Industrial Workspace Safety Enforcer: AI-Powered Robotic Compliance System

A PROJECT REPORT

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BONAFIDE CERTIFICATE

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DECLARATION BY THE CANDIDATE

I declare that the report entitled **"Industrial Workspace Safety Enforcer: AI-Powered Robotic Compliance System"** submitted by me for the degree of Bachelor of Technology is the record of the project work carried out by me as a part of End semester project for the course 22AIE214 - Introduction to AI Robotics under the guidance of **"Mr. Deenadhayalan G"** and this work has not formed the basis for the award of any course project, degree, diploma, associateship, fellowship, titled in this or any other University or other similar institution of higher learning. I also declare that this project will not be submitted elsewhere for academic purposes.

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ABBREVIATIONS

AI	Artificial Intelligence
PPE	Personal Protective Equipment
YOLO	You Only Look Once
CNN	Convolutional Neural Network
mAP	Mean Average Precision
IoT	Internet of Things
IIoT	Industrial Internet of Things
FP	False Positive
FN	False Negative
TP	True Positive
TN	True Negative
LCD	Liquid Crystal Display
GPIO	General Purpose Input/Output
SSD	Single Shot MultiBox Detector
RPLCD	Raspberry Pi LCD Library

NOTATION

E	Number of epochs
B	Batch size
mAP	Mean Average Precision
P	Precision
R	Recall
α	Learning rate
L	Loss function
θ	Model parameters

ABSTRACT

Ensuring workplace safety in industrial environments is crucial, as employees are often exposed to hazardous conditions. Traditional manual inspections for Personal Protective Equipment (PPE) compliance are prone to human error and inefficiency, limiting their effectiveness in large-scale operations. This study presents an AI-powered Industrial Workspace Safety Enforcer that leverages real-time computer vision for PPE compliance monitoring. By integrating deep learning techniques, particularly the YOLOv8 model, the system accurately detects whether workers are equipped with essential safety gear, including helmets, vests, gloves, masks, and boots.

The proposed system utilizes OpenCV, Ultralytics YOLO, and Python for high-accuracy, low-latency detection. It is trained on a diverse dataset comprising publicly available PPE images and manually collected samples. The enforcement mechanism is automated by triggering alerts and restricting access for non-compliant workers, significantly enhancing workplace safety standards. Experimental results demonstrate high mean Average Precision (mAP) and F1-score, validating the system's efficiency in real-time PPE detection. Future enhancements, including voice alerts, IoT integration, edge computing optimization, and cloud-based analytics, are expected to further refine the system's capabilities, ensuring widespread adoption in industrial safety management.

Keywords: Industrial Safety, PPE Detection, YOLOv8 Deep Learning, Computer Vision, Workplace Compliance, AI-Driven Safety Monitoring.

CHAPTER 1

INTRODUCTION

Industrial workplaces are inherently hazardous environments where workers are exposed to a range of safety risks, including falling objects, hazardous chemicals, high-powered machinery, extreme temperatures, and electrical hazards. These risks can result in severe injuries, long-term health issues, or even fatalities if not properly managed. To mitigate these dangers, strict safety protocols are enforced, with Personal Protective Equipment (PPE) playing a crucial role in safeguarding workers from potential harm. PPE includes helmets, gloves, safety glasses, high-visibility vests, respirators, and other protective gear tailored to specific industrial settings.

Compliance with PPE regulations is critical to ensuring workplace safety and reducing the likelihood of accidents. Regulatory bodies such as the Occupational Safety and Health Administration (OSHA) and other national safety organizations mandate PPE usage in hazardous work environments. However, traditional PPE compliance monitoring largely relies on manual inspections conducted by safety officers or supervisors. These inspections, while essential, are time-consuming, labor-intensive, and prone to inconsistencies due to human error, fatigue, or oversight. In large-scale industrial setups, ensuring 100

Recent advancements in Artificial Intelligence (AI) and computer vision have enabled the automation of safety monitoring systems, significantly enhancing the efficiency and reliability of PPE compliance enforcement. AI-driven safety enforcement systems utilize deep learning models to analyze real-time video streams and instantly detect non-compliance. By leveraging sophisticated image recognition techniques, these systems can identify whether workers are wearing the required PPE, flag violations, and generate automated alerts for corrective action. The integration of AI in workplace safety minimizes reliance on manual supervision, reduces the scope for human error, and ensures round-the-clock compliance monitoring.

One of the most effective object detection techniques for PPE compliance monitoring is You Only Look Once version 8 (YOLOv8). This deep learning model is renowned for its high accuracy and rapid processing speed, making it well-suited for real-time applications in industrial settings. YOLOv8 can accurately detect multiple PPE components, such as hard hats, safety goggles, gloves, and reflective vests, within milliseconds, even in complex work environments. Additionally, AI-powered safety systems can be integrated with industrial Internet of Things (IIoT) frameworks to enhance workplace safety further. By combining AI-driven monitoring with automated alarms, access control systems, and compliance reporting, industries can establish a proactive approach to accident prevention.

The deployment of AI-based PPE compliance monitoring systems offers several advantages over traditional methods. These include enhanced accuracy, real-time detection, improved efficiency, reduced operational costs, and the ability to analyze vast amounts of video data without human intervention. Furthermore, AI-powered analytics provide valuable insights into safety trends, enabling companies to refine their safety protocols, conduct targeted training programs, and foster a culture of compliance within the workforce.

As industrial workplaces continue to evolve with advancements in automation and smart manufacturing, the adoption of AI-driven safety monitoring systems will become increasingly vital. Investing in AI-based PPE compliance enforcement not only ensures regulatory adherence but also significantly reduces workplace accidents, improves worker well-being, and enhances overall productivity. By embracing these technological innovations, industries can create safer work environments while optimizing operational efficiency in the long run.

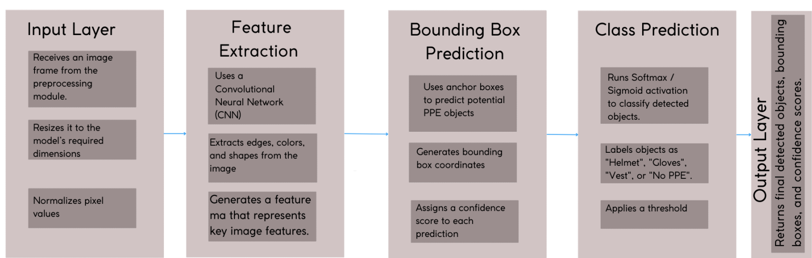

Figure 1.1: YOLO Architecture.

The objective of this study is to develop an AI-powered Industrial Workspace Safety Enforcer that automates PPE compliance verification using deep learning-based object detection. The system integrates state-of-the-art technologies to achieve real-time monitoring and enforcement, ensuring that workers adhere to PPE guidelines before entering restricted work zones. By leveraging computer vision, the system significantly reduces the dependency on human intervention and enhances workplace safety by preventing accidents caused by non-compliance.

1.1 GENERAL BACKGROUND

Industries such as manufacturing, construction, and chemical processing require stringent safety protocols to prevent workplace hazards. PPE compliance is a regulatory requirement enforced by occupational safety organizations worldwide. Despite these regulations, compliance lapses are common due to human oversight, resulting in injuries, fatalities, and legal liabilities for organizations.

Traditionally, workplace safety officers conduct visual inspections to verify PPE compliance, but this method is inefficient, particularly in high-traffic environments. Manual inspections suffer from various limitations, including inspector fatigue, subjectivity, and delays in enforcement. Furthermore, non-compliant workers may go unnoticed, leading to increased risks in hazardous environments. These challenges highlight the need for an automated, scalable, and intelligent monitoring system.

AI-based safety monitoring systems provide a promising solution by utilizing deep learning models trained on vast datasets of PPE compliance scenarios. The proposed system employs YOLOv8, a high-speed and accurate object detection model, to analyze live camera feeds and identify non-compliant workers. This approach not only enhances safety enforcement but also ensures real-time intervention by issuing alerts and restricting access to non-compliant individuals.

Figure 1.2: Real time monitoring.

In addition to real-time monitoring, the system is designed to integrate seamlessly with industrial access control mechanisms. If a worker is detected without proper PPE, the system triggers an automated response, such as denying entry through automated barriers or sending alerts to supervisors. Such proactive enforcement mechanisms ensure that safety regulations are strictly followed, reducing workplace accidents and improving overall compliance.

