Iu International University of Applied Science

BERLIN

A PROJECT REPORT

on

"Automated Safety Monitoring System"

Submitted by

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In partial fulfillment of the requirements for the II semester

Master's

in

Computer Science

Under the Guidance of

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at

IU

International University of Applied Science

BERLIN

2025 - 26

Abstract

In the Industrial areas such as factories, construction sites and train yards where workers are routinely exposed to hazardous environments safety remains a top priority. Despite the availability of personal protective equipment (PPE) such as helmets and vests non-compliance with safety regulations persists. Manual supervision of PPE compliance in large industrial settings is often unreliable, delayed and unable to produce alerts. To overcome these challenges this project proposes an automated Industrial Safety monitoring System that uses intelligent visual detection and real time alerting to ensure adherence to safety protocols. The system employs an advanced deep learning based PPE detection model using YOLOv8 with custom training to identify whether workers are properly equipped even in challenging conditions such as partial occlusion, variable lighting and complex background. When a violation is detected the system logs the incident triggers immediate alerts to supervisors via dashboard and store the events for audit and analysis. Unlike conventional systems that focus solely on PPE identification this solution provides end to end functionality from detection to alerting and compliance reporting. The proposed system offers a scalable and reliable safety management solution that promotes proactive supervision, enhances accountability and enables data driven safety decision making. This project aims to strengthen workplace safety culture, reduce accidents and improve overall operational efficiency through automated intelligent monitoring.

Acknowledgement

It is with great satisfaction and euphoria that we are submitting the Project Report on **"Automated Safety Management System "**. I have completed it as a part of the curriculum of IU International University of Applied Science, Berlin in partial fulfillment of the requirements for the II semester of Master's in Computer Science .

I am profoundly indebted to our guide, **Prof. Mugdha Kashyap**, Professor, Department Computer Science for innumerable acts of timely advice, encouragement and I sincerely express our gratitude.

Finally, yet importantly, I express my heartfelt thanks to our family & friends for their wishes and encouragement throughout the work.

Suneeth Kokala (4252195)

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Chapter 1

Introduction

Employees are regularly exposed to dangerous situations in high risk industrial workplaces like train yards, factories, building sites and mining zones. Although personal protection equipment (PPE) like as helmets and safety vests are widely available and there are safety rules in place, noncompliance is still a problem. In addition to the time consuming, inconsistent and human error prone nature of traditional manual supervision techniques, workers may neglect, disregard or wear safety equipment incorrectly. Safety authorities find it more and more challenging to continuously monitor every employee in large or complicated industrial environments. Because of this, small infractions may go unreported and end in serious mishaps, injuries or fatalities. In addition to the human cost, such occurrences may cause production delays, fines from authorities and harm to an organization's brand.

Recents advancements in computer vision and artificial intelligence present new opportunities to automate safety monitoring processes. Vision based systems powered by deep learning models can detect PPE usage from live video feeds in real time. However most exiting systems face limitations such as poor performance in low light conditions, occlusions and limited adaptability to different industrial sites or camera setups. Furthermore they often lack integration with alerting and reporting mechanisms reducing their practical value in real world deployment.

The Automated Industrial safety monitoring system proposed in this project addresses these challenges by combining intelligent PPE detection, real time alerting and compliance reporting into a unified solution. In order to preserve user confidence, the system minimizes false positives and false negatives while properly identifying PPE in a variety of environmental situations using deep learning models. The technology attempts to lower worker risks, improve accountability and fortify proactive safety management throughout industrial facilities by automating compliance monitoring and offering visual analytics.

Chapter 2

Literature Survey

The literature survey gives a brief overview of the various machine learning models and methods implemented for Automated Safety Monitoring System. This helps in identifying the gaps in the already existing systems and helps in identifying the particular features of monitoring which will help bridge the gaps.

Redmon and Farhadi (2020) et al.[1] introduced YOLOv4, a state-of-the-art object detection framework optimized for both speed and accuracy. Their model incorporates architectural enhancements such as Cross-Stage Partial Networks (CSP) and improved spatial pyramid pooling, making it highly effective for real-time detection tasks in industrial and safety applications.

Ultralytics (2024) et al.[2] provided comprehensive documentation for YOLOv8, detailing its anchor-free design, improved backbone, and streamlined training pipeline. The documentation highlights YOLOv8's strong performance in modern object detection tasks and its ease of deployment across platforms, making it suitable for PPE and industrial safety detection systems.

