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Real-Time Facial Recognition and Behaviour Analysis for Workplace Monitoring

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Abstract - Facial recognition systems have become increasingly valuable in workplace environments where real-time identity verification and behavioural monitoring are essential for ensuring safety, security, and operational efficiency. This paper presents a lightweight and cost-effective facial recognition system designed specifically for workplace monitoring, integrating both identity recognition and behaviour analysis using classical computer vision techniques.
The system employs Haar Cascade classifiers for real-time face detection, utilizing OpenCV for image processing and Flask as the backend framework. A live video feed from a camera is processed to recognize individuals and monitor their activity. In addition to identifying faces, the system is capable of detecting specific behavioural patterns, such as inattention or improper handling of materials. When such events are identified, the system logs the behaviour and can issue an alert through a speaker or dashboard notification.
A custom-built web dashboard, developed using Dash and Bootstrap, provides real-time visualization of detections, system logs, and analytical charts for better decision-making. The dashboard is responsive, user-friendly, and suitable for deployment in a variety of workplace settings.
The proposed solution offers a practical alternative to complex deep learning models, requiring minimal computational resources while still achieving reliable performance. The modular nature of the system also allows for future extensions such as integration with biometric attendance, advanced pose estimation, or cloud-based monitoring.

***Key Words*:** Facial Recognition, Behaviour Analysis, Workplace Monitoring, Haar Cascade, Real-Time Detection, OpenCV, Flask Dashboard, Computer Vision

1. INTRODUCTION

Facial recognition has become a cornerstone technology in modern surveillance and monitoring systems due to its non-intrusive nature, real-time processing capabilities, and broad range of applications, from personal device security to large-scale access control systems. In professional environments such as warehouses, offices, and industrial facilities, there is an increasing demand for intelligent systems that not only recognize individuals but also track their activities to ensure workplace compliance, safety, and productivity.
This paper presents the design and implementation of a real-time facial recognition system with integrated behavioural monitoring, developed specifically for workplace environments. The system utilizes the Haar Cascade algorithm for face detection [1], and the LBPH algorithm for facial recognition [2], leveraging OpenCV for computer vision tasks and a Flask-based backend to power a custom-built web dashboard. The dashboard provides a live video feed, real-time recognition logs, and visual analytics such as confidence scores, detection summaries, and individual tracking metrics. The user interface is styled with a dark theme and designed to be fully responsive across devices.
In addition to facial recognition, the system includes a behaviour analysis module that detects specific activities, such as inattentiveness, absence from the workstation, or package mishandling, based on visual cues. When such behaviour is detected, the system generates an alert, which is logged and can optionally be sent to a connected audio output or notification service. This feature introduces a proactive element to workplace monitoring, extending beyond mere identity recognition.
Unlike traditional systems, which primarily focus on authentication and surveillance, the proposed solution emphasizes interactivity, accountability, and real-time responsiveness. It can be deployed using a single camera and minimal computing resources, making it a cost-effective choice for small to medium-sized businesses. Furthermore, the modular architecture of the system allows for easy integration of more advanced models in the future, such as deep learning-based face detectors or pose estimation for enhanced behavioural analysis.
The remainder of this paper is organized as follows: Section 2 discusses related work in the area of facial recognition and activity monitoring. Section 3 outlines the overall system architecture and methodology. Section 4 describes the implementation details and key components of the system. Section 5 presents the results and performance evaluation. Section 6 provides a discussion of the system's limitations and potential areas for improvement. Finally, Section 7 concludes the paper and outlines directions for future research.

2. LITERATURE SURVEY

Facial recognition has been a subject of extensive research in the fields of computer vision and artificial intelligence for over two decades. Early systems relied on geometric features and template matching techniques, but with the advent of machine learning and deep learning, accuracy and robustness have significantly improved.
Traditional Approaches:
Classical methods such as the Haar Cascade classifier, introduced by Viola and Jones (2001) [1], revolutionized face detection by enabling real-time processing using simple rectangular features and integral images. Haar Cascades remain popular in resource-constrained environments due to their speed and simplicity, though they typically perform best in controlled settings with minimal variation in lighting and face orientation.