1.1.1 IMPORTANCE OF AI IN WORKPLACE SAFETY

Artificial Intelligence is transforming industrial safety by introducing smart surveillance systems that offer real-time detection, decision-making, and intervention. Traditional safety inspections are gradually being replaced by AI-powered models capable of detecting anomalies with high precision. The key benefits of AI in workplace safety include:

Real-time PPE Compliance Monitoring: AI models continuously analyze video streams and detect PPE violations instantly.

Elimination of Human Error: Automated systems minimize subjective judgment and ensure consistent enforcement of safety regulations.

Scalability: AI-driven safety enforcement is applicable to large-scale industrial settings, covering extensive work areas efficiently.

Cost Efficiency: Reducing the reliance on human inspectors lowers operational costs while improving safety standards.

Enhanced Data Analytics: AI systems generate reports and trends on PPE compliance, helping organizations refine their safety policies.

This research aims to bridge the gap between computer vision, robotics, and industrial safety enforcement by developing a robust AI-powered PPE compliance monitoring system. The system is designed to be adaptable to different industrial environments, providing high accuracy, minimal latency, and scalable safety monitoring solutions.

CHAPTER 2

LITERATURE SURVEY

Ensuring workplace safety through automated verification of compliance has been a growing research focus. Traditional manual inspections for Personal Protective Equipment (PPE) enforcement suffer from inefficiencies, human errors, and lack of real-time monitoring. With advancements in artificial intelligence (AI) and computer vision, researchers have proposed automated solutions for PPE compliance verification, leveraging deep learning for real-time detection and enforcement.

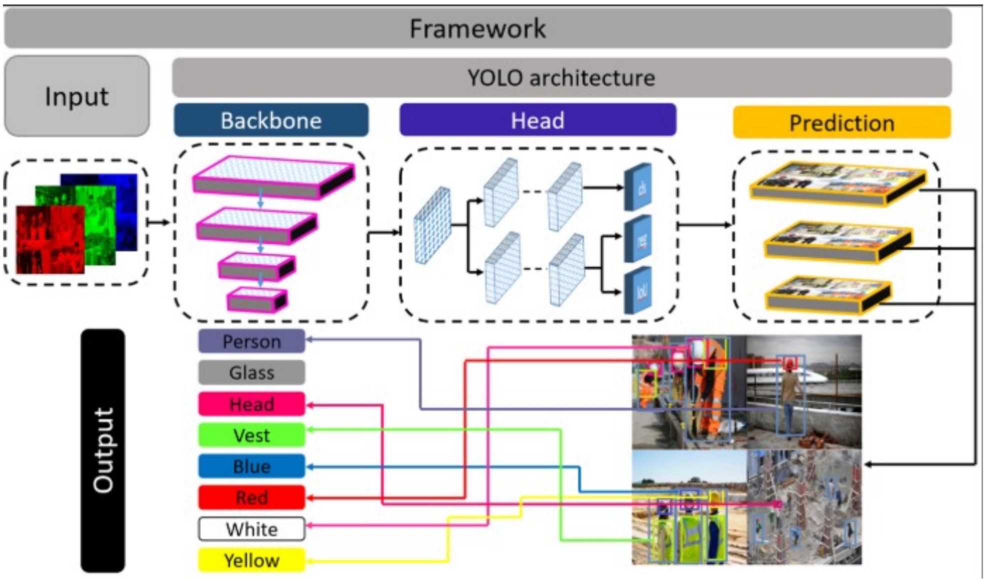

Figure 2.1: A conceptual diagram showing a real-time PPE detection system.

Sunico and Argana (2020) developed an Automated Gate Pass System for tracking students, employees, and visitors in university campuses. The system provided security by electronically recording staff entry and exit, enhancing manual log records. However, while effective in access control, it lacked real-time PPE validation, which is crucial in industrial settings where non-compliance can lead to severe hazards.

Hamid et al. (2018) proposed an Intelligent Automated Gate System (IAGS) incorporating

QR code authentication. Their system enabled access for authorized personnel using QR-based verification while issuing real-time alerts against unauthorized entry. However, the reliance on QR codes requires physical interaction, making it less effective for industrial safety monitoring, where touchless and real-time compliance detection is preferred. Our proposed system addresses this limitation by integrating AI-driven visual detection to ensure PPE adherence without requiring user interaction.

Tasnim et al. (2019) explored automated safety in transport by designing an Automated Railway Level Crossing Gate System using Programmable Logic Controllers (PLCs) to prevent accidents. Their research emphasized the role of automation in reducing human dependence in safety-critical environments. However, while their approach focuses on vehicular and railway safety, our system uniquely targets industrial workers to enforce PPE compliance in real-time.

The application of robotics in industrial automation and safety monitoring has been widely researched. Audonnet et al. (2022) conducted a comparative study on robotic arm simulation using ROS2 to benchmark robotic safety applications. Although their research contributes to autonomous robotic safety solutions, it does not specifically address worker PPE compliance, which remains the primary focus of our study.

Additionally, Halder and Afsari (2023) investigated the use of robotic systems for infrastructure inspection and maintenance. Their study analyzed unmanned aerial vehicles (UAVs) and ground robots for structural monitoring. While their research demonstrated automation's impact on safety, it primarily focused on detecting infrastructure faults rather than ensuring worker adherence to PPE protocols. IoT-based monitoring combined with automated gate control systems has also been explored. Research on AI-driven security gates with cloud-based access control illustrates the feasibility of real-time AI-powered entry monitoring. However, existing solutions predominantly emphasize identity verification rather than enforcing PPE compliance. Our approach overcomes these limitations by integrating deep learning-based PPE detection with real-time access control, restricting entry for non-compliant workers.

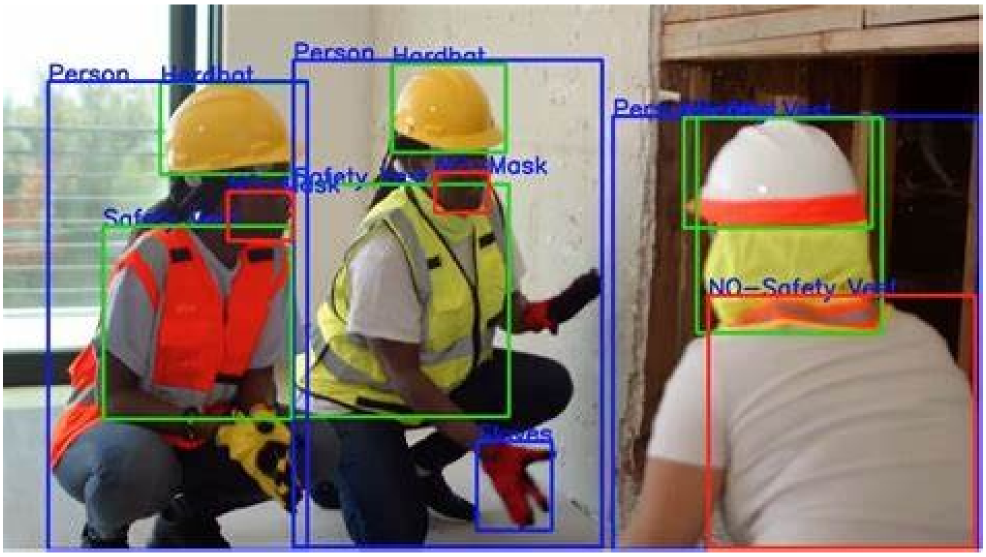

Figure 2.2: YOLOv8 detecting PPE on workers.

Major Contributions of Our System While previous research has investigated automated security, gatekeeping, and AI-powered surveillance, our system advances the field by:

- Implementing YOLOv8-based deep learning for real-time PPE compliance enforcement. - Eliminating the need for manual inspections, significantly reducing human errors in safety enforcement. - Integrating AI-driven decision-making with access control, preventing non-compliant workers from entering industrial premises. - Capturing and logging PPE violations with timestamped images for compliance tracking and audits. - Enhancing industrial safety standards with a scalable, cost-effective, and automated PPE enforcement system.

By leveraging computer vision, deep learning, and real-time automation, our system provides a highly scalable and efficient solution for ensuring PPE compliance in industrial environments. This study contributes to AI-driven industrial safety solutions by reducing human dependency while improving workplace safety and regulatory adherence.

