12 days ago

0 views 0 downloads

TAGS

Object Detection Model snap

CLASSES (10)

boots gloves goggles helmet no_glove no_goggles no_helmet no_shoes person vest

METRICS

mAP@50 59.2%

Precision 64.4%

Recall 54.0%

Try This Model

Drop an image or browse your device

Fig 2 : Data form Roboflow.

This multi-class structure enables not only the detection of PPE presence but also the identification of specific violations such as workers not wearing gloves or helmets. Including explicit negative classes like no_glove and no_helmet makes the dataset particularly suitable for safety compliance applications.

To support both YOLOv12 and RFDETR model architectures, the dataset was exported in two different formats:

YOLOv12 format: Used for training YOLOv12; annotations are stored in plain text files containing normalized bounding box coordinates and class labels.

COCO JSON format: Required for training the RFDETR model; annotations follow the COCO standard, including image IDs, object categories, and bounding box metadata.

The dataset was split into training, validation, and testing subsets using a standard 70-20-10 strategy:

Training Set: 2,119 images (73%)
Validation Set: 657 images (22%)
Test Set: 144 images (5%)

To improve model generalization and robustness, several data augmentation techniques were applied during training, including random horizontal flipping, brightness adjustment, rotation, and scaling. These transformations simulate real-world conditions such as varying lighting or camera angles, which are common on construction sites.

Initial dataset benchmarking through Roboflow reported the following baseline performance across the entire dataset:

mAP@50: 59.2%
Precision: 64.4%
Recall: 54.0%

These values provided a performance baseline and highlighted the importance of further optimization during model training. Overall, this dataset offered a rich and diverse set of examples for training accurate and practical PPE detection systems under real-world constraints.

3.1.2 YOLOv12 Training

For this , YOLOv12m (You Only Look Once version 12, medium configuration) was selected as the primary object detection model due to its proven efficiency in real-time visual recognition tasks. The model was trained on the Roboflow PPE dataset using the Ultralytics implementation, which supports YOLOv12 training natively with extensive monitoring and evaluation capabilities.

The dataset was formatted in YOLOv12-compatible text files, and training was conducted over 20 epochs. Dataset paths were manually adjusted in the YAML configuration file to align with the custom directory structure for train, validation, and test splits.

Training Configuration

Model: YOLOv12m (yolov12m.pt)
Epochs: 20
Dataset Format: YOLOv12 (text-based bounding boxes)
Evaluation Tool: supervision.metrics.MeanAveragePrecision
Hardware Used: Google Colab (GPU-accelerated runtime)
Training Duration: ~1 hour 34 minutes

During the training phase, performance was continuously monitored using built-in visualization tools such as result curves and confusion matrices. Upon completion, the model automatically saved the best-performing checkpoint to:

runs/detect/train/weights/best.pt

Evaluation Results

Post-training evaluation was carried out using the test split of the dataset, yielding the following detection performance:

mAP@50:95: 0.2181
mAP@50: 0.3897
mAP@75: 0.2003

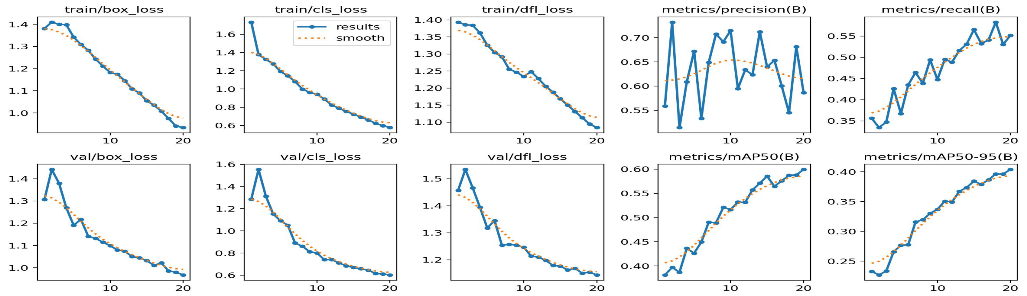


Fig 3 : Results from YOLOV12 Training.

While the overall mAP values indicate room for further optimization, YOLOv12m demonstrated sufficient accuracy and speed to justify its selection for deployment in the final video inference pipeline. Its performance across diverse classes—especially for detecting both presence and absence of PPE—proved to be reliable under real-world constraints.