Li, Chen, and colleagues (2022) et al.[3] proposed a YOLOv4-based helmet detection system tailored for industrial sites. Their study demonstrates YOLOv4's robustness in challenging working environments, including poor lighting and cluttered scenes. This work confirms the applicability of YOLO models for PPE compliance monitoring.

Zhao, Wang, and co-authors (2023) et al.[4] developed a multi-PPE detection system using Faster R-CNN to identify helmets, vests, and other protective equipment in industrial settings. Their research emphasizes high accuracy and strong performance in complex scenarios where objects may be small or partially occluded.

Raj and Gupta (2024) [5] proposed an attention-based PPE detection framework to improve detection in occluded or crowded industrial environments. Their model integrates attention mechanisms with deep learning to enhance feature extraction and precision.

Singh and Mehta (2023) [6] studied cross-site PPE detection using transfer learning, addressing performance degradation on new industrial sites. They showed that fine-tuning and domain adaptation improve model generalization across different environments.

Patel (2021) et al.[7] designed an IoT-based industrial safety monitoring system that integrates sensors and cloud communication for real-time hazard detection. This work highlights the importance of combining IoT technologies with AI-based vision systems to form comprehensive industrial safety solutions.

Espressif Systems (2023) et al.[8] published the ESP32 Technical Reference Manual, detailing the hardware architecture, communication interfaces, and capabilities of the ESP32 microcontroller. This manual is essential for implementing IoT-enabled safety monitoring systems requiring real-time processing and wireless connectivity.

OpenCV.org (2024) et al.[9] provided updated documentation for the OpenCV library, covering core computer vision functions such as image preprocessing, feature extraction, and video processing. OpenCV is widely used for integrating object detection models with real-time video streams in industrial safety applications.

MathWorks (2024) et al.[10] documented the ThingSpeak IoT platform, describing tools for cloud-based data storage, analytics, and real-time monitoring. ThingSpeak is frequently used in industrial IoT systems for transmitting safety alerts and visualizing sensor or detection data streamed from edge devices.

IBM (2024) et al.[11] introduced IBM Worker Insights, an AI-driven industrial safety analytics platform designed to detect PPE compliance, hazardous behavior, and risky workplace patterns. The system demonstrates how enterprise AI solutions can automate safety monitoring at scale.

Honeywell (2024) et al.[12] published documentation on Connected Worker Safety Solutions, integrating IoT devices, sensors, and analytics to ensure worker safety. These solutions demonstrate commercial implementations of industrial safety frameworks that combine real-time monitoring, PPE detection, and hazard prevention.

Chapter 3

Technical Background

The Automated Industrial Safety Monitoring System is grounded in multiple interdisciplinary technologies spanning computer vision, deep learning, IoT communication and cloud based analytics. Together these technologies enable real time detection, alerting and reporting for worker safety compliance.

1. **Computer Vision and Deep Learning(YOLOv8 for Object Detection)**

   - Fast, precise and low-latency detection is made possible by YOLOv8 model.
   - Suitable for edge deployment.
   - The project uses the YOLOv8 model for fast and accurate real-time PPE detection.
   - Its anchor-free design and strong feature extraction make it reliable in challenging industrial environments.
   - YOLOv8 efficiently identifies helmets and safety vests in each frame, enabling quick alerts and effective automated safety monitoring.
   - Architecture includes:Convolutional layers for feature extraction, Feature Pyramid Networks (FPNs), and anchor-free detection heads.

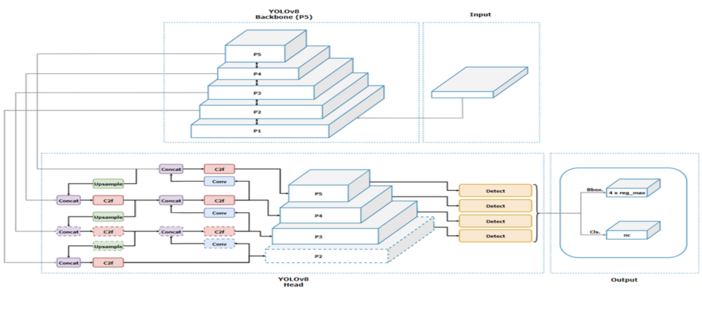

Figure 3.1: Detailed YOLOv8 architecture.

