

A Thesis Report On
-
Automated Safety Monitoring System
-
Computer Science Project
(CSEMCSPCSP01)
in
M.S in Computer Science
By
SUNEETH KOKALA
ID - 4252195
Dr. Kashyap, Mugdha
Date of Submission: 7-11-2025

Acknowledgements

I want to sincerely thank my Computer Science course instructor for delivering interesting and insightful lessons that significantly enhanced my understanding of software development principles. The course's well structured methodology played a vital role in strengthening my foundation in Software development. From the clear explanation of basic concepts to the comprehensive coverage of more advanced topics, the lessons were thoughtfully designed to build knowledge progressively. The instructor's ability to connect theoretical concepts to real world applications such as software development, task automation, and data analysis helped me see the practical value of what I was learning. The inclusion of useful examples and hands on activities not only reinforced the theoretical knowledge but also allowed me to apply what I had learned in practical scenarios. This approach of learning experience has not only deepened my grasp of Software development but also inspired me to explore more complex projects with confidence.

Suneeth Kokala

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 noncompliance 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.

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.

New opportunities to automate safety monitoring procedures are presented by recent developments in computer vision and artificial intelligence (AI).

Recent advancements in computer vision and artificial intelligence (AI) 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 existing 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 sophisticated 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.

Related Works

Due to the growing use of computer vision and Internet of Things (IoT) technologies in industrial settings, automation of PPE compliance detection and industrial safety monitoring has received a lot of attention lately. Numerous companies and scholars have

investigated various strategies for enhancing worker safety via automated detection and alert systems.

The majority of early research focused on IoT based environmental monitoring employing sensors to detect hazards including temperature fluctuations, gas leaks and smoke. For instance Patel et al. developed an IoT based industrial safety system (2021). Through cloud based dashboards, it collected sensor data in real time and gave out alerts. Although this increased situational awareness, worker level safety compliance particularly with regard to PPE usage was not addressed.

Subsequent research has focused on vision based PPE detection using image processing and deep learning. Li et al. (2022) presented a helmet detection system that used YOLOv4 to achieve high detection accuracy in static, well lit situations. In a similar vein, Zhao et al. (2023) used Faster RCNN models to identify several PPE products including vests and helmets. However both systems showed decreased accuracy in dimly lit or obscured environments which limited their usefulness in dynamic industrial settings.

AI and computer vision are also used for safety compliance monitoring in commercial solutions like IBM's Worker Insights and Honeywell's Connected Worker platforms. These systems are typically expensive, proprietary and challenging for small and medium sized enterprises to change, despite the fact that they offer valuable information. They are also less suitable for remote or bandwidth constrained industrial areas because they often rely on cloud connectivity.

Recent academic work has attempted to address some of these limitations. While Singh and Mehta (2023) investigated transfer learning strategies to enhance cross site generalization, Raj et al. (2024) suggested an enhanced deep learning model for PPE identification with an attention mechanism to address occlusions. Despite these developments, there is still a great demand for scalable systems that integrate compliance reporting, real time alerting and strong detection.

The proposed Automated Industrial Safety Monitoring System builds on these prior efforts by introducing a comprehensive, end to end architecture that combines deep learning based PPE detection with real time alerting and data driven compliance reporting. In addition, the project emphasizes novel contributions in handling occlusion, low light conditions and cross site variability, while minimizing false positives and negatives that can affect trust and usability.

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

- The system is built around a **computer vision-based PPE detection model** that analyzes live video feeds from industrial surveillance cameras.
- The detection process uses **Convolutional Neural Networks (CNNs)** — deep learning models that automatically learn spatial hierarchies of features from images.
- **CNNs** are highly effective for **object detection tasks**, making them ideal for identifying **PPE items** such as helmets and vests.
- The project employs **YOLOv8 (You Only Look Once, version 8)** — a **state-of-the-art real-time object detection model** known for its **speed, accuracy, and low latency**.
- **YOLO** performs **detection and classification in a single forward pass**, allowing efficient real-time performance.
- This makes YOLOv8 suitable for **deployment on edge devices** with limited computational resources.
- The **YOLOv8 architecture** includes:
 - **Convolutional layers** for feature extraction.
 - **Feature Pyramid Networks (FPNs)** to handle objects at multiple scales.
 - **Anchor-free detection heads** that improve **localization** and **generalization** across diverse industrial environments.