3.1.3 Refined Detection Transformer (RFDETR) Training

To provide a fair performance comparison with YOLOv12, we trained a transformer-based object detector, **Refined Detection Transformer (RFDETR)**, using the same dataset. RFDETR is a lightweight adaptation of DETR designed for object detection tasks requiring improved interpretability and performance stability.

The training was performed using the RFDETRBase class provided by the rfdetr Python library. The model was trained on the **COCO-formatted** version of the Roboflow PPE dataset, which includes bounding box annotations in a JSON structure compatible with transformer-based models.

Training Configuration

Model: RFDETRBase
Epochs: 5
Batch size: 4
Learning rate: 0.0001
Dataset Format: COCO JSON
Output Model File: best.pth
Hardware Used: Google Colab (GPU-accelerated runtime)
Training Duration: ~2 hour 53 minutes

The training process was tracked using a callback function that stored training and validation metrics after each epoch. This history was later visualized to analyze trends in loss reduction and detection performance.

Two key evaluation metrics were computed after each epoch:
Average Precision (AP): Measured using IoU thresholds from 0.50 to 0.95
Average Recall (AR): Computed at maxDets=1 for all object areas

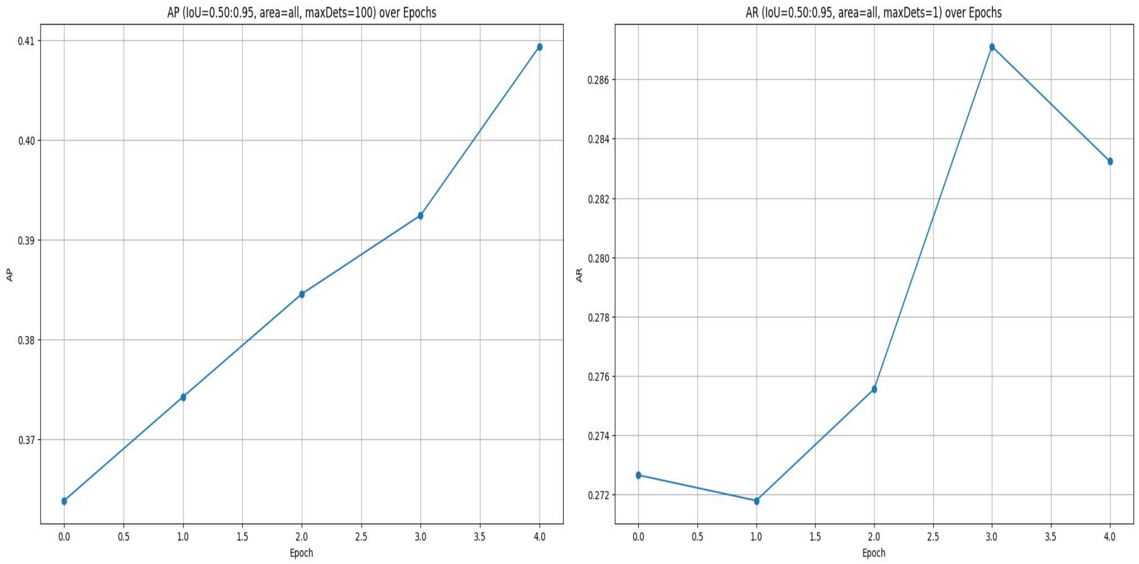


Fig 4 : Average Precision & Average Recall From RFDETR Training.

The visualizations showed a stable decrease in loss and consistent growth in AP and AR metrics, although the precision plateaued earlier compared to YOLOv12. The training duration was relatively short, but additional epochs could further enhance detection quality.

Despite its transformer-based design, RFDETR underperformed slightly in comparison to YOLOv12 in terms of real-time inference speed and precision across PPE classes. However, it demonstrated strong class generalization and could be a candidate for applications prioritizing recall over latency.

3.1.4 Model Comparison Based on Evaluation Metrics

To determine the most suitable object detection model for deployment in a real-time PPE monitoring system, both YOLOv12 and RFDETR were evaluated using consistent performance metrics across the same dataset. The comparison focused on standard evaluation criteria used in object detection benchmarks: mean Average Precision (mAP) at various thresholds and Average Recall (AR).