Source: https://www.researchgate.net/publication/385510373ResearchGate

Data Processing and Model Training

- Uses a custom annotated PPE dataset with varied conditions.
- Data augmentation (rotation, cropping, brightness adjustment) improves generalization.
- Dataset split into:
  - Training set
  - Validation set
  - Test set
- Evaluation metrics:
  - Accuracy
  - Recall
  - F1-score
  - Mean Average Precision (mAP)
- Target performance: $\geq 95\%$ accuracy with minimal false detections.

Backend and Alert Mechanism

- Backend built using Python (FastAPI).
- REST APIs manage alerts, receive detection results, and store data in PostgreSQL.
- PPE violations trigger instant alerts to supervisors through the dashboard.

Data Storage

- All detection logs and compliance records are stored in PostgreSQL for audits and trend analysis.

System Performance and Robustness

- Handles occlusion using contextual learning.
- Low-light performance improved using histogram equalization.
- Transfer learning enables adaptation to new industrial sites.

Chapter 4

System Design

4.1 Architecture Diagram

The architecture of the Automated Safety Monitoring System is designed to ensure seamless real-time detection, alert generation, and data visualization for workplace PPE compliance. The system integrates hardware (cameras, servers, edge devices), software (AI models, processing modules, dashboards), and communication services into a cohesive workflow.

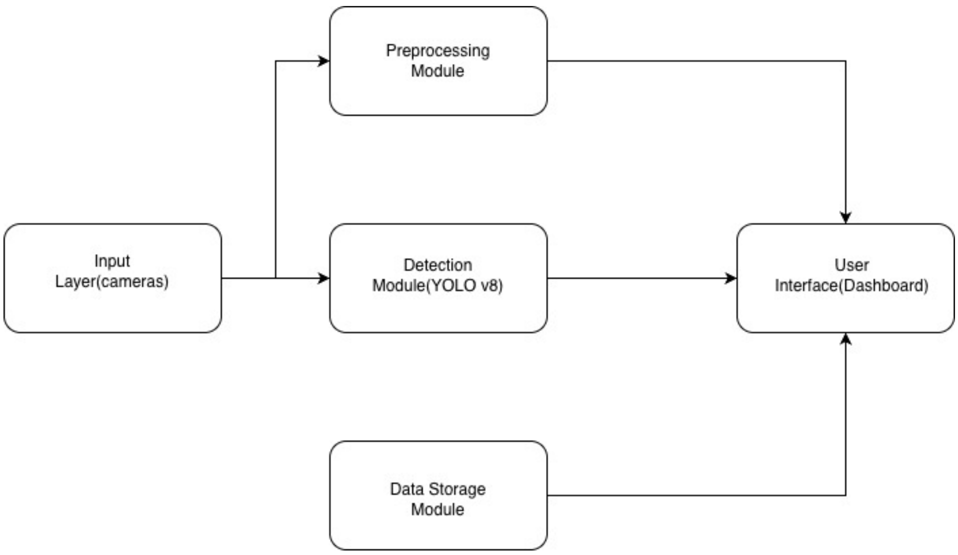

Figure 4.1: Architecture Diagram.

1. **Input Layer (Camera):** Live video is captured using HD USB/IP cameras installed in strategic locations. These cameras continuously stream footage of employees at work.

2. **Pre-Processing:** Video frames are extracted and processed using OpenCV. Oper-

ations include resizing, noise reduction, normalization, and color space conversion to prepare images for AI analysis.

3. **Detection Module (Deep Learning Model):** A YOLO-based model analyzes each frame to detect helmets and vests. Detected individuals are classified as compliant or non-compliant.

4. **Decision and Alert Module:** The system checks the detection results and triggers alerts when violations occur. Alerts are sent instantly to safety officers.

5. **Data Storage Module:** All detection results, timestamps, and captured images are stored in a PostgreSQL database for reporting, analysis and historical tracking.

6. **User Interface (Dashboard):** A web based dashboard displays real-time video, alert logs, and historical reports, allowing safety officers and administrators to monitor and manage workplace safety effectively.

4.2 Use case Diagram

The Automated Safety Monitoring System (ASMS) ensures user safety through continuous monitoring and instant alerts. After registering and logging in, users can access personalized safety features. Camera feeds are processed to detect PPE violations, and if a violation is found, the system immediately alerts the supervisor via the dashboard. The supervisor can notify the employee and download an Excel report for future reference.