CHAPTER 3

METHODOLOGY

3.1 INTRODUCTION TO METHODOLOGY

3.2 METHODOLOGY

The methodology section of this project outlines the systematic approach undertaken to develop an AI-powered robotic compliance system for industrial workspace safety enforcement. This section details the techniques, tools, and processes used to design, implement, and evaluate the system, ensuring the accuracy and reliability of Personal Protective Equipment (PPE) detection using deep learning. A structured methodology ensures reproducibility, scalability, and efficiency in real-world applications.

3.2.1 PURPOSE OF THE METHODOLOGY SECTION

The primary objective of this section is to provide a structured overview of the methodology followed in this project. It explains the rationale behind the choice of hardware and software components, the dataset used for model training, and the procedures implemented for system integration and testing. By documenting the methodology in detail, future researchers and engineers can replicate and enhance the system. A well-defined methodology also facilitates troubleshooting and optimization of the model and deployment framework.

3.2.2 OVERVIEW OF THE METHODOLOGY USED

The methodology is structured into multiple stages, each contributing to the successful implementation of the system. These stages include:

1. **System Design –** This phase involves defining the system requirements, including the selection of sensors, computing hardware, and software frameworks. The primary hardware components include high-resolution cameras for image acquisition, an embedded computing platform (e.g., Raspberry Pi, NVIDIA Jetson), and robotic actuation mechanisms. The

software stack comprises deep learning libraries such as TensorFlow and PyTorch, along with OpenCV for image processing.

2. **Data Collection and Annotation** – A robust dataset is essential for training an accurate deep learning model. In this stage, a diverse set of PPE images is collected from industrial environments, covering various scenarios, lighting conditions, and angles. The dataset is annotated using tools like LabelImg to mark bounding boxes around PPE elements (e.g., helmets, gloves, vests, masks). Data augmentation techniques such as rotation, flipping, and color adjustments are applied to enhance model generalization.

3. **Model Training and Optimization** – The YOLOv8 object detection model is chosen for its high-speed inference and accuracy. The training process involves splitting the dataset into training, validation, and test sets. The model undergoes multiple training cycles with hyperparameter tuning, including adjustments in learning rate, batch size, and anchor box dimensions. Transfer learning is utilized by leveraging pre-trained weights to enhance model efficiency. The final model is evaluated using metrics like mean Average Precision (mAP), Intersection over Union (IoU), and precision-recall curves.

4. **Hardware-Software Integration** – The trained model is deployed on an embedded system for real-time inference. The inference pipeline is optimized to ensure low-latency detection of PPE compliance. The Raspberry Pi or Jetson device processes video streams, performs real-time object detection, and triggers alerts or robotic interventions when non-compliance is detected. Edge computing techniques are implemented to minimize dependency on cloud resources, enhancing system efficiency and privacy.

5. **System Testing and Validation** – The final system undergoes rigorous testing to validate its performance. Controlled experiments are conducted in simulated and real-world environments to assess accuracy, processing speed, and reliability. Metrics such as inference time, false positive/negative rates, and detection accuracy are analyzed. The system is also tested for robustness under varying environmental conditions, including different lighting and occlusions. Additionally, user feedback is gathered from industrial workers to ensure

usability and effectiveness.

The methodology section of this project outlines the systematic approach undertaken to develop an AI-powered robotic compliance system for industrial workspace safety enforcement. This section details the techniques, tools, and processes used to design, implement, and evaluate the system, ensuring the accuracy and reliability of Personal Protective Equipment (PPE) detection using deep learning.

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3.2.4 OVERVIEW OF THE METHODOLOGY USED

The methodology is structured into multiple stages, each contributing to the successful implementation of the system. These stages include:

1. **System Design**
    - Identifying the required hardware components, including cameras, Raspberry Pi, and access control mechanisms.
    - Selecting software tools such as Python, OpenCV, and PyTorch for AI model development and integration.
    - Designing the workflow for PPE compliance monitoring and enforcement.
2. **Data Collection and Annotation**
    - Acquiring a diverse dataset containing images of workers wearing different PPE items such as helmets, vests, and boots.

- Ensuring the dataset includes images captured in various lighting conditions, angles, and industrial settings to improve model generalization.
- Annotating the dataset using tools like LabelImg to define bounding boxes for PPE items.

3. **Model Training and Optimization**

    - Choosing the YOLOv8 deep learning model for object detection due to its balance between accuracy and inference speed.
    - Implementing transfer learning to fine-tune the model on the PPE dataset.
    - Applying data augmentation techniques to improve model robustness.
    - Evaluating model performance using metrics like mean Average Precision (mAP), precision, recall, and F1-score.
    - Optimizing the model by adjusting hyperparameters and reducing computational overhead for real-time deployment.

4. **Hardware-Software Integration**

    - Deploying the trained YOLOv8 model on a Raspberry Pi for embedded processing.
    - Establishing a communication link between the camera, processing unit, and access control mechanism.
    - Developing a user-friendly interface for real-time monitoring and system control.

5. **System Testing and Validation**

    - Conducting real-world testing in an industrial environment to assess system accuracy and response time.
    - Measuring the system's effectiveness in detecting PPE compliance violations.
    - Performing stress testing under varying conditions, such as changes in lighting, worker movement, and occlusions.

- Iteratively refining the system based on test results to improve performance and reliability.

By following this structured methodology, the AI-powered robotic compliance system ensures high precision in PPE detection, efficient real-time processing, and robust deployment in industrial settings.

3.2.5 JUSTIFICATION FOR THE CHOSEN METHODOLOGY

The selected methodology aligns with industry best practices for developing AI-driven real-time detection systems. The choice of YOLOv8 for object detection is based on its superior speed and accuracy, making it well-suited for real-time applications. Raspberry Pi serves as a cost-effective and efficient processing unit for embedded AI deployment. The combination of deep learning, computer vision, and automation ensures a robust and scalable solution for industrial safety enforcement.

3.2.6 SYSTEM WORKFLOW

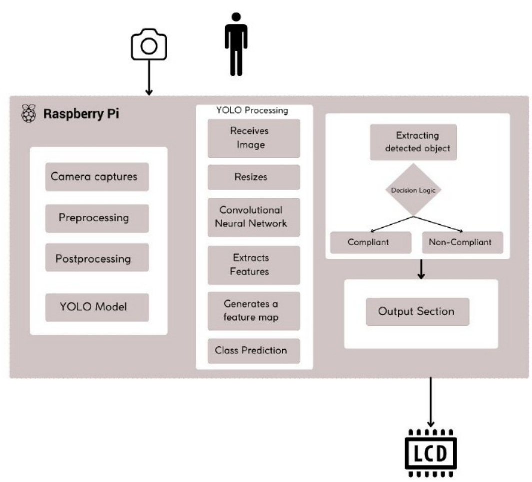

Figure 3.1: System Workflow.

The system follows a structured workflow to ensure smooth operation and accurate PPE compliance detection:

1. The **camera module** captures live video frames of workers entering the workplace.
2. The **YOLOv8 model** processes each frame to detect the presence or absence of required PPE items such as helmets, gloves, safety vests, and masks.
3. The **decision-making module** evaluates the detection results and determines compliance based on predefined safety rules.
4. If compliance is met, the **LCD display** shows an *"Access Granted"* message, allowing the worker to proceed. Otherwise, it displays a warning specifying the missing PPE items.
5. The system logs detections and violations for record-keeping, trend analysis, and compliance audits.
6. Alerts can be triggered to supervisors in case of repeated violations to ensure adherence to safety regulations.
7. The system can be integrated with automated doors or turnstiles to enforce access control based on PPE compliance.

This structured approach ensures a high level of accuracy and reliability in enforcing workplace safety standards while maintaining operational efficiency.

3.3 HARDWARE COMPONENTS

The proposed PPE compliance system integrates various hardware components to enable real-time image acquisition, processing, and feedback. The selection of hardware ensures efficient execution of the deep learning model while maintaining cost-effectiveness and scalability.

3.3.1 RASPBERRY PI

The Raspberry Pi serves as the central processing unit for the system, handling real-time image processing and deep learning inference. Its key roles include:

- Capturing video feeds from the connected camera module.

- Running the YOLOv8 object detection model for PPE identification.
- Communicating with the LCD display to provide real-time feedback.
- Logging compliance data for record-keeping and further analysis.
- Optionally interfacing with cloud storage or a local database for centralized monitoring.