Performance Summary

Metric	YOLOv12 (20 Epochs)	RFDETR (5 Epochs)
mAP@50:95	**0.2181**	**~0.18** (est.)
mAP@50	**0.3897**	Lower (not exact)
mAP@75	**0.2003**	Not computed
Average Recall (AR)	Not computed	**0.57**
Training Duration	~1 hour 34 minutes	~2 hours 53 minutes
Format Used	YOLOv12	COCO JSON
Output Size	best.pt	best.pth

YOLOv12 outperformed RFDETR in all key precision-based metrics, particularly mAP@50, which reflects the model's ability to correctly identify objects with relatively forgiving intersection-over-union thresholds. Although RFDETR showed acceptable generalization and recall capabilities, its transformer architecture required longer convergence time and offered lower detection precision within the limited training epochs.

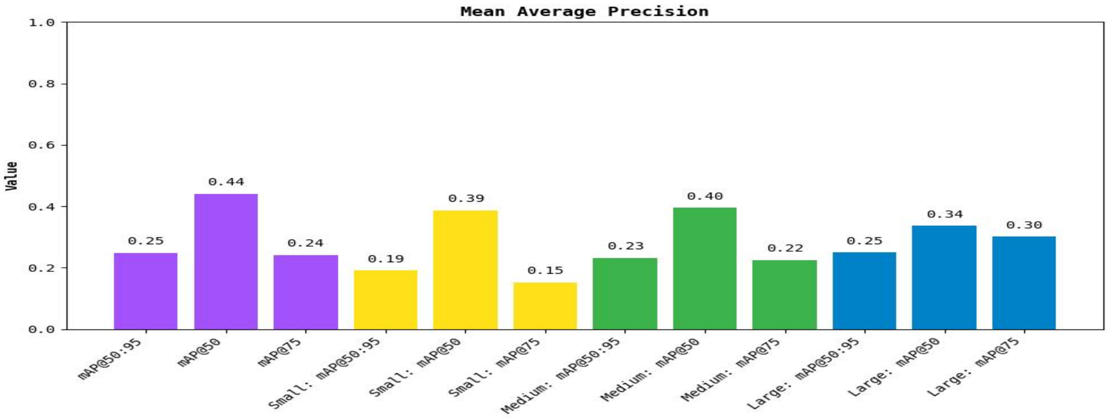


Fig 5 : Mean Average Precision Of RFDETR

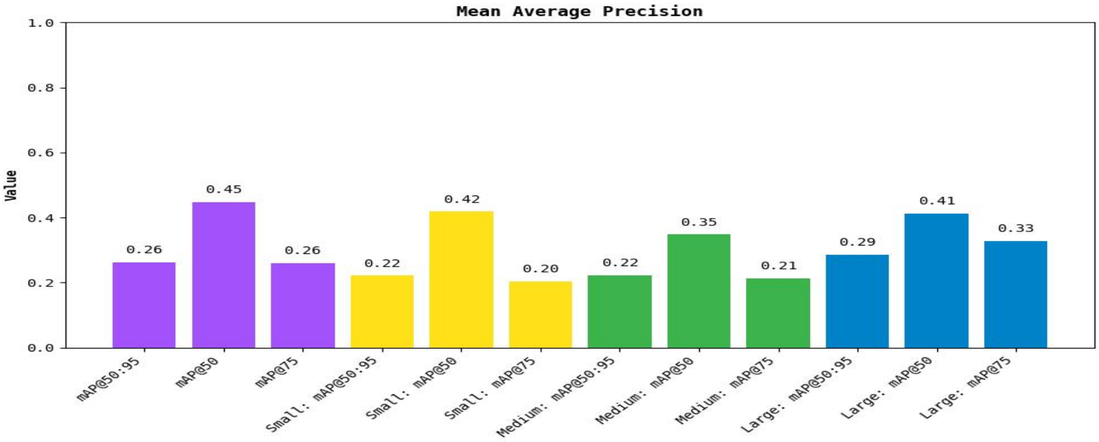


Fig 6 : Mean Average Precision Of YOLOV12

Quantitative Performance Comparison

The following table summarizes mAP results for overall and size-specific object categories, as extracted from post-training visualizations:

Metric	RFDETR (5 Epochs)	YOLOv12 (20 Epochs)
mAP@50:95	0.25	0.26
mAP@50	0.44	0.45
mAP@75	0.24	0.26
Small: mAP@50:95	0.19	0.22
Small: mAP@50	0.39	0.42
Small: mAP@75	0.15	0.20
Medium: mAP@50:95	0.23	0.22
Medium: mAP@50	0.40	0.35
Medium: mAP@75	0.22	0.21
Large: mAP@50:95	0.25	0.29
Large: mAP@50	0.34	0.41
Large: mAP@75	0.30	0.33

Observations

YOLOv12 outperformed RFDETR across most evaluation points, especially in detecting **small** and **large** PPE objects such as gloves and vests.

