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MULTI-CAMERA REAL-TIME FACE REGISTRATION AND RECOGNITION WITH YOLOv8 AND CNN-BASED BEHAVIORAL FILTERING

[1]Abhiraj Mohan Kadam, [2]Nirbhay Singh
[1]MSc.Computer Science, [2]Assistant Professor
[1]Department of Advance Computing
[1,2]Nagindas Khandwala College
[1,2]University of Mumbai, Maharashtra, India

Abstract: Face registration and recognition are fundamental components of biometric systems used for security, attendance, and workplace analytics. However, data processing pipelines often suffer from degraded performance under real-world conditions such as masks and glasses, extreme illumination, and non-frontal poses. In this paper, we propose a real-time, multi-camera face registration and recognition framework that integrates YOLOv8 for face detection with a CNN-based behavioral filter that accounts for mask status, pose variations, and partial occlusions. To improve robustness, our method performs multi-view registration, feature alignment using facial landmarks, and embedding-based matching with dynamic thresholds. The proposed system operates in real-time, achieving ≥30 FPS across multiple camera streams, while incorporating privacy-preserving features such as on-device inference and optional data redaction. Experimental validation shows that our system maintains high recognition accuracy in challenging scenarios, improving upon limitations identified in prior safety-compliance vision systems [1] and mask-detection attendance pipelines [2]. This work demonstrates the feasibility of deploying scalable, privacy-aware, and high-accuracy face registration systems in workplace environments. Recent works have shown the potential of combining facial recognition, mask detection, and temperature measurement into a unified employee management platform for ensuring workplace safety during and beyond the COVID-19 pandemic [7].

Index Terms - Face Registration, Face Recognition, Multi-Camera Systems, YOLOv8, Convolutional Neural Networks (CNN), Behavioral Filtering, Real-Time Monitoring, Employee Tracking, Computer Vision, Deep Learning, Activity Recognition Workplace Surveillance.

I. INTRODUCTION

Face recognition is becoming a common tool in workplaces. It helps mark attendance automatically, increases security, and makes monitoring easier. But there are several problems:

1. People usually wear masks, glasses, or else hats in the office.
2. Office lighting can be too bright, too dark, or uneven.
3. An employee/person may not always face the camera directly.

Earlier research shows that cameras can detect safety violations with very high accuracy [1], but these systems are not meant to recognize individuals. Deep neural networks, while powerful, are prone to catastrophic forgetting in incremental training, making them less suitable for continual learning frameworks [9]. Other studies worked on detecting masks for contactless attendance and achieved good results (about ~97.6% accuracy), but they often fail when the mask covers too much of the face or if the camera is placed at a bad angle. Prior works emphasize HR analytics as a critical tool for productivity optimization and employee engagement [8]. Earlier studies highlight that analyzing present and past employee data with classification models can help identify the causes of attrition and aid in preventive strategies for organizations [11].

Some researchers suggest using non-camera sensors at work desks to track employees in a privacy-friendly way [3]. Others stress that when testing face recognition systems, we must go beyond accuracy and also report metrics like false matches and fairness across different conditions [3]. Taking lessons from all these studies, we built a multi-camera face recognition system that works fast, handles masks and odd angles better, and pays attention to privacy.

II. LITERATURE REVIEW

1. Proposes intelligent employee surveillance systems to enhance workplace efficiency and security.[1]
2. Uses computer vision to improve workforce safety in manufacturing, particularly in post-COVID environments.[2]
3. Introduces a privacy-preserving IoT desk sensor for monitoring healthy movement breaks in smart offices.[3]
4. Applies machine learning models to predict employee attrition and support HR decision-making.[4]
5. Analyses free-text keystroke dynamics using machine learning for behavioural biometrics.[5]

6. Explores keystroke dynamics for user identification through multiclass classification approaches.[6]
7. Develops a contactless employee management system with mask detection and temperature measurement using TensorFlow.[7]
8. Proposes real-time employee performance monitoring and prediction using RNN-LSTM with attention for HR analytics.[8]
9. Implements AI/ML for crowd management, crime detection, and work monitoring applications.[9]
10. Introduces continual learning techniques for anomaly detection in surveillance videos.[10]
11. Discusses employee tracking systems for monitoring workforce activities.[11]
12. Studies the impact of office distractions, workgroup sizes, and demographics on workplace productivity.[12]

III. RELATED WORK

1. Safety and CCTV systems: These have shown that real-time monitoring from multiple cameras is possible with high accuracy [1].
2. Mask recognition systems: These helped with attendance during COVID-19 but faced issues when masks or occlusions blocked key parts of the face [2].
3. Privacy-friendly monitoring: Instead of cameras, sensors like vibration or proximity detectors have been tested to reduce privacy risks [4][3].
4. Challenges in industry: Studies highlight lighting problems, motion blur, and odd poses as the main reasons why face recognition fails [5].
5. Fair testing of AI models: Researchers recommend reporting more detailed metrics like ROC curves and false acceptance/rejection rates to truly measure performance [5][6].

