Human Detection Monitoring in Decoiler Area Using Raspberry Pi 5B

Mr.Atul Chaudhari[1], Tanushree Chintaman Pagare[2], Sneha Samir Jadhav[3], Akshada Jagdish Kakade[4]
[1]*Assistant Professor, MVPS's KBT COE Nashik*
[234]*Student, MVP'S KBTCOE, Nashik*

Abstract—Industrial safety in decoiler zones remains a critical challenge, where unauthorized human presence near high-speed rotating machinery poses severe injury risks. This paper presents an intelligent real-time human detection and monitoring system deployed on a Raspberry Pi 5 (BCM2712, Cortex-A76 @ 2.4 GHz) for use at steel plant decoiler entry points. The system integrates YOLOv8n-based person detection with polygon region-of-interest (ROI) zone monitoring and biometric face recognition to identify, track, and log all personnel entering the restricted zone. A risk-scoring engine aggregates detection signals to issue GRANT, WARN, or DENY access decisions via GPIO-controlled actuators. Evaluated over 150 controlled trials, the system achieves 94.7% face recognition accuracy, 89.6% PPE detection mAP@0.5, and 93.3% overall decision accuracy at a mean latency of 312 ms—well within real-time requirements. The fully edge-deployed pipeline consumes approximately 8 W, requiring no cloud infrastructure, and logs all events to an SQLite database accessible via a Flask web dashboard.

Index Terms—Decoiler Zone Safety, Edge AI, Face Recognition, Human Detection, Industrial Monitoring, Raspberry Pi 5, Real-Time Vision, YOLOv8.

I. INTRODUCTION

Industrial decoiler zones in steel processing plants are among the most hazardous operational areas, where coils weighing several tonnes rotate at high speed and any unauthorized human presence can lead to fatal accidents. According to the Bureau of Labor Statistics, 967 electrical and machinery-related worker fatalities occurred in the United States between 2011 and 2021 [1]. In Indian manufacturing facilities, the Directorate General Factory Advice Service & Labour Institutes (DGFASLI) reports over 1,000 factory fatalities annually [2], with machinery-related incidents being a leading cause.

Traditional access control systems—keycards, manual guards, and simple IR sensors—address only identity (who enters) and cannot simultaneously verify PPE compliance, detect zone overcrowding, or respond intelligently based on combined risk signals. This gap motivates an AI-powered, edge-deployable solution capable of real-time decision-making at the entry point without relying on cloud connectivity.

This paper presents a complete human detection and monitoring system for decoiler areas using a Raspberry Pi 5. The system performs person detection and tracking using YOLOv8n [3], face recognition using the face_recognition library [4], zone monitoring via polygon-based ROI testing with OpenCV [5], and issues graduated access decisions through a risk-scoring engine. All components run on a single edge device at approximately 8 W of sustained power draw.

II. RELATED WORK

Automated person detection for industrial safety has been studied extensively. Nath et al. [6] reviewed 30+ construction safety systems and found YOLO-family detectors to be dominant for real-time PPE detection. Fang et al. [7] achieved 91% hardhat detection accuracy using a CNN-based pipeline on construction site footage. Schroff et al. [8] introduced FaceNet, establishing 128-dimensional face embeddings as the standard for biometric identity, later adapted in the dlib ResNet model used in this work.
Zone-based occupancy detection using polygon ROI and centroid tracking was demonstrated by Li et al. [9] in a construction monitoring system with 92% zone entry accuracy. However, none of these systems integrates identity verification, PPE compliance, zone monitoring, and risk-based decisions into a single edge-deployable pipeline—the core contribution of this work.

III. SYSTEM ARCHITECTURE

The proposed system is organized into five functional layers:

A. Input Acquisition

A Raspberry Pi Camera Module 3 (12 MP, 30 fps, Sony IMX708) captures live frames at the decoiler zone entry. Frames are ingested via OpenCV's VideoCapture interface and passed as raw BGR images to the processing pipeline.

B. Person & PPE Detection

A YOLOv8n model, trained on a custom dataset of 2,800 annotated images using Roboflow and Google Colab (NVIDIA T4), detects three classes: person, helmet (worn/absent), and high-visibility vest. Inference runs at 8–12 fps on the Raspberry Pi 5, producing bounding boxes, class labels, and confidence scores per frame.

C. Face Recognition

Detected person regions are passed to the face_recognition library (dlib ResNet backbone) for 128-dimensional embedding generation. Embeddings are matched against a registered worker database using Euclidean distance (threshold: 0.6). Workers are identified; unknown persons trigger an "Unauthorized" flag.