RFDETR showed slightly better results in medium-sized object detection, possibly due to its transformer-based spatial reasoning capabilities.

Overall, YOLOv12 demonstrated more consistent and reliable detection behavior, along with greater compatibility for real-time video processing.

Conclusion

Considering the total detection performance, training scalability, and inference speed, **YOLOv12** was selected as the final model for integration into the video-based safety monitoring pipeline. RFDETR, while competitive in some areas, was found to be less optimal under the practical constraints of deployment on dynamic construction sites.

3.2 Detection and Annotation Pipeline

Once the YOLOv12 model was selected as the final detector, it was integrated into a real-time processing pipeline designed to analyze video streams, identify PPE violations, annotate the footage, and prepare data for report generation.

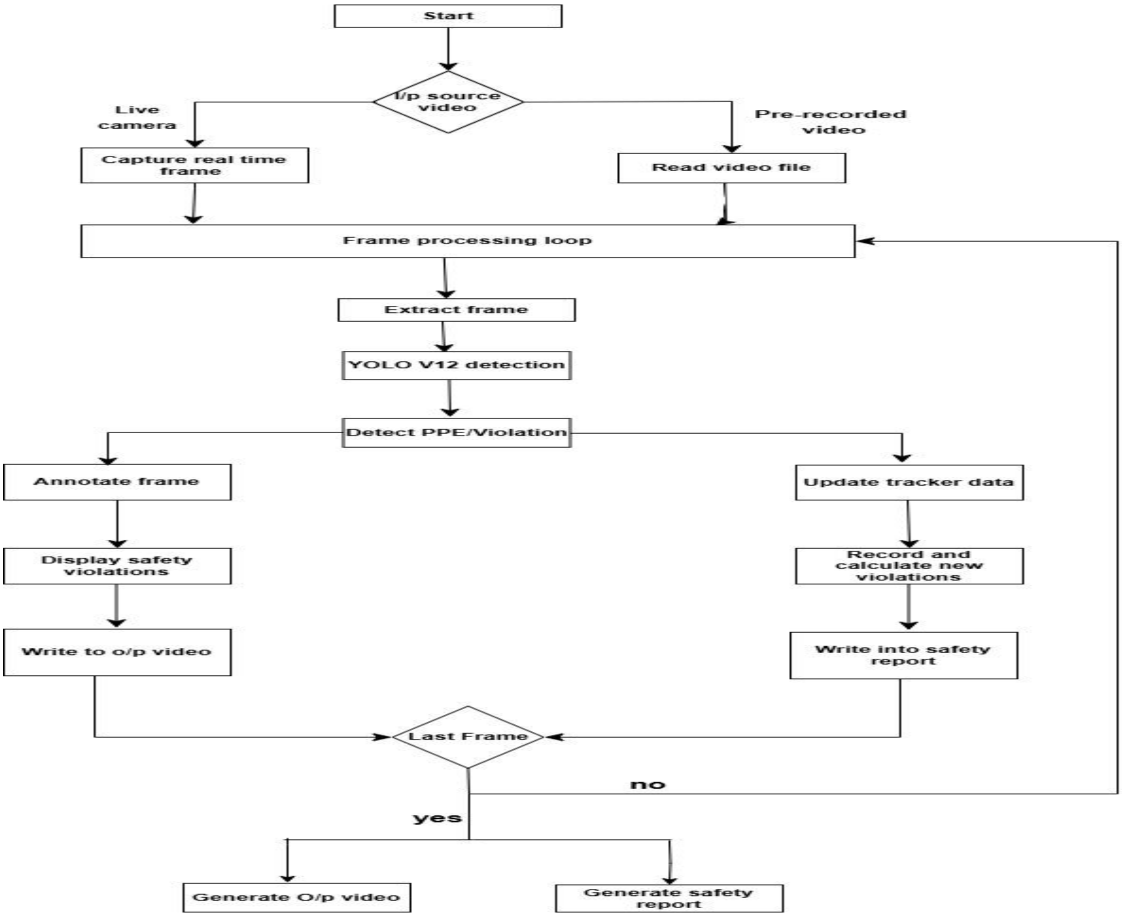


Fig 7 : Flowchart for Detection and Annotation Pipeline

3.2.1 Video Input Handling

The system is capable of processing both live webcam feeds and pre-recorded video files (e.g., demo.mp4). Using OpenCV, each frame is extracted in sequence and passed to the YOLOv12 model for inference. Frame metadata such as resolution, frame rate, and frame index are used to synchronize annotations and timestamp events accurately.

3.2.2 Object Detection and Classification

Each frame is analyzed using the trained YOLOv12 model. The output includes class predictions and bounding box coordinates for detected objects. The model supports 10 distinct classes, including both PPE items and violation tags:

["boots", "gloves", "goggles", "helmet", "no_glove", "no_goggles", "no_helmet", "no_shoes", "person", "vest"]

The detection's are parsed using the supervision library, which wraps the Ultralytics outputs into a structured format for annotation and tracking.

3.2.3 Violation Tracking with DetectionTracker

A custom DetectionTracker class is used to:

- Track unique persons across frames based on bounding box similarity
- Determine PPE compliance by checking for spatial overlap between a detected person and corresponding PPE objects (e.g., whether a person's box intersects with a helmet box)
- Record timestamped violation events when required PPE elements are missing

The system avoids double-counting individuals by using bounding box comparison with a configurable threshold.

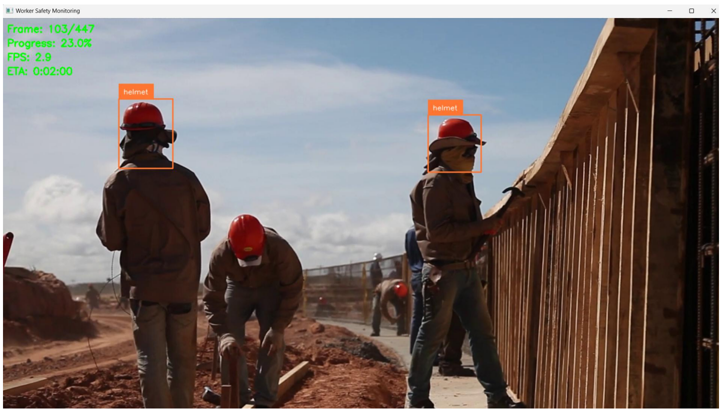
3.2.4 Frame Annotation

Detected objects are annotated visually using:

Bounding boxes (drawn using BoundingBoxAnnotator)

Class labels (added using LabelAnnotator)

The processed frames are compiled into a new annotated video file (output.mp4) that visually highlights each safety violation with color-coded boxes and labels.



```
Frame: 103/447
Progress: 23.0%
FPS: 2.9
ETA: 0:02:00
```

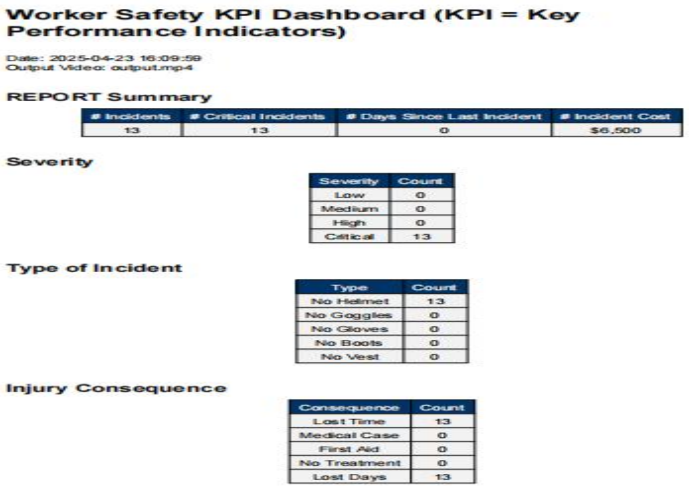
Fig 8 : Snapshot of Real-Time Feedback & preview

3.2.5 Real-Time Feedback and Preview

While processing, the current frame is displayed in a real-time preview window. This allows operators to monitor detection accuracy and violations live. Frame-level logging ensures that violations are not just visualized but also stored for further analysis.