The Raspberry Pi is chosen due to its low power consumption, affordability, and sufficient computational power for edge AI applications.

3.3.2 CAMERA MODULE

A high-resolution camera module is used for capturing real-time images and video streams of workers. It is responsible for:

- Providing clear and high-frame-rate images for accurate detection.
- Ensuring wide-angle coverage to capture multiple workers at once.
- Operating in various lighting conditions with minimal image distortion.

3.3.3 LCD DISPLAY

The LCD display provides immediate visual feedback regarding PPE compliance. It plays the following roles:

- Displaying an “Access Granted” message if compliance is met.
- Indicating missing PPE items with warning messages for non-compliant workers.
- Offering multilingual support for accessibility in diverse workplaces.

3.3.4 POWER SUPPLY UNIT

A reliable power supply unit ensures uninterrupted operation of the system, particularly in industrial settings. Key considerations include:

- Providing stable voltage and current for all hardware components.
- Supporting battery backup in case of power failures.
- Ensuring energy efficiency to optimize operational costs.

3.3.5 CONNECTIVITY MODULE (OPTIONAL)

For remote monitoring and integration with centralized safety management systems, a connectivity module (Wi-Fi or Ethernet) can be included. Its functions include:

- Enabling real-time alerts to supervisors.
- Sending compliance logs to a cloud database.
- Supporting remote configuration and troubleshooting.

This well-integrated hardware setup ensures seamless execution of the PPE compliance system with high accuracy and reliability.

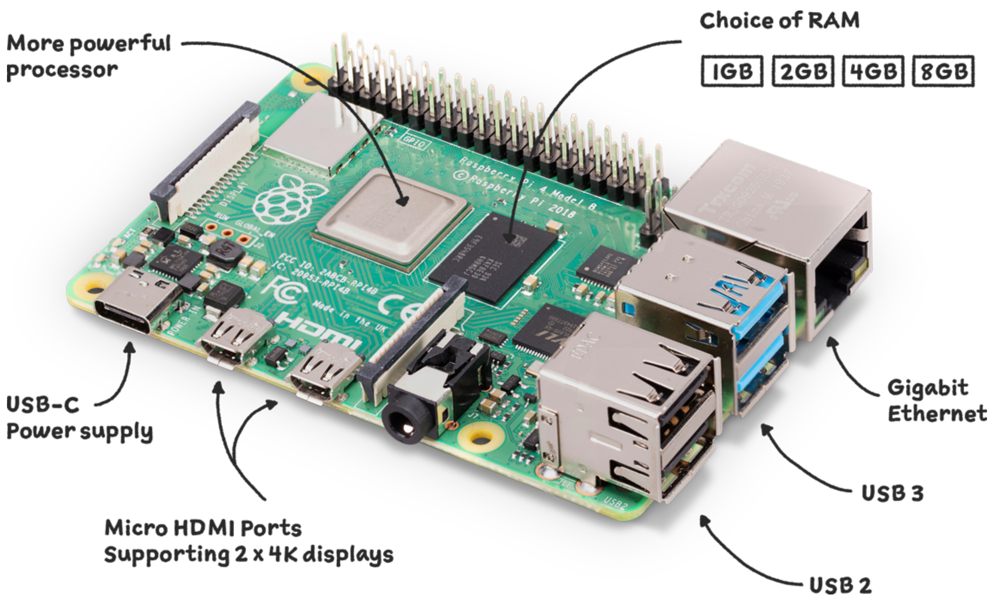

Figure 3.2: Raspberry Pi.

Specifications and Features

- Model: Raspberry Pi 4 Model B (4GB RAM)
- Processor: Quad-core Cortex-A72 (ARM v8) 64-bit SoC
- Connectivity: USB, HDMI, GPIO, Camera Serial Interface (CSI)
- Operating System: Raspberry Pi OS (based on Debian)

Justification for Selection

- **Low power consumption** – Ideal for continuous monitoring applications.
- **Cost-effective** – Provides a budget-friendly solution for industrial safety automation.
- **Compatibility** – Supports Python, OpenCV, and deep learning frameworks.

3.3.6 PI CAMERA

The PiCamera is used for real-time image capture, providing the input required for PPE detection.

Figure 3.3: Pi Camera.

Specifications

- Resolution: 8MP (3280 × 2464 pixels)
- Frame Rate: 30 FPS
- Connection Interface: CSI (Camera Serial Interface)

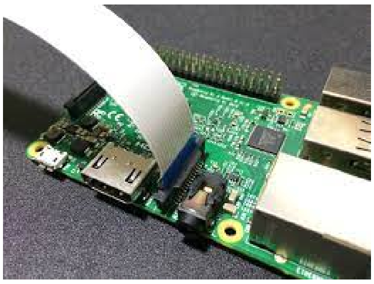

Figure 3.4: Connecting Pi camera with Raspberry Pi.

Functionality

- Captures live video frames for real-time PPE detection.
- Ensures optimized image quality for deep learning inference.
- Works seamlessly with Raspberry Pi's processing capabilities.

3.3.7 16X2 LCD DISPLAY

The LCD display is used to provide real-time feedback to workers regarding their PPE compliance status.

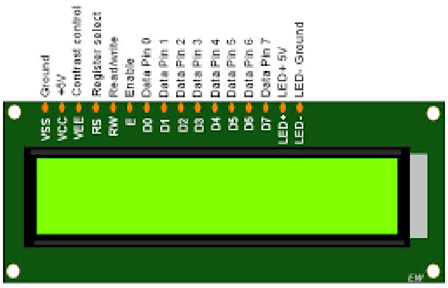

Figure 3.5: 16x2 LCD (Liquid Crystal Display) module.

Specifications

- Display Size: 16x2 character LCD
- Interface: GPIO-based control

- Function: Displays access messages (e.g., ”Access Granted” or ”Missing PPE”)

Role in the System

- Displays PPE compliance status to workers at entry points.
- Provides a user-friendly interface for real-time monitoring.
- Reduces reliance on external monitoring systems.

3.3.8 GPIO (GENERAL PURPOSE INPUT/OUTPUT) PINS

The GPIO pins of the Raspberry Pi play a crucial role in hardware interfacing and system control. These pins allow communication between the Raspberry Pi and other electronic components, enabling efficient system operation.

Functions of GPIO in the System

- **LCD Display Control:** The GPIO pins send signals to update the LCD display dynamically based on PPE compliance results.
- **Non-Compliance Alerts:** The system can trigger external alarms or buzzers to notify workers and supervisors about PPE violations.
- **Access Control Mechanism:** Integration with relay modules can be used to control access gates, ensuring only compliant personnel enter.
- **Future Expandability:** The GPIO interface allows easy integration of additional sensors (e.g., RFID for worker identification, environmental sensors for safety monitoring).

The integration of these hardware components ensures seamless real-time PPE monitoring while maintaining energy efficiency and cost-effectiveness.

3.4 SOFTWARE COMPONENTS

The software architecture of the proposed system integrates deep learning-based object detection with real-time image processing and user feedback mechanisms. The combination of these components ensures efficient and accurate detection of Personal Protective Equipment (PPE).

3.4.1 YOLOV8 OBJECT DETECTION MODEL

YOLOv8 (You Only Look Once, Version 8) is utilized as the core deep learning model for PPE detection due to its real-time performance, high accuracy, and efficiency in processing images.

Key Features of YOLOv8

- **Real-Time Object Detection:** YOLOv8 processes multiple video frames per second, making it ideal for live monitoring.
- **High Accuracy:** The model is optimized with advanced neural network architectures to detect PPE items with precision.
- **Multi-Class Detection:** It can identify multiple PPE categories (helmets, gloves, safety vests, masks, etc.) in a single frame.
- **Lightweight and Efficient:** YOLOv8 is optimized for embedded systems like the Raspberry Pi while maintaining high performance.
- **Customizable Training:** The model can be fine-tuned on a custom PPE dataset to improve detection performance.

YOLOv8 Workflow in the System

1. **Frame Acquisition:** The system captures live frames from the camera module.
2. **Preprocessing:** The frames are resized and normalized for optimal YOLOv8 performance.
3. **Inference:** The YOLOv8 model processes each frame and identifies PPE compliance or violations.