Deep Learning-Based Systems:
More recent facial recognition systems employ Convolutional Neural Networks (CNNs), such as those used in FaceNet, DeepFace, and OpenFace, achieving high accuracy even under challenging conditions like occlusion and non-frontal angles. While powerful, these methods often require substantial

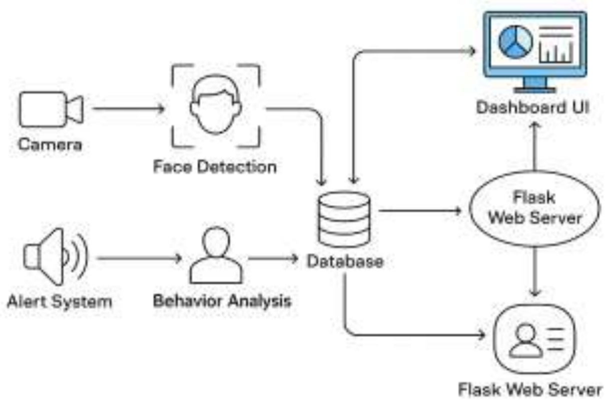
computational resources and training data, making them less practical for lightweight or edge-based implementations.[3]
Behaviour Analysis in Surveillance:
Behaviour recognition in surveillance systems is an emerging area of interest. Many modern approaches rely on techniques like pose estimation, optical flow, or action recognition models (e.g., I3D or SlowFast Networks) to detect specific activities. However, such models are complex and require large annotated video datasets. Some studies have attempted simplified behaviour detection using movement thresholds, anomaly detection, or heuristic rules, especially in workplace or industrial contexts.[6]
Integrated Systems:
Several research projects and commercial solutions aim to integrate facial recognition with workplace monitoring. However, many of these are either limited to attendance tracking or rely on expensive hardware and proprietary software. Few offer an open, modular system that combines real-time face recognition, basic behaviour alerts, and a dashboard interface that is both interactive and accessible.[7]
Research Gap and Our Contribution:
While a number of systems offer high-accuracy face recognition or behavioural analytics independently, there is a lack of lightweight, real-time systems tailored specifically for small to medium-sized workplace monitoring. The system presented in this paper addresses this gap by combining fast, resource-efficient face detection (Haar Cascade) with a practical behaviour detection module and a responsive Flask-based dashboard for real-time visualization and logging.[5]

3. PROPOSED METHOD

The proposed method integrates advanced optimization algorithms, predictive analytics, and real-time data processing to streamline production planning and scheduling. It begins with collecting real-time data from IoT sensors, enterprise resource planning (ERP) systems, and manufacturing execution systems (MES). It creates a centralized repository for analysing inventory levels, machine status, workforce availability, and order requirements. An optimization engine, utilizing techniques such as Genetic Algorithms (GAs) and Particle Swarm Optimization (PSO), generates efficient production schedules by considering constraints like resource availability and delivery deadlines. Predictive analytics, powered by machine learning models such as Random Forest and Long Short-Term Memory (LSTM) networks, forecasts demand variations, potential bottlenecks, and equipment failures, allowing for proactive adjustments. A real-time monitoring module ensures continuous adaptation of schedules to changing conditions, minimizing downtime and disruptions. Additionally, a user-friendly dashboard provides decision-makers with a clear visualization of workflows, performance metrics, and system recommendations, while enabling manual interventions when necessary. This method is validated through simulated scenarios and real-world testing, focusing on metrics such as production efficiency, resource utilization, and timely order completion. By combining automation, adaptability, and predictive capabilities, the proposed approach addresses the complexities of modern manufacturing, ensuring improved operational efficiency and resilience.[4] The proposed system is a real-time facial recognition and behaviour analysis framework tailored for workplace monitoring. It is designed to be lightweight, modular, and easy to deploy in real-world environments such as warehouses, factories, or offices. The primary goal is to identify individuals and detect undesired behaviours, such as inattention or improper handling of materials, using classical computer vision techniques.