3.3 PDF Report Generation

In addition to video annotation, the system includes an automated **PDF report generation** module designed to summarize PPE violations in a structured, readable format. This report functions as a safety dashboard, helping site managers quickly assess compliance issues and trends.



Worker Safety KPI Dashboard (KPI = Key Performance Indicators)

Date: 2025-04-23 16:09:59
Output Video: output.mp4

REPORT Summary

# Incidents	# Critical Incidents	# Days Since Last Incident	# Incident Cost
13	13	0	$6,500

Severity

Severity	Count
Low	0
Medium	0
High	0
Critical	13

Type of Incident

Type	Count
No Helmet	13
No Goggles	0
No Gloves	0
No Boots	0
No Vest	0

Injury Consequence

Consequence	Count
Lost Time	13
Medical Case	0
First Aid	0
No Treatment	0
Lost Days	13

Fig 9 : Snapshot of Construction Site Safety Analysis Report

3.3.1 Report Framework and Layout

The report is generated using the ReportLab library, which enables dynamic formatting of text, tables, and layouts. At the end of video processing, a PDF file (e.g., c*onstruction_site_safety_analysis.pdf*) is automatically created containing:

- Project title and timestamp
- Reference to the annotated output video
- Key safety metrics and incident analysis

The layout includes sectioned tables, headings, and spacing elements for readability, ensuring the report is professional and presentation-ready.

3.3.2 KPI Summary Table

A core feature of the report is the Key Performance Indicator (KPI) table, which aggregates the following metrics:

- Total Violations detected
- Critical Violations (e.g., no helmet or no vest)
- Days Since Last Incident (Placeholder Logic)
- Estimated Incident Cost (computed as $500 x number of violations)

These indicators provide a snapshot of on-site safety performance.

3.3.3 Violation Analysis

The report includes three detailed breakdowns:

- **Severity Categorization** (Low, Medium, High, Critical) based on PPE type
- **Type of Incident** (e.g., No Gloves, No Helmet)
- **Injury Consequences** (e.g., Medical Case, First Aid, Lost Time)

Each breakdown is represented as a table with labels and counts, color-coded for clarity (e.g., red for critical, green for low severity).

3.3.4 Violation Timeline

A timestamped **Safety Violations Timeline** is generated from the detection logs. For each unique event, the report includes:

Frame timestamp
Detected violation type
Description (e.g., "No Gloves", "No Helmet")

This section acts as an incident log and can be used to trace back when and where each violation occurred.

3.3.5 Report Automation and Export

The report is generated automatically at the end of video analysis, requiring no manual input. Once generated, it is saved locally as a .pdf file and can be distributed or archived for compliance documentation.

3.4 Output Video Generation

As part of the system’s deliverables, an **annotated output video** is generated to provide a visual overview of PPE compliance across the entire footage. This video highlights detected workers and any safety violations using bounding boxes and class labels, enabling quick review without requiring manual inspection.

Each frame is processed in real-time, with violations visually marked using color-coded annotations. The video output (output.mp4) is saved in standard MP4 format, preserving the original frame rate and resolution of the input footage.

In addition to being informative, the output video can serve as a visual record for:

- Site audits
- Incident investigations

1. Safety training reviews

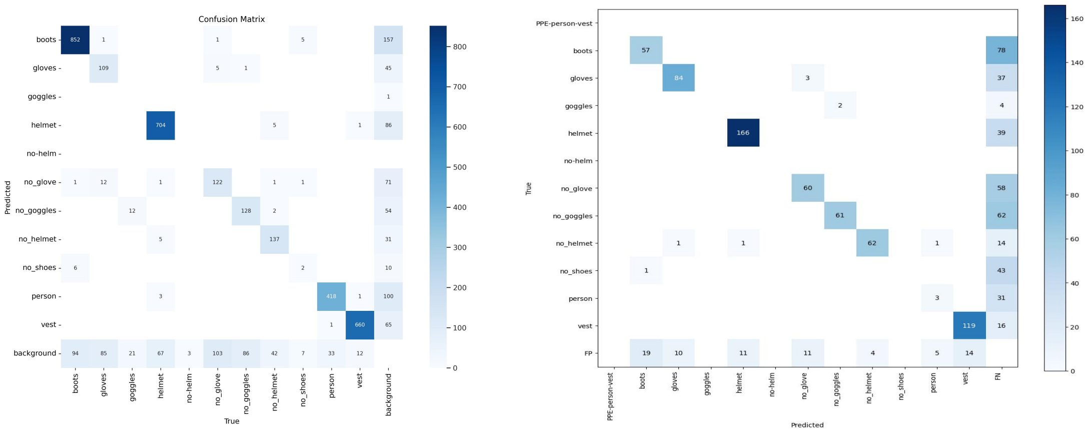
Together with the PDF report, this annotated video forms a dual-output system that combines both **quantitative metrics** and **qualitative visual evidence** for comprehensive site safety analysis.