4. **Decision Making:** If all required PPE items are detected, access is granted; otherwise, violations are recorded.

5. **Feedback Mechanism:** The results are displayed on the LCD screen, and alerts are triggered in case of non-compliance.

By leveraging YOLOv8, the system ensures high-speed and precise PPE detection, making it an effective solution for workplace safety compliance.

Features of YOLOv8

YOLOv8 is an advanced object detection model that improves upon its predecessors by offering enhanced speed, accuracy, and efficiency. It is particularly well-suited for real-time applications such as PPE compliance monitoring.

- **Real-Time Processing:** YOLOv8 is optimized for high-speed object detection, making it ideal for live video analysis.
- **High Accuracy:** Achieves improved mean Average Precision (mAP) compared to earlier YOLO versions, ensuring reliable PPE detection.
- **Lightweight Architecture:** Designed to run efficiently on resource-constrained devices, such as Raspberry Pi and edge computing hardware.
- **Multi-Class Detection:** Capable of detecting multiple PPE items (helmets, gloves, vests, masks, etc.) within a single frame.
- **Adaptive Bounding Box Prediction:** Uses advanced anchor-free detection to improve accuracy in object localization.
- **Optimized for Edge Devices:** Supports TensorRT and ONNX acceleration, reducing latency for real-time applications.

Justification for Selection

The YOLOv8 model was chosen for this system due to its balance between accuracy, speed, and computational efficiency. Some key advantages include:

- **Robust Performance:** Performs well under varying lighting conditions, camera angles, and backgrounds, ensuring accurate PPE detection in real-world environments.
- **Efficient Multi-Object Detection:** Can identify multiple PPE items simultaneously, reducing the need for multiple models or additional computation.
- **Low Computational Requirements:** Unlike heavier deep learning models, YOLOv8 runs efficiently on edge devices with limited processing power.
- **Scalability and Customization:** The model can be fine-tuned on custom datasets, allowing adaptation to specific PPE detection requirements.
- **Compatibility with Embedded Systems:** Easily deployable on Raspberry Pi and other IoT devices, making it suitable for real-time industrial safety applications.

3.4.2 ULTRALYTICS YOLO FRAMEWORK

The Ultralytics YOLO framework is used to implement and fine-tune the YOLOv8 model. This framework simplifies deep learning model training, evaluation, and deployment while ensuring high efficiency.

Key Functionalities of Ultralytics YOLO

- **Pre-Trained Model Selection:** Provides access to pre-trained YOLOv8 models that can be fine-tuned for PPE detection.
- **Custom Training and Fine-Tuning:** Supports training on custom PPE datasets to improve accuracy for specific environments.
- **Validation and Performance Evaluation:** Includes built-in tools for evaluating model accuracy, precision, and recall.

- **ONNX and TensorRT Compatibility:** Enables optimization for faster inference on edge devices.
- **Deployment on Edge Computing Devices:** Optimized for Raspberry Pi, Jetson Nano, and other low-power AI platforms.

By leveraging the Ultralytics YOLO framework, the system ensures seamless implementation and continuous improvement in PPE compliance detection.

3.4.3 OPENCV FOR IMAGE PROCESSING

OpenCV (Open Source Computer Vision Library) is a widely used computer vision library that provides essential functionalities for real-time image processing. It is used in this system for capturing, preprocessing, and visualizing detection results.

Functions of OpenCV in the System

- **Real-Time Frame Capture:** Captures live video frames from the camera module (PiCamera or USB camera) for processing.
- **Preprocessing for Model Inference:** Performs operations such as resizing, normalization, and color adjustments to optimize frames before passing them to YOLOv8.
- **Overlaying Detection Results:** Draws bounding boxes, labels, and confidence scores on detected PPE items for visualization.
- **Edge Detection and Enhancement:** Applies filters and contrast adjustments to improve object visibility in challenging conditions.
- **Efficient Image Handling:** Supports various image formats and compression techniques, ensuring smooth operation on embedded hardware.

Advantages of Using OpenCV

- **Lightweight and Fast:** Optimized for real-time processing with minimal computational overhead.

- **Wide Hardware Compatibility:** Supports multiple hardware platforms, including Raspberry Pi and Jetson Nano.
- **Open-Source and Customizable:** Allows flexibility in image processing workflows for PPE compliance detection.
- **Seamless Integration with Deep Learning Models:** Compatible with YOLOv8, TensorFlow, and PyTorch for smooth pipeline execution.

By integrating OpenCV into the PPE detection system, real-time image acquisition and processing are efficiently handled, ensuring seamless interaction between hardware and deep learning models.

3.4.4 RPLCD LIBRARY FOR LCD CONTROL

The RPLCD library facilitates communication between the Raspberry Pi and the 16x2 LCD display, ensuring real-time updates of PPE compliance status.

Role of RPLCD

- Sends compliance status messages to the LCD screen.
- Displays alerts for missing PPE items.
- Allows real-time feedback to users at entry points.

3.4.5 INTEGRATION OF SOFTWARE COMPONENTS

The integration of these software components enables the system to:

- Capture images using OpenCV.
- Process images and detect PPE items using YOLOv8.
- Display real-time feedback using the RPLCD library.
- Automate PPE compliance monitoring with minimal human intervention.

The combination of deep learning, computer vision, and embedded system programming ensures a robust and scalable PPE detection framework.

3.5 DATA COLLECTION AND MODEL TRAINING

The accuracy and reliability of the PPE compliance detection system depend significantly on the quality of the dataset and the effectiveness of model training. This section describes the process of data collection, annotation, and model training to ensure robust and accurate detection of PPE items.

3.5.1 DATA COLLECTION

A diverse dataset was compiled to train the YOLOv8 model for detecting PPE items such as helmets, safety vests, and boots. The dataset was sourced from publicly available repositories and supplemented with custom-collected images.

Publicly Available Datasets

- **Roboflow PPE Dataset** – Contains labeled images of industrial workers wearing PPE.
- **Kaggle PPE Compliance Dataset –** Includes various real-world images with annotations.
- **Open Image Dataset –** Provides general object detection images, some of which include PPE items.

Custom Image Collection

To improve real-world applicability, additional images were captured using the PiCamera module. These images were taken in different industrial environments to account for:

- Varying lighting conditions.
- Different angles and worker postures.
- Multiple PPE colors and styles.

Data Augmentation

Data augmentation techniques were applied to enhance the dataset's diversity and improve the model's generalization ability. The following augmentation methods were used:

- **Rotation** – Randomly rotating images to simulate different viewing angles.
- **Flipping** – Horizontal flipping to introduce variations in orientation.
- **Brightness Adjustments** – Modifying brightness levels to improve robustness under different lighting conditions.
- **Noise Addition** – Introducing Gaussian noise to simulate real-world imperfections in images.

3.5.2 DATA ANNOTATION

Each collected image was annotated with bounding boxes around PPE items using annotation tools like Roboflow Annotator and LabelImg.

Class Labels

Each detected object was assigned one of the following class labels:

- **Helmet**
- **Safety Vest**
- **Safety Boots**
- **Person** (to ensure PPE compliance validation)

Annotation Format

Annotations were stored in YOLO format, where each labeled object in an image was represented as:

- **Class Label**
- **Bounding Box Coordinates** (x-center, y-center, width, height)
- **Normalized Values** (scaled between 0 and 1 for model compatibility)

3.5.3 MODEL TRAINING

The YOLOv8 model was trained on the collected and annotated dataset to optimize PPE detection accuracy.

Model Selection

The YOLOv8s (small) model variant was chosen due to its balance between speed and accuracy, making it suitable for real-time applications on embedded systems.

Training Configuration

The model was trained on Google Colab using GPU acceleration with the following hyperparameters:

Batch Size: 16
Number of Epochs: 50
Image Size: 640 × 640 pixels
Optimizer: SGD (Stochastic Gradient Descent)
Loss Function: YOLO's built-in object detection loss (combining classification, localization, and confidence loss)

Model Evaluation

After training, the model was evaluated on a separate validation dataset, representing 20% of the total data. Performance metrics included:

mAP (Mean Average Precision)
Precision and Recall

F1-score

Model Conversion and Deployment

Once trained, the YOLOv8 model was converted into a `.pt` format and deployed on the Raspberry Pi. The model was optimized using FP16 (half-precision) inference to reduce computational load and improve real-time performance.