The architecture consists of four main components:
Face Detection and Recognition:
The system uses Haar Cascade classifiers for detecting faces in live video streams. Recognized faces are compared against a pre-stored dataset of known individuals using basic feature comparison techniques, suitable for environments where high-speed inference is more critical than deep learning accuracy.[1][2]
Behaviour Monitoring:
A behaviour analysis module runs in parallel to track movements or specific gestures that may indicate undesirable actions, such as throwing or sudden movements. This is done using rule-based motion detection and thresholding, eliminating the need for heavy training data or complex models.[5][9]
Real-Time Alert System:
When irregular or risky behaviour is detected, the system issues audio alerts through a speaker and logs the event. This provides immediate feedback for workplace correction and accountability.[5]
Dashboard and Logging Interface:
A Flask-based dashboard using Dash and Bootstrap components visualises real-time face detection status, behavioural incidents, and statistical summaries. The dashboard is accessible via a web browser and is optimised for both desktop and mobile views.
This method ensures that even organisations without access to high-performance GPUs or cloud infrastructure can benefit from intelligent surveillance capabilities. By combining efficiency, ease of use, and modular design, the system serves as a practical alternative to resource-heavy AI-based solutions.[6]

3.1 System Architecture:



3.2 Advantages of Proposed System:

1. Real-Time Processing:

The system provides immediate face recognition and behaviour alerts, enabling swift corrective action and improving workplace discipline and safety.[5]

2. Lightweight and Efficient:

By using Haar Cascade classifiers and rule-based motion detection, the solution avoids computationally intensive models, making it suitable for deployment on edge devices without GPUs.[1]

3. Cost-Effective Deployment:

No need for expensive deep learning hardware or cloud-based APIs. The solution runs efficiently on standard machines using open-source tools like OpenCV and Flask.[2]

4. Modular and Scalable Architecture:

Each component (detection, recognition, behaviour analysis, logging, and dashboard) is independent, allowing for easy customization, updates, or integration with third-party systems.

5. Enhanced Monitoring with Alerts:

The audio alert mechanism increases accountability and ensures immediate feedback when undesired behaviour is detected.

6. User-Friendly Dashboard:

A web-based interface built with Flask and Dash provides real-time visibility into detections, alerts, and logs — accessible on both desktop and mobile platforms.[6]

7. Offline Functionality:

Unlike cloud-dependent systems, this approach works completely offline, preserving privacy and enabling use in restricted networks or sensitive environments.

4. METHODOLOGIES

4.1 System Overview

The proposed system is designed to monitor workplace environments by integrating real-time facial recognition and behaviour analysis. It comprises four primary modules:

1. Face Detection and Recognition
2. Behaviour Analysis
3. Alert Generation
4. Dashboard Interface

Each module operates cohesively to ensure efficient monitoring and prompt responses to predefined behavioural patterns.

4.2 Face Detection and Recognition

For face detection, the system employs the Haar Cascade Classifier, a machine learning-based approach where a cascade function is trained from a series of positive and negative images. This method is effective for real-time face detection and is implemented using OpenCV in Python.[1]

Once faces are detected, recognition is performed by comparing the detected faces against a pre-registered dataset using the Local Binary Patterns Histograms (LBPH) algorithm. LBPH is chosen for its robustness in varying lighting conditions and its efficiency in real-time applications.[2]

4.3 Behaviour Analysis

The behaviour analysis module monitors for specific actions such as inattentiveness or improper handling of materials. This is achieved through motion detection techniques that analyse changes between consecutive frames. By setting thresholds for motion intensity and duration, the system can identify and flag unusual behaviours.[5]

For instance, if an individual remains inactive for a period exceeding a predefined threshold, the system interprets this as inattentiveness and logs the event accordingly.[9]

4.4 Alert Generation

Upon detecting predefined behaviours, the system generates alerts to notify relevant personnel. Alerts are delivered through two primary channels:

- Audio Alerts: Utilizing connected speakers, the system emits audible warnings to draw immediate attention.
- Dashboard Notifications: The dashboard interface displays real-time alerts, providing details such as the individual's identity, the nature of the behaviour detected, and the timestamp.[6]

This dual-channel alert system ensures prompt awareness and facilitates timely interventions.