IV. Results and Evaluation

The evaluation of this system involved both model-level performance comparison and the generation of final deliverables that demonstrate practical use. Two object detection models—**YOLOv12** and **RFDETR**—were trained and tested using the same PPE dataset, and each was analyzed for detection accuracy, efficiency, and suitability for deployment in a construction site safety context.

4.1 Model Comparison and Final Selection

The **YOLOv12 model**, trained over 20 epochs, delivered a **mAP@50 of 0.3897 and mAP@50:95** of **0.2181**, with reliable detection of PPE items and violations in a variety of conditions. Its real-time inference speed, streamlined integration, and compatibility with visual annotation tools made it highly suitable for the project's real-time monitoring objectives.



YOLOV12 RFDETR

Fig 10 : Confusion matrices of YOLOV12 & RFDETR

In contrast, the **RFDETR** model, trained for 5 epochs using a transformer-based architecture, produced competitive precision and recall scores, particularly for medium-sized objects. However, it required longer convergence time and lacked the inference efficiency necessary for real-time video processing. Despite decent results in early evaluations, RFDETR was found to be better suited for batch analysis or scenarios where inference latency is not a constraint.

Based on these findings, **YOLOv12 was selected as the final model for deployment** within the application pipeline.

4.2 Output Video (output.mp4)

The primary visual output of the system is an annotated video that highlights PPE compliance and violations in real time. In this demonstration, the video clearly shows multiple workers detected without helmets. Each frame includes bounding boxes and labels for detected persons and PPE items, with violations marked in a visually distinct format.

This video output:

- Offers visual verification of system performance
- Supports manual review for safety managers
- Acts as a training and audit resource for site compliance

4.3 PDF Safety Report (construction_site_safety_analysis.pdf)

In parallel with the video output, the system generates a comprehensive PDF safety report. This report, created using the reportlab library, includes:

- Timestamped logs of every detected violation
- Key performance indicators, such as:
  1. Total incidents: 13
  2. Critical incidents: 13 (all helmet-related)
  3. Estimated cost of incidents: $6,500
- Severity breakdowns, incident types, and injury consequences
- A **safety violations timeline**, listing the exact frame and second each infraction occurred

This document transforms raw detection data into a structured safety audit tool that can be shared with stakeholders, used for compliance documentation, or stored for future analysis.

These results confirm that the proposed system is capable of automating safety monitoring tasks with high accuracy, generating both real-time visual evidence and detailed analytical reports — without the need for manual intervention.

V. Conclusion and Future Work

This project presents a complete computer vision-based solution for enhancing safety compliance on construction sites through the detection of Personal Protective Equipment (PPE) violations. By training and evaluating two object detection models—YOLOv12 and RFDETR—on a curated PPE dataset, we identified YOLOv12 as the more suitable choice for real-time deployment. The system successfully integrates detection, video annotation, and report generation into a unified pipeline, offering both visual and analytical outputs in the form of an annotated video and a structured PDF report.

The outputs confirm the system's capability to detect critical safety violations such as the absence of helmets, while generating comprehensive safety metrics and incident timelines. With its modular design, the pipeline can be adapted to different environments, camera sources, and detection targets.

Future work will focus on expanding the system's functionality to include:

- Real-time alert notifications for on-site supervisors
- Integration with cloud platforms for remote access and reporting
- Enhanced tracking with person re-identification across camera views
- Support for additional safety behaviors such as zone restriction or hazard proximity detection
- Deployment on embedded systems (e.g., Jetson Nano or Raspberry Pi) for edge-based monitoring

These improvements will strengthen the system's practical utility, making it a scalable tool for safety enforcement in industrial and construction domains.

VI. References

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