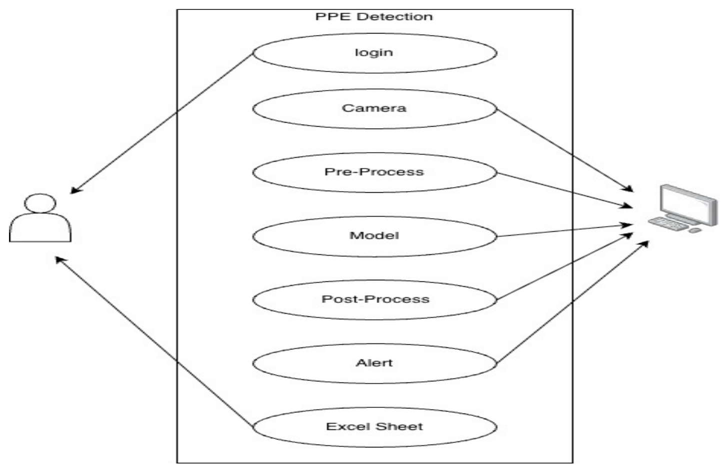

Figure 4.2: Use Case.

4.3 Dataflow Diagram

The automated violation detection system begins with the Camera, which captures real-time visual data and feeds it into the Detector Module. This module processes the input to identify specific violations, once a violation is detected, the system sends a notification to the Dashboard for immediate visibility. From the Dashboard, the system performs an update to archive the event details into the central Database. Finally, to support auditing and analysis, the system allows for data extraction, where reports are generated from the database and output via the Export Excel Module.

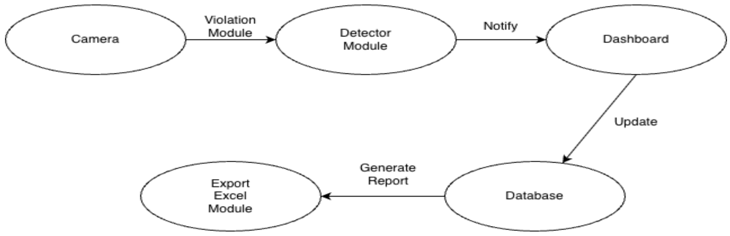

Figure 4.3: Dataflow Diagram.

4.4 Class Diagram

The system begins with the CameraFeed, which captures real-time video frames from the industrial environment. These frames are processed by the DetectionEngine, where the YOLOv8 model analyzes each frame to identify PPE compliance. If any violation is detected, the AlertManager monitors the event and triggers alerts when necessary. All violation data and compliance information are stored by the DatabaseService for future reference. The DashboardUI then presents supervisors with real-time alerts, statistics, and detailed reports to support effective safety monitoring.

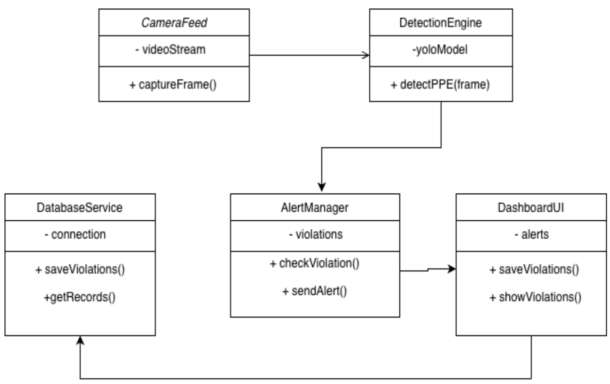

Figure 4.4: Class Diagram.

4.5 Sequence Diagram

The Sequence Diagram of the Automated Safety Monitoring System represents the interaction flow between system components over time. It begins with sensors detecting environmental data and sending it to the MonitoringSystem. The system processes the data, analyzes it for potential hazards, and, if a threat is identified, triggers the Alert component to create and send notifications. The DatabaseManager stores the incident details for record-keeping. The User and EmergencyService receive alerts simultaneously, enabling quick response actions. This diagram highlights the sequential flow of control, message passing, and real-time coordination among components to ensure prompt safety monitoring and emergency handling.