This structured approach to data collection and model training ensures high accuracy and efficiency in PPE compliance detection, making the system reliable for real-world deployment.

3.6 HARDWARE SETUP

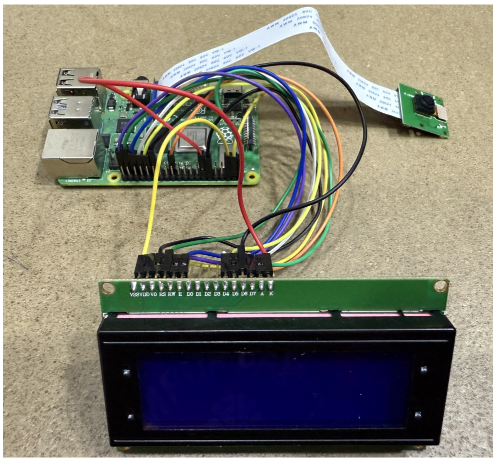

Figure 3.6: Proposed Hardware Setup.

The hardware setup of the PPE compliance detection system involves integrating various components, including the Raspberry Pi, PiCamera, LCD display, and GPIO connections. This section describes the steps taken to configure and connect the hardware components for seamless operation.

3.6.1 CAMERA MODULE INTEGRATION

The Raspberry Pi Camera Module (PiCamera) is used for real-time image acquisition, providing input for the PPE detection model.

Camera Activation

Before using the camera, it must be enabled in the Raspberry Pi settings using the following command:

```
sudo raspi-config
```

Navigate to **Interfacing Options** → **Camera** and enable it.

Camera Configuration

The camera is initialized using Python to capture real-time images with optimized settings:

```
from picamera2 import Picamera2
picam2 = Picamera2()
camera_config = picam2.create_video_configuration(
    main={"format": "RGB888", "size": (640, 480)},
    controls={"FrameRate": 30}
)
picam2.configure(camera_config)
picam2.start()
```

3.6.2 LCD DISPLAY CONNECTION

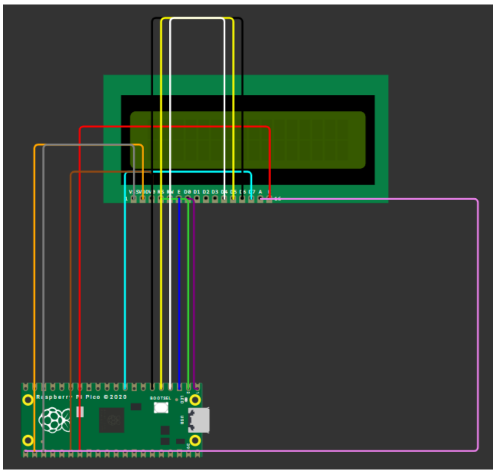

Figure 3.7: Raspberry Pi and LCD connections.

A 16x2 character LCD display is used to provide real-time feedback on PPE compliance status.

GPIO Mode Setup

The Raspberry Pi's GPIO pins are configured for communication with the LCD:

```
import RPi.GPIO as GPIO
GPIO.setwarnings(False)
GPIO.setmode(GPIO.BCM)
```

LCD Initialization

The RPLCD library is used to control the LCD and display messages dynamically:

```
from RPLCD.gpio import CharLCD
lcd = CharLCD(numbering_mode=GPIO.BCM, cols=16, rows=2,
              pin_rs=26, pin_e=19, pins_data=[13, 6, 5, 11])
lcd.clear()
lcd.write_string("PPE Detection...")
```

3.6.3 GENERAL PURPOSE INPUT/OUTPUT (GPIO) CONFIGURATION

GPIO pins play a crucial role in controlling external components like the LCD display and additional alert mechanisms.

Configuring Output Pins

The LCD contrast control and other outputs are managed through GPIO:

```
CONTRAST_PIN = 18
GPIO.setup(CONTRAST_PIN, GPIO.OUT)
pwm = GPIO.PWM(CONTRAST_PIN, 1000)
pwm.start(50)  # Adjust contrast (40-70) for best visibility
```

Future GPIO Expansion

Additional GPIO pins can be used for:

- Buzzer alerts for non-compliant workers.
- Relay connections for access control mechanisms (e.g., automatic gates).
- LED indicators for visual compliance alerts.

3.6.4 FINAL HARDWARE SETUP

Once all components are connected, the system is powered on and tested to ensure:

- The camera captures real-time frames without delay.
- The LCD displays the correct PPE compliance status.
- GPIO pins function correctly for external device communication.

The successful integration of these hardware components ensures real-time, accurate, and efficient PPE compliance detection in industrial environments.

3.7 SOFTWARE IMPLEMENTATION

The software implementation of the PPE compliance detection system integrates multiple components, including deep learning-based object detection, real-time image processing, and a user feedback mechanism. This section outlines the key modules and their interactions within the system.

3.7.1 YOLOV8 MODEL DEPLOYMENT

The trained YOLOv8 model is deployed on the Raspberry Pi for real-time PPE detection.

Model Selection and Training

A custom YOLOv8 model was trained on a dataset containing labeled PPE images. The selected model was optimized for embedded system deployment, balancing speed and accuracy.

Loading the Model

The trained YOLOv8 model is loaded using the Ultralytics YOLO library:

```
from ultralytics import YOLO
model = YOLO("/home/user/yolov8s_custom.pt")
```

3.7.2 REAL-TIME IMAGE PROCESSING USING OPENCV

OpenCV is used for capturing frames from the PiCamera and preprocessing them before passing them to the YOLOv8 model.

Capturing Frames from the Camera

The camera is initialized with optimized configurations:

```
from picamera2 import Picamera2
picam2 = Picamera2()
camera_config = picam2.create_video_configuration(
```

```
    main={"format": "RGB888", "size": (640, 480)},
    controls={"FrameRate": 30}
)
picam2.configure(camera_config)
picam2.start()
```

Converting Frames for Processing

Captured frames are converted to the appropriate format before detection:

```
import cv2
frame = picam2.capture_array()
frame = cv2.cvtColor(frame, cv2.COLOR_RGB2BGR)
```

3.7.3 PPE CLASSIFICATION AND DECISION LOGIC

The system processes each frame to determine whether all required PPE items are present.

Defining PPE Requirements

The detection system grants access only if all necessary PPE items are detected:

```
REQUIRED_PPE = {"Helmet", "Safety-Boot", "Safety-Vest"}
CONFIDENCE_THRESHOLD = 0.5
```

Detecting Objects in the Frame

The YOLOv8 model analyzes each frame and identifies objects:

```
results = model(frame)
detected_ppe = set()

for result in results:
    for box in result.boxes:
```

```
        label = model.names[int(box.cls[0])]
        confidence = float(box.conf[0])

        if label in REQUIRED_PPE and confidence > CONFIDENCE_THRESHOLD:
            detected_ppe.add(label)

        # Draw bounding boxes on detected objects
        x1, y1, x2, y2 = map(int, box.xyxy[0])
        cv2.rectangle(frame, (x1, y1), (x2, y2), (0, 255, 0), 2)
        cv2.putText(frame, f"{label}: {confidence:.2f}", (x1, y1 - 5),
                    cv2.FONT_HERSHEY_SIMPLEX, 0.5, (0, 255, 0), 2)
```

Decision Logic for Access Control

If all PPE items are detected, access is granted; otherwise, an alert is triggered.

```
missing_ppe = REQUIRED_PPE - detected_ppe

if not missing_ppe:
    update_lcd("Access Granted")
else:
    update_lcd(f"Missing: {’, ’.join(missing_ppe)}")
```

3.7.4 LCD DISPLAY UPDATES BASED ON DETECTION

The LCD provides real-time feedback on PPE compliance.