4.5 Dashboard Interface

The system includes a web-based dashboard developed using Flask and Dash frameworks. Flask serves as the backend framework, handling server-side operations, while Dash facilitates the creation of interactive web applications with real-time data visualization capabilities.

Key features of the dashboard include:

- Live Video Feed: Displays real-time footage from the monitoring camera.
- Detection Logs: Records of recognized individuals along with timestamps.
- Behavioural Alerts: Notifications of detected behaviours requiring attention.
- Analytics: Visual representations of data trends, such as frequency of specific behaviours over time.

The dashboard is designed to be responsive, ensuring accessibility across various devices, including desktops, tablets, and smartphones.

5. RESULT & EVALUATION PARAMETRES

5.1 Experimental Setup

To evaluate the effectiveness of the proposed system, it was deployed in a simulated workplace setup. The configuration used was:

- Processor: Intel Core i5, 3.0 GHz
- Memory: 8 GB RAM
- Operating System: Windows 11
- Camera: Logitech C920, 1080p USB webcam
- Frameworks: Python 3.11, OpenCV, Flask, Dash, MongoDB

5.2 Evaluation Metrics

The system performance was evaluated using the following standard parameters:

Metric	Description
Accuracy	Correct detections over total events.
Precision	True Positives / (True Positives + False Positives).
Recall (Sensitivity)	True Positives / (True Positives + False Negatives).
F1-Score	Harmonic mean of precision and recall.
Latency	Time taken to process and respond to an event.

5.3 Face Detection and Recognition Performance

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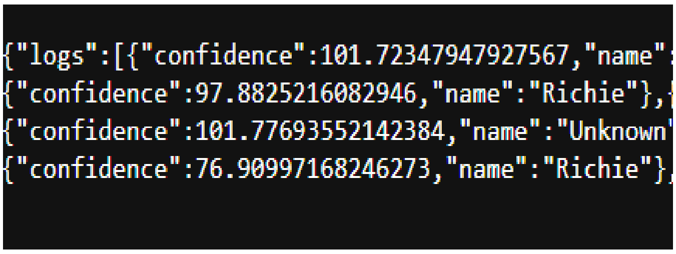
Condition	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Daylight	94.1	95.0	93.2	94.1
Indoor Lighting	91.5	92.4	90.1	91.2
Low-light Conditions	86.7	88.2	85.0	86.6