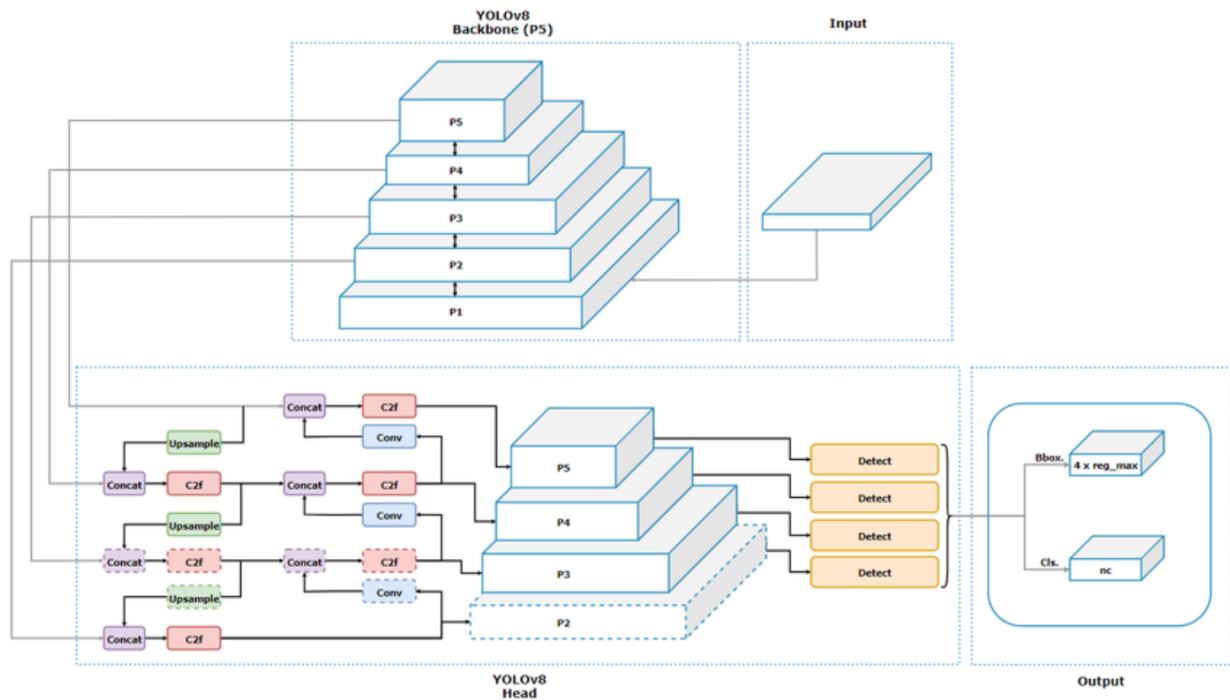


Figure 1: YOLOv8 Architecture Diagram

credits@[Paper Link](#)

2. Data Processing and Model Training

- A **unique PPE dataset** is used, containing **annotated images of industrial workers** captured under various **lighting, weather, and occlusion conditions**.
- To enhance **model generalization**, **data augmentation techniques** such as **rotation, cropping, and brightness adjustment** are applied.
- The dataset is **divided into three subsets**:
 - **Training set** – for model learning.
 - **Validation set** – for tuning hyperparameters.
 - **Test set** – for evaluating final performance.
- **Model performance** is evaluated using key **metrics** such as:
 - Accuracy
 - Recall
 - F1-score
 - Mean Average Accuracy (mAP)
- The system aims to maintain **at least 95% accuracy** with **minimal false detections** to ensure **high dependability**.