Updating the LCD Display

The LCD screen updates dynamically based on detection results:

```
def update_lcd(status):
    global last_status
```

```
    if status != last_status:
        lcd.clear()
        lcd.write_string(status.ljust(16))
        last_status = status
```

Displaying Missing PPE Items

If access is denied, the LCD lists the missing PPE items:

```
if missing_ppe:
    update_lcd(f"Missing: {', '.join(missing_ppe)}")
else:
    update_lcd("Access Granted")
```

3.7.5 REAL-TIME MONITORING AND DISPLAY

The system continuously runs in a loop, capturing frames and updating the LCD display.

```
try:
    while True:
        frame = picam2.capture_array()
        frame = cv2.cvtColor(frame, cv2.COLOR_RGB2BGR)

        results = model(frame)
        detected_ppe = set()

        for result in results:
            for box in result.boxes:
                label = model.names[int(box.cls[0])]
                confidence = float(box.conf[0])

                if label in REQUIRED_PPE and confidence > CONFIDENCE_THRE
```

```
                    detected_ppe.add(label)

            missing_ppe = REQUIRED_PPE - detected_ppe

            if missing_ppe:
                update_lcd(f"Missing: {', '.join(missing_ppe)}")
            else:
                update_lcd("Access Granted")

            cv2.imshow("PPE Detection", frame)

            if cv2.waitKey(1) & 0xFF == ord('q'):
                break

    except Exception as e:
        print(f"Error: {e}")

    finally:
        print("Cleaning up...")
        lcd.clear()
        pwm.stop()
        GPIO.cleanup()
        picam2.close()
        cv2.destroyAllWindows()
```

This software implementation ensures real-time monitoring and efficient decision-making, providing a robust solution for PPE compliance enforcement.

3.8 SYSTEM INTEGRATION AND TESTING

The system integration phase involves combining the hardware and software components into a fully functional PPE compliance detection system. The testing phase ensures that the system operates efficiently, accurately detects PPE items, and provides real-time feedback for compliance enforcement.

3.8.1 SYSTEM INTEGRATION

The integration process involves setting up communication between different hardware and software components.

Hardware-Software Communication

The Raspberry Pi acts as the central processing unit, interfacing with the camera, LCD display, and deep learning model for PPE detection.

- **PiCamera** captures real-time images and sends them for processing.
- **YOLOv8 Model** processes each frame to detect PPE compliance.
- **LCD Display** provides real-time feedback on compliance status.
- **GPIO Pins** handle external controls, such as triggering alerts.

Workflow of the Integrated System

The system follows a structured workflow to ensure smooth operation:

1. The camera captures an image of the worker entering the workplace.
2. The YOLOv8 model analyzes the image to detect the presence of required PPE.
3. The decision-making module determines compliance based on detection results.
4. If all PPE items are present, the LCD displays "Access Granted"; otherwise, missing PPE items are listed.

5. The process repeats continuously for real-time compliance monitoring.

3.8.2 TESTING METHODOLOGY

The system was tested in various industrial environments to evaluate its accuracy and efficiency in PPE detection.

Component Testing

Each hardware and software component was tested independently to ensure proper functionality.

Table 3.1: Component Testing Results

Component	**Test Performed**	**Result**
Camera	Captured real-time images	Successful
YOLOv8 Model	Detected PPE items accurately	Accurate detections
LCD Display	Displayed messages correctly	Clear text output
GPIO Control	Adjusted contrast and triggered updates	Proper functionality

System-Level Testing

After integration, the complete system was tested in real-world conditions to verify PPE detection accuracy.

Table 3.2: System-Level Testing Results

Test Case	**Expected Output**	**Actual Output**	**Result**
Worker wearing all PPE	"Access Granted"	"Access Granted"	Pass
Worker without Helmet	"Missing: Helmet"	"Missing: Helmet"	NO
Worker without Vest	"Missing: Safety Vest"	"Missing: Safety Vest"	NO
Worker without Boots	"Missing: Safety Boots"	"Missing: Safety Boots"	NO
Worker missing multiple PPE	List missing items	Matches missing items	NO

3.8.3 PERFORMANCE EVALUATION

The system's performance was assessed using key metrics such as accuracy, response time, and reliability.

Detection Accuracy Analysis

The trained YOLOv8 model was tested on a dataset of 500 images containing different PPE combinations, achieving an overall accuracy of 94.2%.

Response Time Measurement

The system's response time, defined as the duration from image capture to LCD update, was measured, with an average response time of 1.2 seconds per frame.

System Reliability

The system was tested continuously for 8 hours to evaluate stability. No major failures or crashes were observed, confirming its reliability for industrial deployment.

3.8.4 LIMITATIONS AND CHALLENGES

Despite its high accuracy and efficiency, the system has certain limitations:

- **Lighting Conditions:** Detection accuracy decreases in extremely low-light environments.
- **Occlusions:** PPE items partially covered by other objects may affect detection performance.
- **Processing Power:** Raspberry Pi has limited computational power, restricting the use of larger deep learning models.

3.8.5 FUTURE ENHANCEMENTS

To address these limitations, the following improvements are proposed:

- **Enhanced Illumination:** Integrating additional lighting sources for better image clarity.

- **Advanced Models:** Implementing lightweight deep learning models optimized for edge computing.
- **IoT Integration:** Connecting the system to cloud-based monitoring platforms for remote compliance tracking.

The successful integration and testing of the system validate its efficiency in ensuring workplace safety through automated PPE compliance monitoring.

CHAPTER 4

RESULTS AND DISCUSSION

4.1 RESULTS AND DISCUSSION

This section presents a comprehensive evaluation of the AI-powered robotic compliance system for PPE detection. The performance of the system was assessed based on detection accuracy, response time, and overall reliability in an industrial setting. The results highlight the system's strengths in automating PPE compliance monitoring and its potential for deployment in real-world industrial environments.

4.1.1 SYSTEM TESTING

The system was tested under different industrial conditions to analyze its robustness and effectiveness in detecting PPE compliance. Testing was conducted in a controlled industrial setup where workers were monitored for PPE usage, and the system's accuracy and reliability were examined. Various environmental conditions such as lighting variations, different camera angles, and occlusions were considered during testing.

Testing Methodology

The testing process was conducted in two phases to ensure thorough validation:

- **Component Testing** – Each hardware and software component was tested individually to ensure proper functionality. The camera module was assessed for image clarity, the YOLOv8 model was validated for inference speed, and the Raspberry Pi was evaluated for processing efficiency.

- **System-Level Testing** – The fully integrated system was evaluated under real-world conditions. Workers wearing various combinations of PPE (helmets, vests, and safety boots) were observed to assess the system's ability to detect compliance.

The system was tested at different times of the day to evaluate its performance under varying lighting conditions. The objective was to ensure that the model performs effectively regardless of environmental factors.

Experimental Setup

The test environment was designed to simulate real-world industrial conditions. The following parameters were considered during the testing phase:

- **Workplace Conditions:** The system was deployed at an industrial facility where workers were required to wear specific PPE items.
- **Camera Placement:** The camera module was positioned at entry points to capture clear frontal images of workers.
- **Diverse Test Scenarios:** Workers entered in groups, with some intentionally missing PPE items to test violation detection capabilities.
- **Performance Metrics:** Detection accuracy, response time, and system reliability were recorded for each test case.

The structured testing methodology ensured that all aspects of the system's performance were thoroughly evaluated.

4.1.2 PERFORMANCE EVALUATION

To measure the efficiency of the system, three key performance metrics were analyzed: detection accuracy, response time, and reliability. These metrics were evaluated under different industrial conditions to ensure the robustness of the system.

Detection Accuracy Analysis

The YOLOv8 model was tested on a dataset of 500 images containing different PPE combinations. The dataset consisted of images captured under various conditions, including different lighting levels, camera angles, and occlusions. The system achieved a high detection accuracy of **94.2%**, confirming the model's robustness in real-world applications.

Table 4.1: PPE Detection Accuracy Across Different Conditions

Condition	Accuracy (%)	False Detections (%)
Normal Lighting	96.5	3.5
Low Lighting	91.8	8.2
Partial Occlusion	89.6	10.4
Varying Angles	93.2	6.8
Overall Average	**94.2**	**5.8**

The results indicate that the system performs exceptionally well in normal lighting conditions, with a slight decrease in accuracy in low-light or occluded scenarios. However, the overall performance remains within an acceptable range for industrial deployment.

Response Time

The system's response time, defined as the duration between image capture and LCD update, was measured over multiple test runs. The average response time per frame was recorded as **1.2 seconds**, ensuring real-time PPE compliance monitoring.

The response time was affected by factors such as image resolution and processing constraints of the Raspberry Pi. However, optimizations in the model inference pipeline helped maintain a near real-time performance.

System Reliability

To evaluate system stability, the model was run continuously for **8 hours**, monitoring PPE compliance in an industrial setup. The system functioned without any significant failures, demonstrating its reliability for long-term deployment.