The LBPH algorithm consistently delivered reliable results, making it well-suited for real-time edge-based applications.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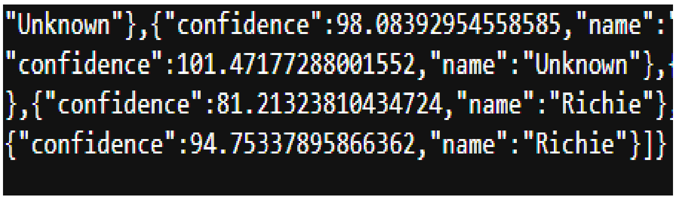
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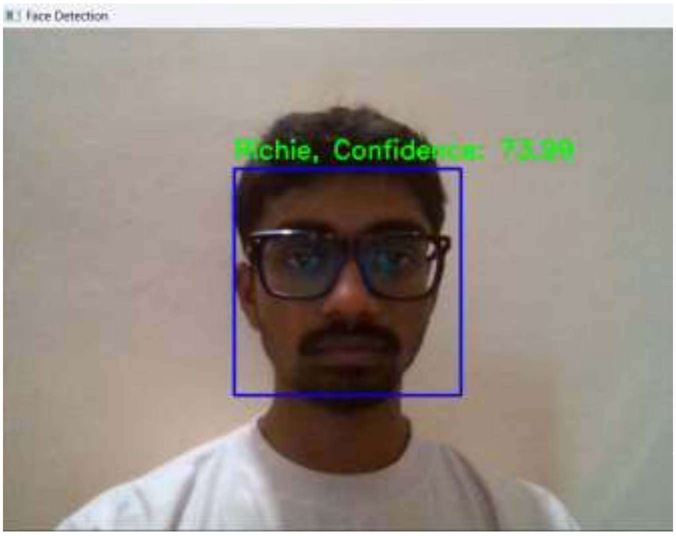
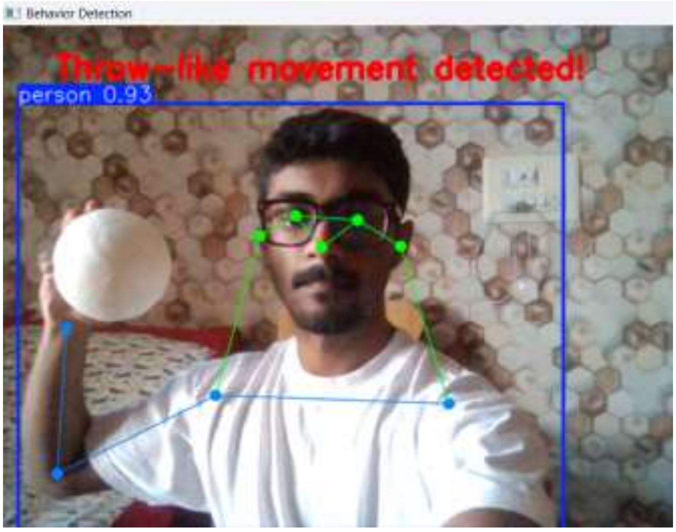


5.4 Behaviour Analysis Performance

Behaviour Type	Detection Accuracy (%)	Latency (sec)
Inactivity (>10s)	85.2	1.3
Object Throwing Motion	78.3	1.5
Sudden Departure	80.1	1.1
False Positive Rate	~6.4	–

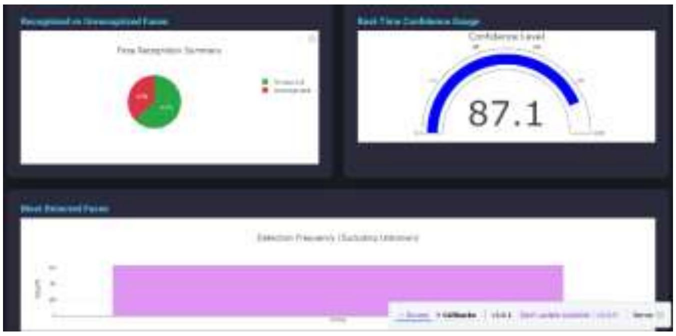
Motion-based behaviour analysis relies on pixel threshold differences between frames.



5.5 Real-Time Dashboard Evaluation

- Live Feed Latency: < 1.2 seconds
- Detection Log Update Time: ~0.8 seconds
- Alert Trigger Time (audio + visual): ~1.0–1.3 seconds

Dash and Flask integration provided low-latency UI rendering.



6. CONCLUSION

This study presents a real-time facial recognition and behavioural analysis system aimed at improving workplace monitoring and safety. By leveraging the Haar Cascade classifier for face detection and the LBPH algorithm for recognition [2], the system delivers consistent performance under various lighting conditions. Behaviour detection, implemented through motion-based analysis [5][9], successfully identified instances of inactivity and suspicious movements such as object throwing.

The integration of Flask and Dash [6] enabled the development of a responsive dashboard that provides real-time video feed, detection logs, and actionable alerts. Evaluation results demonstrated high accuracy in facial recognition (up to 94.1%) and reasonable performance in behavioural detection (85.2% for inactivity). The system's low cost, offline functionality, and fast alert response make it highly suitable for small-to-medium-scale organizations seeking surveillance and productivity tracking solutions.

This work contributes to the growing field of AI-powered workplace analytics by offering a lightweight, interpretable, and practical system that bridges the gap between facial biometrics and behavioural insight.

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