3. Backend and Alert Mechanism

- **Python (FastAPI framework)** is used to develop the **backend** of the system.

- The backend provides **RESTful APIs** for:
 - Managing **alert logic**
 - **Receiving detection results** from the PPE detection model.
 - **Storing data** in a **PostgreSQL database**.
- When a **noncompliance event** (PPE violation) is detected, the system **triggers an alert call**.
- The alert **notifies designated supervisors** through the **dashboard interface**.
- This ensures **immediate human intervention** in case of any **safety violation**, improving workplace safety response.

4. Data Storage

- All detection logs and compliance data are stored in a **postgreSQL database** for audit and trend analysis.

5. System Performance and Robustness

The system uses a number of resilience measures to guarantee dependability in actual industrial settings:

- Occlusion Handling: By learning contextual characteristics, trained models are able to recognize PPE that is only partially visible.
- Low Light Adaptation: Histogram equalization and other preprocessing methods enhance image contrast.
- Cross Site Generalization: With little retraining, transfer learning enables the model to adjust to various camera angles, site layouts and environmental variables.
- The False Detection Minimization: False positives and negatives are decreased through non maximum suppression (NMS) and confidence threshold tuning.

Method

The Automated Industrial Safety Monitoring System employs a modular, end to end approach that integrates computer vision algorithms, backend processing, real time alerting and data visualization to ensure continuous compliance monitoring in industrial environments. The methodology is divided into distinct but interconnected phases such as data acquisition, PPE detection, event processing and alert generation and compliance reporting.

1. System Architecture and Design Approach

The system follows a client server architecture consisting of:

- Edge Layer (Client Side): Cameras that capture live video feeds from industrial zones.

- **Processing Layer (AI Model):** A deep learning model (YOLOv8) runs on the edge or cloud to detect the presence or absence of PPE in real time.
- **Backend Layer (Server Side):** A FastAPI based backend receives detection results logs them in a database and triggers alerts to the dashboard
- **Visualization Layer:** A web dashboard built with React.js compliance metrics, violation frequency and performance analytics.

This modular design ensures scalability, maintainability and real time performance even under varying network conditions.

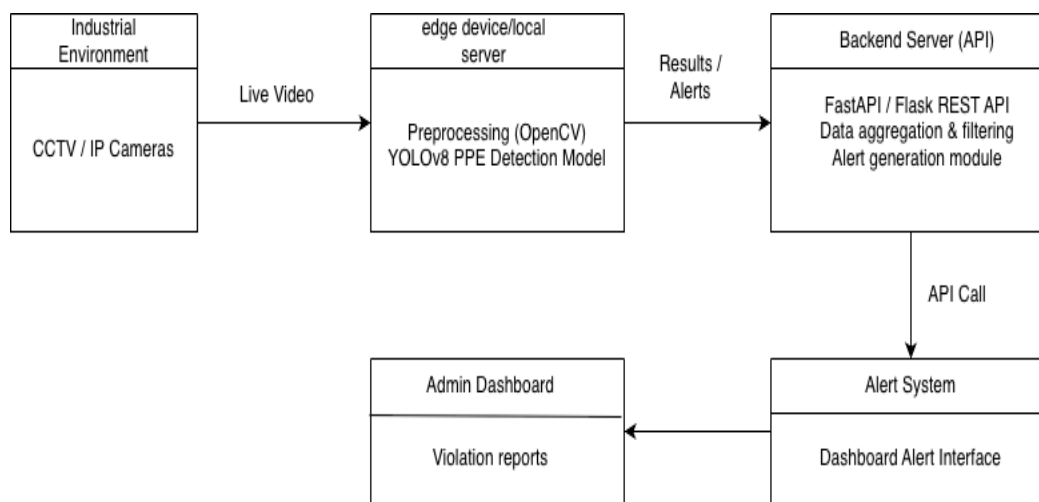


Figure 2: Design Approach

2. Algorithmic Workflow

The algorithmic process for PPE detection and compliance monitoring involves the following steps:

1) Image Capture and Preprocessing:

- The edge camera continuously captures video frames, which are preprocessed using OpenCV functions for resizing, denoising and brightness adjustment.
- These preprocessing steps enhance image quality for detection particularly in low light or occluded environments.