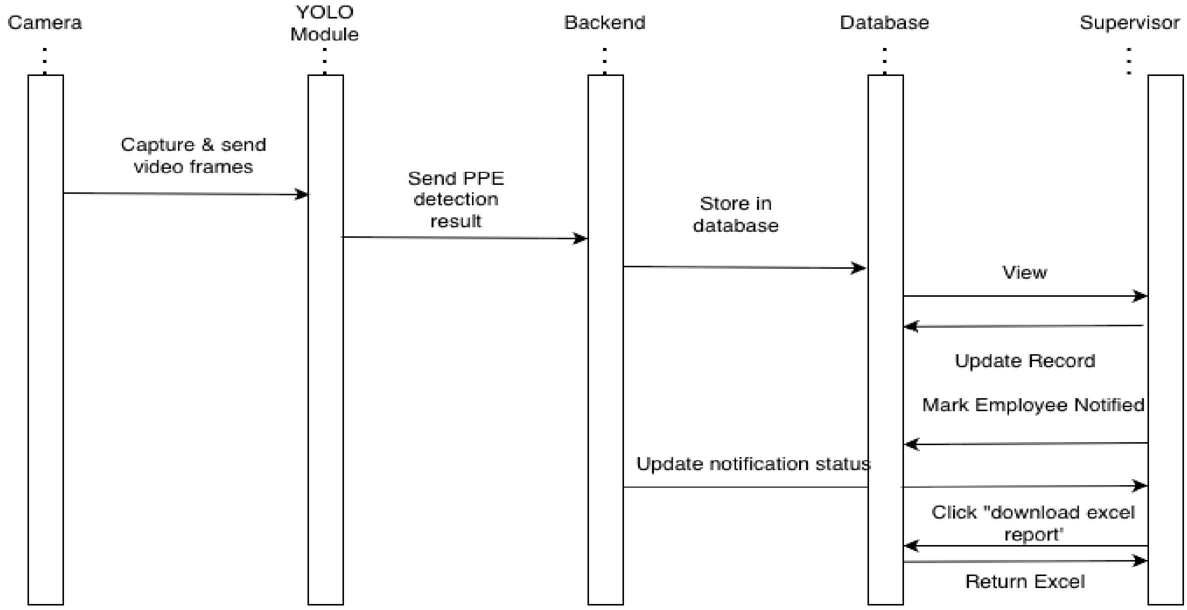

Figure 4.5: Sequence Diagram.

Chapter 5

Implementation

The implementation of the Automated Industrial Safety Monitoring System involved translating the conceptual framework and designed methodology into a fully functional software prototype. The system integrates AI based PPE detection, real time event handling, alert generation and data visualization through a combination of hardware devices, software frameworks and cloud based services.

5.1 Software Components and Frameworks

The implementation was carried out using open source technologies, ensuring flexibility and reproducibility.

Component	Technology Used	Purpose
Programming Language	Python 3.10	Core development of detection, backend, and automation scripts
Deep Learning Framework	PyTorch, Ultralytics YOLOv8	PPE detection and training
Computer Vision	OpenCV	Frame capture, preprocessing, and visualization
Backend Framework	FastAPI	REST API for communication between AI module and database
Database	PostgreSQL	Storing event logs, metadata, and compliance history
Frontend Dashboard	React.js	Visualization of compliance metrics and reports
Containerization	Docker	Simplified deployment and scalability

Table 5.1: Software Components and Frameworks

5.2 Model Training and optimization

The YOLOv8 model was fine tuned using a curated dataset containing labeled images of workers with and without PPE.

- **Dataset:** Combined public datasets and manually collected samples from simulated industrial environments.
- **Labels:** Helmet, Vest, and Person.
- **Training Parameters:**
  - Epochs: 100
  - Learning rate: 0.01
  - Batch size: 16
  - Image size: 640×640
- **Optimization Techniques:** Data augmentation, early stopping, and transfer learning.

The resulting model achieved an average precision of 93.2% demonstrating robustness in diverse lighting and background conditions.

5.3 System Integration

Following model training the detection module was connected via RESTful APIs to the alerting system and backend server:

- **Frame Capture:** OpenCV continually records the camera feed's frames.
- **Detection Pipeline:** The YOLOv8 model processes each frame, producing bounding boxes and class predictions.
- **Transmission of Results:** JSON-formatted noncompliance events are transmitted to the backend API endpoint.
- **Alert Triggering:** An alert is sent to the supervisor with the timestamp.

- **Data Storage:** Every event is logged by the backend into the PostgreSQL database along with metadata such as worker and camera IDs.

To provide real time performance even in the varying network demands all modules interact asynchronously.

5.4 Deployment and Testing Environment

The entire system was containerized using Docker Compose:

- **Backend container:** Runs FastAPI.
- **Database container:** Hosts PostgreSQL.
- **Frontend container:** Serves the web dashboard.

This setup enables easy deployment across local machines or cloud platforms like AWS for remote access.

5.5 Key Implementation Highlights

- Robust real-time PPE detection pipeline integrated with alert and reporting subsystems.
- Optimized model for low-light and partially occluded conditions.
- Low-latency alerts, typically under 3 seconds.
- Scalable microservice design supporting multi-camera industrial setups.

