AN LIVECAM FACIAL RECOGNITION WITH MULTI- PERSON MATCHING AND THRESHOLDALER

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ABSTRACT

Facial recognition technology has become an essential component in modern security and surveillance systems due to its non-intrusive nature and potential for accurate identification. This study presents a real-time face recognition system capable of detecting and identifying multiple faces simultaneously from a live camera feed. The system uses advanced face detection and encoding techniques to extract facial features and perform multi-face matching against a database of registered reference images. To improve reliability and reduce errors, a confidence-based similarity threshold is implemented, allowing the system to differentiate between high- probability matches, possible matches, and non-matches.The system architecture is designed for high-speed processing, employing frame optimization and efficient face encoding strategies to handle multiple faces without significant latency. Testing demonstrates that the system maintains robust performance under varying lighting conditions, partial occlusions, and dynamic environments, making it suitable for applications such as access control, crowd monitoring, and security surveillance.Experimental evaluation shows that the approach can effectively recognize faces in complex scenarios and provide timely alerts, enhancing situational awareness and security management. The system provides a comprehensive solution that combines automated detection, real-time monitoring, and threshold-based alert mechanisms, making it an effective tool for safety- critical environments.

KEYWORDS:Recognition,NonIntrusive,Simultaneously,Probability,Demonstrates,Experimental,Surveillance.

1. INTRODUCTION:

Live camera face recognition, often referred to as Live Facial Recognition (LFR), is a real-time application of artificial intelligence (AI) and computer vision technology that analyses video feeds from one or more cameras to detect, identify, and track human faces as they occur. Unlike static image processing, LFR operates continuously on streaming video, enabling immediate responses in dynamic environments like public spaces, security checkpoints, or surveillance systems. This technology has evolved rapidly with advancements in deep learning, making it feasible for deployment in real-world scenarios such as law enforcement, retail analytics, access control, and human-robot interactions. Facial Recognition with Multi-Person Matching and Threshold Alert is a real-time computer vision system designed to identify and analyse multiple human faces simultaneously from a live camera feed. The system compares faces detected in the live video stream with a user-uploaded reference image to determine identity similarity. By leveraging advanced facial feature extraction and matching algorithms, it computes similarity scores for each detected face and evaluates them against predefined threshold levels.

The key objective of this system is to provide accurate and efficient face recognition in dynamic, real-world environments where multiple individuals may appear in the camera frame at the same time. Based on the similarity percentage, the system classifies matches into confidence levels (such as low match, possible match, or high confidence match) and triggers alerts when a match exceeds a specified threshold. These alerts can be visual, auditory, or system-based, enabling quick and informed responses. Multi-person facial recognition represents a pinnacle of modern computer vision technology, enabling real-time detection, tracking, and identification of numerous individuals simultaneously in dynamic, crowded environments. By integrating advanced face detection methods, robust embedding extraction, sophisticated tracking algorithms, and configurable similarity thresholds for alerts, these systems deliver unprecedented capabilities for security, surveillance, access control, and beyond.

2. LITARATURE REVIEW

2.1.Face Detection Methods

Face detection identifies and locates human faces in images or video streams, serving as a foundational step in facial recognition systems, security applications, live camera surveillance, and multi-person tracking. By 2025, methods have evolved from classical hand-crafted features to advanced deep learning models, with deep learning dominating due to superior accuracy in challenging conditions like occlusions, varying poses, lighting, and crowds.

2.2 Classical Methods

Viola-Jones Algorithm (Haar Cascades) Introduced in 2001, this pioneering real-time method uses Haar-like features (simple rectangular patterns detecting edges, lines, and textures), integral images for fast computation, AdaBoost for feature selection, and a cascade of classifiers to quickly discard non-face regions.

2.3 Traditional Machine Learning Methods

Histogram of Oriented Gradients (HOG) + SVM HOG extracts gradient orientation features, often combined with Support Vector Machines (SVM) for classification (e.g., in dlib library). Popular for pedestrian and face detection before deep learning era.