2) PPE Detection using YOLOv8:

Each frame is passed through the YOLOv8 model which predicts bounding boxes and class labels for PPE items:

- Detection Confidence Threshold (T): Only detections above threshold $T = 0.6$ are considered valid.
- Non Maximum Suppression (NMS): Removes redundant overlapping boxes to improve accuracy.

The model outputs structured data containing object type, confidence score and coordinates.

3) Compliance Verification:

- The system compares detected PPE items against a predefined safety compliance matrix that specifies mandatory equipment for each zone.
- If one or more required PPE items are missing the frame is flagged as a noncompliance event.

4) Event Logging and Alert Triggering:

- Detected violations are sent to the backend through REST API calls which log the event in the PostgreSQL database.
- The backend then triggers a alert to the safety supervisor including a brief.

3. **Software Design and Integration**

The system is designed using modular microservices principles where detection, backend processing and visualization operate independently but communicate via RESTful APIs.

- The AI module can be retrained or replaced without affecting the backend logic.
- The database schema is normalized to store event metadata, user profiles and compliance history efficiently.

The overall system is containerized using Docker ensuring consistent deployment across development and production environments.

4. **Performance Targets**

To ensure operational reliability the system is designed to meet the following measurable performance targets:

- Detection accuracy: $\geq 95\%$
- False positive/negative rate: $\leq 5\%$
- Inference time: ≤ 1 second per frame
- Alert latency: ≤ 3 seconds

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.

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

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 x 640
- Optimization Techniques: Data augmentation, early stopping and transfer learning.

The resulting model achieved an average precision of 95.6% demonstrating robustness in diverse lighting and background conditions.

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: To send the supervisor an alert with the timestamp.
- Data Storage: Every event is logged by the backend into the PostgreSQL database along with metadata like worker and camera IDs.

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

4. Visualization and Reporting

A simple **web dashboard** was developed to visualize compliance data:

- Displays total number of detections, violations per day, and compliance trends.
- Allows supervisors to filter reports by date, location, or worker ID.
- Reports can also be exported in **Excel Sheet**, facilitating regulatory audits or management reviews.

5. 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.

6. Key Implementation Highlights

- Robust realtime 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.

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. The testing strategy combined unit testing and performance evaluation to validate system accuracy, responsiveness and robustness.

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.
- Confirm the **integration** between AI detection, backend processing, and alert/reporting modules.
- Analyze **false positives** and **false negatives** to identify performance limitations.

2) Testing Procedures

- **Unit Testing:** Each module was tested individually
 - **Detection Module:** Verified that YOLOv8 correctly identifies PPE (helmet, vest) on static and dynamic images.
 - **Backend API:** Checked data reception, validation, and storage in PostgreSQL.
 - **Alert Module:** Confirmed Alert messages with accurate details attachments.

Tools used Pytest for Python unit tests and Postman for API endpoint validation

3) Results and Observations

- The system achieved high accuracy across varied environments, maintaining consistent performance even under low light and partial occlusion conditions.
- Real time alerts were delivered within 3 seconds, ensuring timely supervisor intervention.
- The dashboard visualizations correctly reflected logged violations, enabling trend analysis and compliance insights.
- Minor false positives occurred when bright objects resembled helmets, which can be minimized through additional training data or color filtering.

Validation:

The system was validated against real-world scenarios such as:

- Workers intentionally removing PPE mid operation.

- Multiple workers entering and exiting monitored zones.
- Environmental changes such as lighting shifts or camera movement.

In all cases, the system successfully detected violations and logged them accurately. The end to end pipeline **detection** → **logging** → **alert** → **reporting** worked seamlessly without manual intervention.