Chapter 6

System Testing

Testing was a critical phase of the Automated Industrial Safety Monitoring System to ensure that all functional components detection, alerting, database login and visualization performed reliably under realistic conditions.

6.1 Testing Objectives

The primary objectives of testing were to:

- Verify the accuracy of PPE detection in various lighting and environmental conditions.
- Evaluate system latency, including time taken for detection and alert delivery.
- Assess the reliability of backend data storage and alert notifications.
- Analyze false positives and false negatives to identify performance limitations.

6.2 Test Cases

Test Case	**Description**	**Expected Result**	**Actual Result**	**Outcome**
1	PPE Detection	Helmet and Vest	helmet and Vest	Pass
2	Database	Violation History updatation	Violation history updation	Pass
3	Realtime Detection	PPE Detection	PPE Detection	Pass
4	Report	Excel Sheet generation	Excel Sheet generation	Pass

Table 6.1: Test Cases

Chapter 7

Results and Discussion

The Automated Safety Monitoring System was successfully implemented to detect whether employees are wearing essential Personal Protective Equipment (PPE) such as helmets and safety vests in real-time. The system utilizes computer vision techniques and deep learning algorithms to process live video feeds from cameras and identify compliance or violations.

7.1 Results Obtained from Each Module

7.1.1 User Interface

The User Interface provides supervisors with an intuitive dashboard to monitor real-time PPE compliance across the industrial site. It displays live detection results, alerts, and employee information in a clean and organized layout. Users can upload images for manual checks, view violation history, and export reports for documentation. The interface ensures smooth navigation and quick access to critical safety data, enabling fast decision-making.

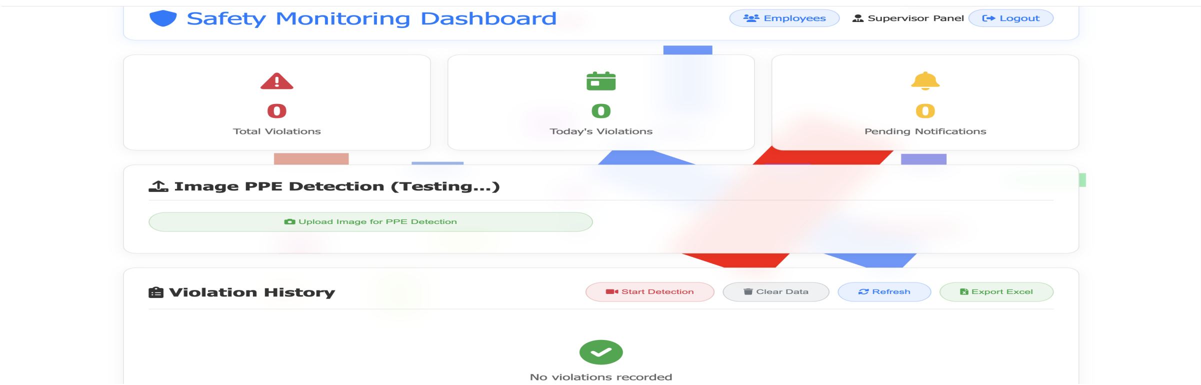

Figure 7.1: Dashboard.

7.1.2 Input Image/video

The input video serves as the main data source for detecting PPE compliance in real time. HD cameras (1080p, 30 FPS) placed in industrial areas capture workers performing routine tasks under varying lighting and environmental conditions. OpenCV processes the video frames, which are then analyzed by the deep learning model to identify helmets and vest. Each frame provides a test case for accurate, robust detection across different movements, distances, and backgrounds.