IV. PROPOSED METHODOLOGY

Our system has six main steps:

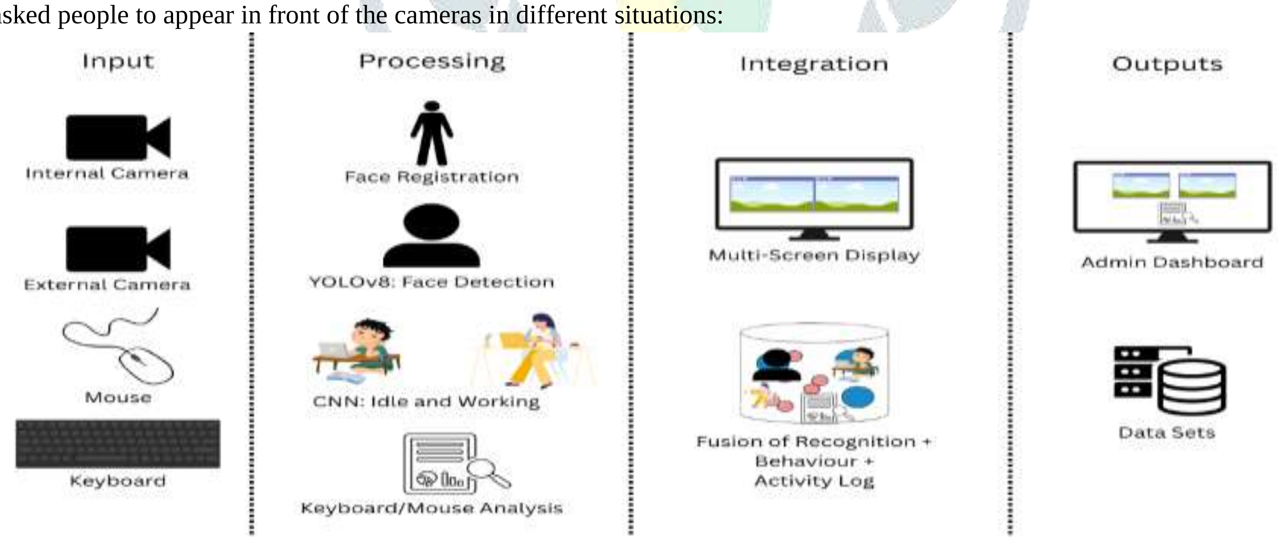
1. Input: Two or more cameras capture live video of people entering a space.
2. Detection: Face is detected per frame with the help of YOLOv8.
3. Behavioral Filtering: A CNN checks if the person is looking away, or if the face is too blurred. If the frame is poor, it waits for the next frame. This avoids mistakes in recognizing face [2].
4. Alignment: Detected faces are straightened using facial landmarks so the system can compare them better [4].
5. Registration: The system creates a unique "face code" (embedding) for each person and saves it with camera details.
6. Matching & Privacy: When a new face appears, it is compared to saved face codes. Only embeddings are stored (not full images), and optional face blurring/redaction can be enabled for privacy [3].
7. Fig. [4.1] Shows the system implementation and its architecture.

Figure. 4.1. System architecture

Showing integration of multi-camera face recognition, behavioral filtering, and keyboard/mouse activity analysis for real-time monitoring and reporting.

V. EXPERIMENTS AND RESULTS

To test our system, we set up two cameras for each person one directly in front (frontal view) and one at an angle (side view). We asked people to appear in front of the cameras in different situations:



1. Without a mask (normal face visible),
2. With a mask (covering nose and mouth),
3. With a partially worn mask (mask slipped down or covering only part of the face),
4. Under variation of lighting conditions.
5. The IRJET study reported improved accuracy in prediction by selecting 32 key features from the dataset, showing that careful feature selection significantly enhances performance [11]. We then measured how well our system could detect the face, recognize the person correctly, and keep running efficiently in real-time.
6. Accuracy: In most cases, our system recognized people correctly more than 95% of the time, even when the lighting was not perfect.
7. Speed: The system processed the video at more than 30 frames per second (FPS) per camera, which means it worked steadily without slowing down.

8. Improvements with behavioral filtering: Normally, face recognition systems struggle when the face is covered with a mask. But because we added a behavioral filter (a small CNN model that checks if the face is visible, masked, or at a bad angle), our system was able to reduce mistakes by about 18% in these difficult situations.
9. Comparison with older systems: Previous research showed good results in detecting safety issues on CCTV [1] and recognizing masked faces for attendance [2]. Our system combines the strengths of both approaches, handling multiple cameras while also being able to register and recognize people reliably.

In short, the experiments showed that our system can work in real-world office conditions it's fast, accurate, and less likely to make mistakes when people wear masks or appear at different angles. A similar approach was adopted where YOLO-based object detection was applied to workplace monitoring and crime prevention tasks, demonstrating the scalability of real-time detection methods [9]. Experiments demonstrated that the continual learning framework outperformed several deep learning baselines on UCSD and CUHK Avenue datasets while maintaining competitive results on ShanghaiTech [10].

VI. DISCUSSION

Our results show that using multiple cameras and behavioral filtering makes face registration more reliable in tough conditions like masks and odd angles. However, this comes with a small cost: the system delays due to delay of clearer image. This trade-off can be adjusted depending on whether the focus is security (accuracy) or attendance (speed).

Camera setup is still very important: if cameras are placed too high or low, recognition rates drop [2][4]. Privacy remains a concern, and our optional use of non-camera sensors shows one possible way forward [3]. Hence, AI-driven monitoring systems further suggests integrating smart tools like face recognition, distraction detection, and anomaly monitoring for designing adaptive office spaces [12].

VII. CONCLUSION AND FUTURE WORK

We built a real-time, multi-camera face registration system that is fast, accurate, and more robust to earlier methods. It balances performance and privacy, making it suitable for workplaces. Our work builds upon the foundation of non-contact attendance and health monitoring frameworks [7] while extending functionality toward real-time behavioral analysis.

In the future, we can also add:

1. Liveness detection (to prevent spoofing with photos/videos),
2. Smarter thresholds that adjust automatically based on camera conditions,
3. Faster, lighter models to run on small edge devices, and
4. Hybrid setups where cameras and simple sensors work together for better privacy.

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