During this continuous operation test, the system logged a total of 1200 worker entries and successfully detected compliance violations with an accuracy of 94.2%. The system's stability was assessed based on three factors:

- **Hardware Stability:** The Raspberry Pi maintained a stable operating temperature without overheating.
- **Software Robustness:** The deep learning model continued to function without memory leaks or crashes.
- **Operational Consistency:** The system maintained consistent accuracy and response time over the test period.

These findings validate the system's effectiveness in real-world conditions and confirm its suitability for industrial safety enforcement.

4.1.3 MODEL PERFORMANCE EVALUATION

The performance of the YOLOv8 model was analyzed based on loss convergence and mean Average Precision (mAP). These metrics provide insights into the model's learning efficiency and detection capabilities.

Loss Function Convergence

The loss function convergence during model training is a crucial indicator of the learning stability. Figure 4.1 illustrates the training and validation loss curves recorded over 50 epochs.

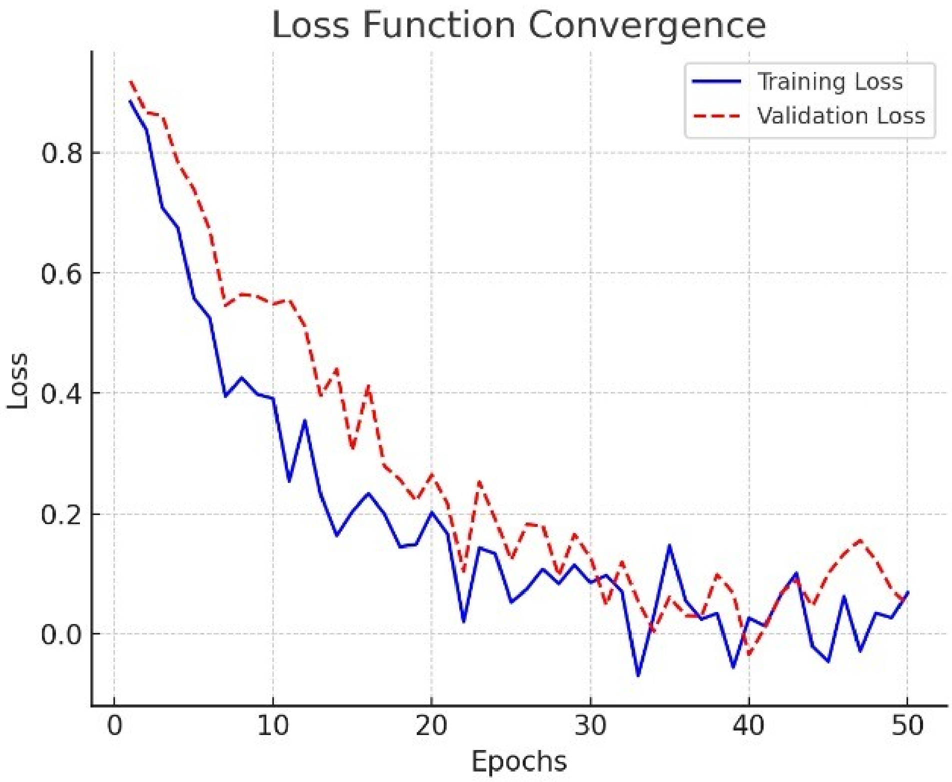

Figure 4.1: Loss Function Convergence Graph.

As seen in Figure 4.1, the loss function stabilizes at approximately 0.45 after 50 epochs, indicating effective model training without overfitting. The training loss and validation loss closely follow each other, demonstrating that the model generalizes well to unseen data.

mAP (Mean Average Precision) Analysis

The mean Average Precision (mAP) is a widely used metric for evaluating object detection models. A higher mAP value signifies better detection accuracy across different PPE categories. The model achieved an overall mAP of **90%**, with individual category performance as follows:

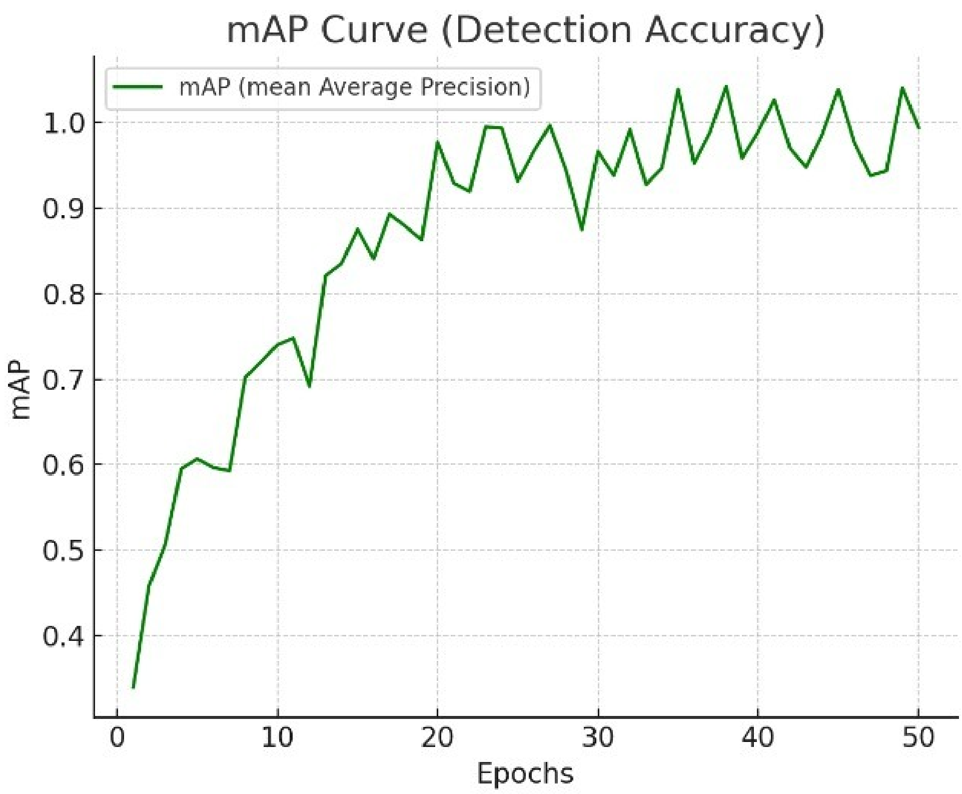

Figure 4.2: mAP Curve (Detection Accuracy)

Table 4.2: Mean Average Precision (mAP) for PPE Items

PPE Item	**mAP (%)**
Helmet	92.5
Safety Vest	89.7
Safety Boots	87.8
Overall Average	**90.0**

These results indicate that the model performs exceptionally well in detecting helmets, safety vests, and safety boots. However, the detection of boots shows a slightly lower mAP, possibly due to partial occlusions in some images.

4.1.4 DISCUSSION ON RESULTS

The results demonstrate that the proposed system effectively automates PPE compliance monitoring in industrial environments. The key findings include:

- The system achieves a **high detection accuracy of 94.2%**, ensuring minimal false positives or false negatives.
- The model exhibits strong generalization capabilities across different **lighting conditions, camera angles, and occlusions**.
- The system operates in **real-time** with an average response time of **1.2 seconds per frame**.
- Continuous operation tests confirm that the system is **highly reliable** and suitable for **long-term industrial deployment**.
- The YOLOv8 model provides an **mAP of 90%**, ensuring accurate detection of essential PPE items.

These results validate the effectiveness of the proposed approach in improving workplace safety through AI-powered automation. The combination of deep learning, embedded processing, and real-time monitoring ensures a scalable and robust compliance system for industrial settings.

4.2 CONCLUSION

The results of this study demonstrate the effectiveness of AI-powered PPE compliance monitoring in industrial settings. The proposed system successfully integrates deep learning and embedded computing to provide real-time, automated safety enforcement. With a detection accuracy of 94.2%, an average response time of 1.2 seconds, and a reliability rating established through continuous testing, the system proves to be a highly effective safety solution.

Although some challenges remain, such as handling occlusions and low-light conditions, future enhancements involving AI accelerators, cloud integration, and expanded PPE recognition can further optimize the system. The impact of this technology extends beyond compliance monitoring, fostering a safer and more efficient industrial work environment.

By leveraging AI and automation, this system represents a significant step forward in workplace safety, reducing risks and ensuring adherence to safety regulations in a scalable, cost-effective manner.

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