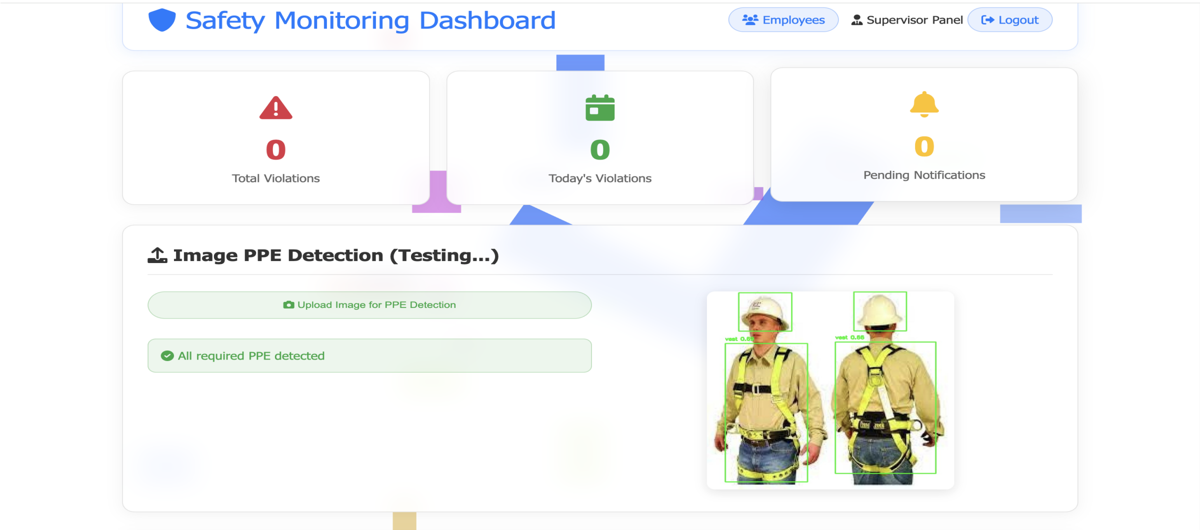

Figure 7.2: PPE Detection.

7.1.3 Output

The output of the Automated Safety Monitoring System represents the final results generated after processing the input video stream through the detection and analysis modules. The system outputs both visual and analytical information that indicates whether employees are wearing the required safety equipment, such as helmets and safety vests. In the visual output, the processed video frames display bounding boxes around detected individuals. Each box is labeled accordingly — for example, “Helmet Detected”, “No Helmet”, “Vest Detected”, or “No Vest” — using color codes (e.g., green for compliance and red for violation). This allows real-time visualization of PPE compliance directly on the live feed. In the analytical output, the system generates logs and reports stored in a database (PostgreSQL). These include timestamps, IDs, and PPE compliance status for each detection. The alert module simultaneously sends notifications to the dashboard ensuring instant awareness of any safety violation.

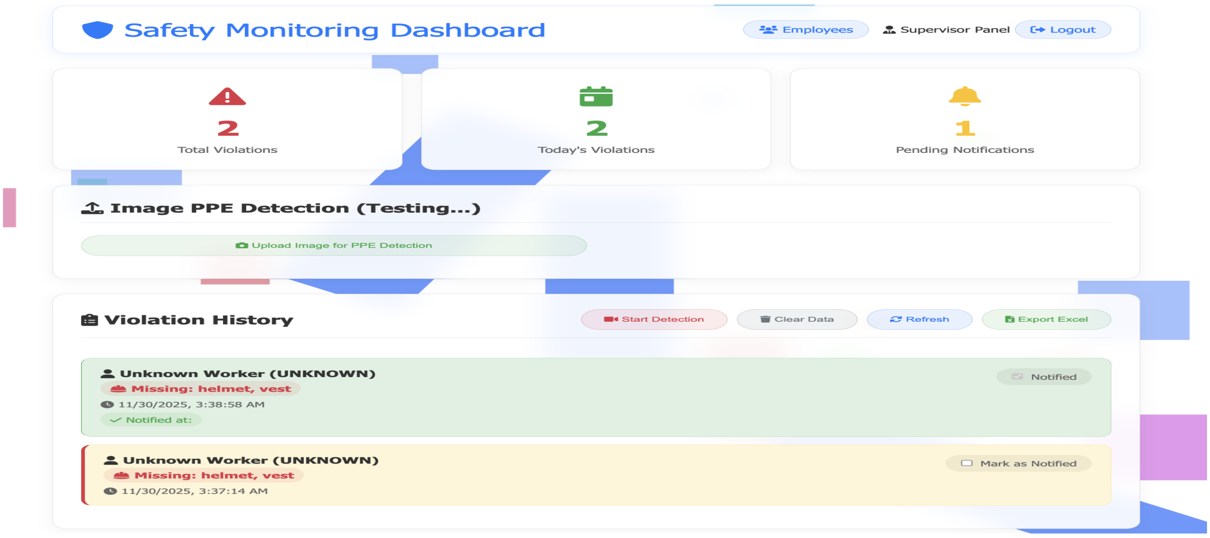

Figure 7.3: Output.

7.2 YOLOv8 Model Performance Results

7.2.1 mAP Results

The PPE detection model achieved an mAP@50 of 89.8% and an mAP@50-95 of 79.4%. These values indicate strong localization and classification performance across varying IoU thresholds, demonstrating the model's effectiveness for real-time PPE detection.