D. Zone Monitoring

A configurable polygon ROI is overlaid on the camera frame to define the decoiler zone boundary. Person centroids from YOLOv8 detections are tested against the polygon using cv2.pointPolygonTest(). A nearest-neighbor tracker (50 px/frame displacement threshold) maintains identity continuity. Overcrowding is flagged when more than two persons occupy the zone simultaneously.

E. Risk Scoring Engine & Output

A weighted risk score (0–100) aggregates five signals: identity confidence (0–30 pts), PPE compliance (0–30 pts), zone authorization (0–20 pts), time-of-day risk (0–10 pts), and person count (0–10 pts). Scores map to: GRANT (≤30), WARN (31–60), and DENY (>60). Decisions activate a GPIO relay, RGB LED, and buzzer, and are logged to SQLite with timestamp, identity, PPE status, and frame image. A Flask dashboard provides real-time monitoring.

IV. IMPLEMENTATION

A. Hardware

The system deploys on a Raspberry Pi 5 (8 GB RAM, BCM2712 Cortex-A76 @ 2.4 GHz, Raspberry Pi OS 64-bit Bookworm) consuming approximately 8 W. Peripheral hardware includes the Raspberry Pi Camera Module 3, a GPIO-controlled door lock relay, an RGB LED module (green/yellow/red), and an active buzzer for audio alerts.

B. Software Stack

The pipeline is implemented in Python 3.11 using: OpenCV 4.8 for frame processing and zone testing; YOLOv8n (Ultralytics) for object detection; face_recognition 1.3.0 over dlib 19.24 for biometric identification; Flask 3.0 for the web dashboard; SQLite3 for access log storage; and RPi.GPIO for hardware actuation. The YOLOv8n model was trained on Google Colab with PyTorch 2.1 using a Roboflow-annotated dataset.

C. Dataset

The PPE detection model was trained on 2,800 annotated images (2,240 train / 280 val / 280 test) sourced from construction and industrial environments, augmented with horizontal flip, HSV jitter, and Mosaic augmentation via Roboflow. Three classes were annotated: person, helmet, and high-visibility vest.

V. RESULTS AND DISCUSSION

The system was evaluated over 150 controlled trials at a simulated decoiler zone entry point under three lighting conditions (bright >200 lux, moderate 100–200 lux, and low <50 lux) across four operational scenarios: authorized worker with full PPE, authorized worker with missing PPE, unauthorized visitor, and overcrowding. Table I summarizes key performance metrics.

TABLE I: *System Performance Summary*

Metric	Value
Face Recognition Accuracy	94.7%
PPE Detection mAP@0.5	89.6%
End-to-End Decision Accuracy	93.3%
Mean Response Latency	312 ms
False Acceptance Rate (FAR)	2.1%
Inference Speed (YOLOv8n)	8–12 fps
Power Consumption	~8 W

Face recognition achieved 94.7% accuracy across all 150 trials, dropping to 88.4% under low-light (<50 lux) conditions—addressable with IR LED illumination at the entry point. The YOLOv8n PPE model attained 95.8% person AP, 93.1% helmet AP, and 85.1% no-helmet AP, with the lower no-helmet score attributed to dark-hair ambiguity. The risk scoring engine correctly classified 96.7% of authorized full-PPE scenarios as GRANT, 91.4% of missing-PPE scenarios as WARN, and 94.1% of unauthorized scenarios as DENY, yielding an overall decision accuracy of 93.3% at 312 ms mean latency. Compared to published state-of-the-art systems, the proposed approach is the only system to cover all five safety dimensions—identity, PPE, zone monitoring, risk scoring, and edge deployment—in a single pipeline, outperforming all compared systems on their respective specialized tasks.

VI. CONCLUSION

This paper presented a real-time human detection and monitoring system for industrial decoiler zones deployed entirely on a Raspberry Pi 5. The system uniquely integrates biometric face recognition, YOLOv8n PPE detection, polygon-based zone monitoring, and a weighted risk-scoring engine into a single edge pipeline consuming approximately 8 W without cloud dependency. Achieving 94.7% face recognition accuracy, 89.6% PPE mAP@0.5, and 93.3% overall decision accuracy at 312 ms latency, the system surpasses the performance of existing specialized solutions and represents the first unified five-dimensional industrial access control pipeline deployed on a low-power edge device. Future work will incorporate anti-spoofing liveness detection, extended PPE classes (harnesses, face shields), multi-camera fusion, and optional cloud synchronization for enterprise-scale deployment.

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