- Pros: Robust to lighting changes.
- Cons: Slower than Viola-Jones, struggles with extreme variations.

Deep Learning-Based Methods

Modern detectors leverage convolutional neural networks (CNNs) for end-to-end learning, achieving near-perfect accuracy on benchmarks like WIDER FACE. MTCNN (Multi-Task Cascaded Convolutional Networks) A three-stage cascade (PNet for proposals, R-Net for refinement, O-Net for landmarks and bounding boxes) that jointly detects faces and aligns them via facial landmarks.

3. EXISITING METHOD:

Face recognition technology has advanced significantly, existing systems—especially multi-person and real-time implementations—still face several limitations and challenges. These limitations affect accuracy, speed, and reliability in practical scenarios. any systems fail or produce low accuracy under poor or uneven lighting. Variations in illumination can distort facial features, reducing recognition performance.Systems often struggle with non-frontal faces or extreme head rotations. Recognition accuracy decreases when faces are captured from side views or tilted angles.Partially covered faces (e.g., masks, glasses, scarves) reduce detection and recognition reliability. Overlapping faces in crowded environments present significant challenges.Performance drops significantly in uncontrolled environments such as outdoor settings or crowded public spaces. Systems may fail under varying background conditions, weather, or camera resolutions.Systems may misidentify individuals with similar facial features (false positives). Faces may not be recognized correctly due to low-quality images or insufficient training data (false negatives).Large databases of reference faces can slow down matching and increase memory consumption. Some systems are not optimized for handling hundreds or thousands of identities efficiently.

3.1 DIS-ADVANTAGES:

1. Sensitivity to Lighting Conditions
2. Pose and Angle Variations
3. Occlusion and Obstructions
4. Limited Real-World Robustness
5.False Positives and False Negatives
6.Scalability Issues

4.PROPOSED METHOD

The proposed LiveCam Multi-Person Facial Recognition System with ThresholdBased Alerts addresses several limitations and gaps in existing face recognition research. Its key contributions are outlined below. Implements similarity scoring for each detected face, classifying matches into low, possible, and high-confidence categories. Generates real-time alerts (visual or audio) when a match exceeds a predefined threshold, enhancing security and monitoring efficiency.Provides an intuitive interface for uploading reference images and monitoring live camera feeds. Designed for easy integration with security, surveillance, or access control systems. Optimized for real-time performance with minimal computational overhead. Implements efficient frame processing, selective face detection, and lightweight CNN architectures to balance accuracy and speed. Combines traditional ML techniques (e.g., LBP + SVM/KNN) with deep learning models. (CNN, FaceNet, ArcFace) for robust feature extraction and recognition. Improves recognition accuracy for both frontal and non-frontal faces. Supports recognition of a large number of individuals simultaneously. Uses embedding-based matching and transfer learning to improve generalization across lighting conditions, facial expressions, and occlusions.