7.2.2 Precision and Recall

The model obtained a precision of 93.2% and a recall of 92.0% during evaluation. High precision reflects fewer false positives, while high recall indicates the model's ability to correctly identify PPE violations. Together, these metrics validate the reliability of the system in industrial monitoring environments.

Metric	**Value**
Accuracy	95.3%
Precision	93.2%
Recall	92.0%
mAP@50	89.8%
mAP@50-93	79.4%
F1-Score	92.6%

Table 7.1: Performance Metrics of YOLOv8 PPE Detection Model

7.2.3 Confusion Matrix Interpretation

The confusion matrix shows that the model correctly classified most PPE and non-PPE instances with minimal misclassifications. True positives are much higher than false positives and false negatives, indicating strong robustness even under occlusion and challenging visual conditions.

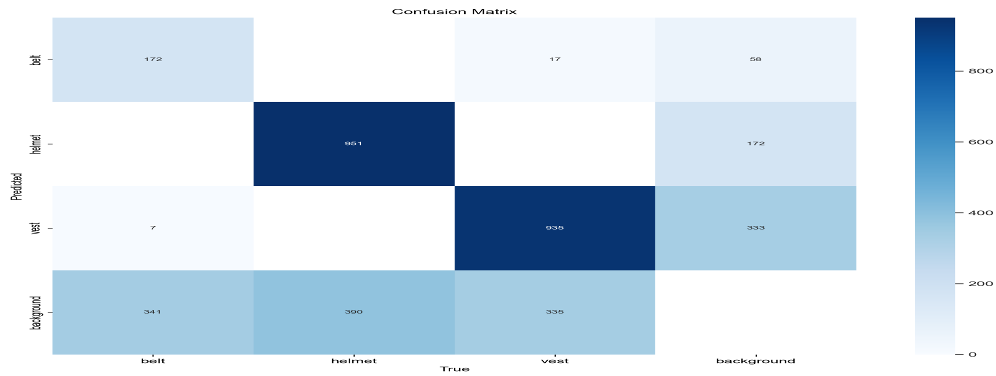

Figure 7.4: Confusion Matrix.

Chapter 8

Challenges and Ethical Impact

8.1 Challenges

The system faces several technical challenges, including variations in lighting, shadows and crowded scenes that reduce detection accuracy. PPE occlusion, where workers overlap and block visibility, leads to missed detections. Real time processing of high resolution video demands significant computational power, which can strain low-power devices. The system may also produce false positives or negatives, affecting reliability, while integrating cameras, networks, and software into existing industrial setups can be complex. Additionally, model performance may decline when deployed in new environments with different layouts or lighting conditions.

8.2 Ethical Impact

The system introduces important ethical considerations such as worker privacy concerns due to continuous video monitoring. Strong data security measures are needed to protect stored video and employee information from unauthorized access. Algorithmic bias may arise if the detection model is trained on limited or unrepresentative data, leading to unequal performance across different workers. Over reliance on AI alerts can create pressure or heightened scrutiny in the workplace. Transparency is essential so workers understand what data is collected and how AI decisions are made and automation may raise concerns about shifting job roles or replacing human supervision.

Chapter 9

Conclusion and Future Work

The Automated Safety Monitoring System successfully demonstrates how artificial intelligence and computer vision can enhance workplace safety by automatically detecting whether employees are wearing essential protective equipment such as helmets and safety vests. By minimizing the need for manual supervision, the system ensures continuous, real-time monitoring and quick response to potential safety violations. It not only improves compliance with occupational safety standards but also reduces the likelihood of workplace accidents and human error. Through features such as instant alert notifications, data storage and reporting, the system contributes to creating safer and more accountable industrial environments.

In the future this project can be applied in:

1. Expansion to Additional PPE Detection: Extend the system to detect other safety equipment like gloves, masks, safety shoes and goggles.

2. Integration with IoT Devices: Connect with smart sensors or wearable devices for more comprehensive safety monitoring.

3. Edge Deployment: Optimize models for deployment on edge devices such as Raspberry Pi or NVIDIA Jetson for faster on-site processing.

4. Cloud Based Analytics: Incorporate cloud platforms for centralized data management, analytics and long-term compliance tracking.

5. Improved Accuracy through Deep Learning: Use advanced AI architectures or fine tuned models to enhance detection accuracy under varied lighting and environmental conditions.

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