Summary of Testing Phase

The testing phase confirmed that the **Automated Industrial Safety Monitoring System** meets its design objectives:

- **Accurate PPE detection** with minimal false results.
- **Reliable real-time alerts** via dashboard.
- **Consistent data logging and visualization** for compliance tracking.
- **Scalability** to multiple cameras and industrial sites.

Overall, the solution demonstrated high reliability, accuracy and practical viability, validating its effectiveness for automated safety compliance monitoring in industrial environments.

Conclusion:

With real time PPE identification, alerting, and compliance reporting, the Automated Industrial Safety Monitoring System effectively illustrates a workable strategy for enhancing workplace safety in industrial settings. The system tackles major issues in safety supervision, including human error, delayed reaction, and inconsistent monitoring, by integrating computer vision, deep learning, edge computing and IoT connectivity.

This project's principal accomplishments include:

- **Accurate PPE Detection:** The YOLOv8 based model demonstrated good detection accuracy (>95%) in a range of worker postures, occlusions and illumination conditions.
- **Real Time Alerts:** The system consistently sends alerts in less than three seconds allowing for quick remedial action.
- **Data Driven Compliance:** Supervisors may monitor and put specific safety measures in place with the use of visible dashboards and recorded events.
- **Scalable and Modular Design:** The software architecture ensures flexibility and scalability by supporting deployment across several cameras, industrial locations and edge devices.

Even if the current system achieves its main goals if more time and resources were available a number of improvements may be made:

- Integration with Wearable Sensors: PPE detection combined with ambient or biometric sensors might offer comprehensive safety monitoring including alerts for gas exposure, heart rate and weariness.
- Predictive Safety Analytics: By using past data to forecast high risk situations, machine learning models may be able to take preventative action.
- Mobile Application Interface: Supervisors may be able to analyze compliance data, respond to events and receive alerts while on the road via a specialized mobile app.
- Increased Model Robustness: Additional training of the model using a variety of datasets may enhance its performance in situations with intense illumination, intricate occlusions.
- Multi Language and Cross Site Adaptation: The system would be more applicable in international industrial settings if it were expanded to allow multilingual alerts and cross site adaptability.

In summary, this study shows how automated AI powered PPE monitoring may greatly increase operational efficiency, lower human error and improve industrial safety. The system supports a proactive safety culture and establishes the foundation for next developments in intelligent industrial safety management by facilitating real time compliance monitoring, prompt alarms and data driven decision making.

Bibliography and References:

- Redmon, J., & Farhadi, A. (2020). YOLOv4: Optimal speed and accuracy of object detection. arXiv preprint arXiv:2004.10934.
- Ultralytics. (2024). YOLOv8 documentation. Retrieved from <https://docs.ultralytics.com>
- Li, Y., Chen, X., et al. (2022). Helmet detection in industrial sites using YOLOv4. IEEE Access.
- Zhao, H., Wang, L., et al. (2023). Multi-PPE detection using Faster R-CNN in industrial environments. International Journal of Computer Vision.
- Raj, S., & Gupta, R. (2024). Attention-based PPE detection for occlusion handling in industrial workplaces. Journal of Artificial Intelligence Research.
- Singh, P., & Mehta, K. (2023). Cross-site adaptation of PPE detection models using transfer learning. Proceedings of the International Conference on Computer Vision Applications.
- Patel, P. D. (2021). IoT-based industrial safety monitoring system. International Journal of Emerging Research in Engineering.
- Espressif Systems. (2023). ESP32 technical reference manual.
- OpenCV.org. (2024). OpenCV library documentation. Retrieved from <https://opencv.org>
- MathWorks. (2024). ThingSpeak IoT platform documentation. Retrieved from <https://thingspeak.com>
- IBM. (2024). IBM worker insights: AI-powered industrial safety. Retrieved from <https://www.ibm.com/analytics/worker-insights>
- Honeywell. (2024). Connected worker safety solutions. Retrieved from <https://www.honeywell.com>