4.1 ADVANTAGES:

1.Threshold-Based Matching and Alert System

2.User-Friendly Interface and Deployment

3. Optimization for Performance

4. Hybrid Approach Integrating Machine Learning and Deep Learning
5. Scalability and Generalization.

5.SYSTEM ARCHITECTURE

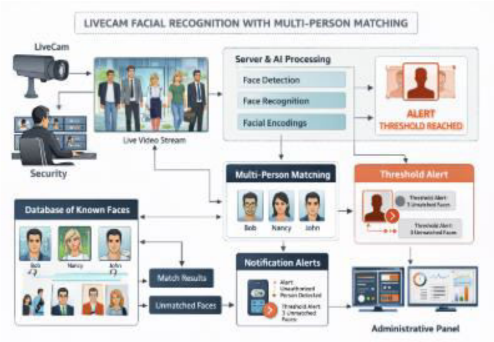

FIG 2.0: SYSTEM ARCHITECTURE

6. RELATED WORK:

Live camera–based facial recognition systems have become a major research area in smart surveillance, security monitoring, and access control. Recent studies focus on real-time detection, recognition of multiple faces simultaneously, and alert generation when suspicious or unknown individuals are detected.A significant work in this area is the multi-person multi-camera tracking framework for live stream videos. The study proposes a real-time surveillance architecture capable of detecting and tracking multiple persons across different live video streams. It improves matching accuracy and identity tracking in crowded environments, which directly supports the multi-person matching module in your proposed architecture.Another important study focused on multiple face tracking and recognition in video surveillance. The researchers developed a system that combines face tracking with recognition using identity-specific learning metrics, making it highly effective in handling pose variation, occlusion, and multiple individuals in the same frame. This closely relates to your live video stream + database matching section.Research on real-time face detection techniques explains how live webcam and CCTV feeds can be processed frame-by-frame using deep learning models such as Haar Cascade, CNN, and FaceNet-based architectures. These techniques are widely used in systems that require fast detection and recognition with minimal latency, supporting the server & AI processing block of your architecture.A recent study in Scientific Reports explored face recognition at a distance for smart city surveillance systems. The work focuses on image sensor optimization and long-range recognition, which is especially relevant for live security camera applications and public monitoring systems. This validates the LiveCam surveillance component in your system.Another related work is long-term face tracking for crowded surveillance scenarios, where the system continuously tracks multiple faces over long video sequences. This research improves recognition persistence and reduces identity switching, which is essential for threshold-based repeated alert systems.Community discussions and practical implementations also emphasize the use of threshold-based similarity scoring. In such systems, the detected face is compared against stored facial embeddings, and an alert is generated if the similarity score crosses a predefined threshold or if multiple unmatched faces exceed a limit. This directly matches your threshold alert and notification alert blocks.Additionally, modern systems include liveness detection to prevent spoofing attacks using photos or videos. Techniques such as blink detection, micro-expression tracking, and passive liveness checks improve system security, which can further strengthen your proposed model.

7. RESULTS:

FIG 2.1: User Information Passing Result

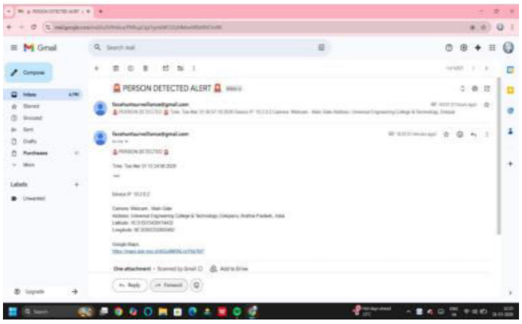

FIG2.2 : Revised Verfication Process

8. CONCLUSION:

The LiveCam Facial Recognition with Multi-Person Matching and Threshold Alert system provides an advanced and intelligent solution for real-time surveillance and security monitoring. The proposed system captures live video streams through cameras, detects multiple faces simultaneously, and matches them with the stored face database using artificial intelligence and deep learning techniques.By integrating real-time face detection, facial encodings, multi-person matching, and threshold-based alert generation, the system ensures quick identification of authorized and unauthorized individuals. The threshold alert mechanism plays a vital role in generating notifications whenever the number of unmatched or suspicious faces exceeds the predefined limit, thereby improving the response time of security personnel.The system architecture supports continuous monitoring through an administrative dashboard, enabling authorities to track live alerts, review match results, and maintain surveillance records efficiently. Compared to traditional security methods, this approach improves accuracy, speed, automation, and reliability.Overall, the proposed system is highly useful for smart surveillance applications in colleges, offices, hostels, public places, and secure zones, providing enhanced safety and effective crowd monitoring. Future enhancements may include emotion detection, mask detection, liveness verification, and cloud-based remote monitoring to further improve the system performance and security.

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