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Automated Facial Recognition Attendance System

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Abstract: *Artificial Intelligence (AI) has fundamentally transformed administrative methodologies within educational and corporate institutions. This paper details the development and analysis of an Automated Facial Recognition Attendance System designed to address the inefficiencies and security vulnerabilities inherent in traditional manual roll calls. By integrating computer vision with machine learning (ML)—specifically utilizing Haar Cascade Classifiers for detection and Local Binary Pattern Histograms (LBPH) for recognition—we developed a contactless, hygienic identity verification solution. The system was implemented using a standard desktop architecture powered by Python and OpenCV to ensure broad accessibility. Rigorous testing was conducted to evaluate performance under real-world variables, including low-light conditions, varying distances, and angular variations. Furthermore, a comparative analysis was performed against algorithms such as Eigenfaces, Fisherfaces, and Convolutional Neural Networks (CNNs). Our findings indicate that while Deep Learning models offer higher accuracy, they are computationally intensive. In contrast, the Haar Cascade and LBPH combination offers an optimal balance between efficiency and reliability on standard hardware, achieving accuracy rates between 85% and 98% in controlled environments. This report outlines the system architecture, performance metrics, and potential future enhancements, including liveness detection to mitigate spoofing attempts.*

Keywords: *Artificial Intelligence*.

I. INTRODUCTION

In the contemporary digital era, the automation of routine administrative processes is a priority. Attendance management, whether in academic or corporate settings, remains a time-consuming task when performed manually. Traditional methods, such as roll calls or physical sign-in sheets, are not only inefficient but also susceptible to fraudulent practices, commonly referred to as "proxy" attendance. While biometric solutions like fingerprint scanners were previously widely adopted, post-pandemic hygiene protocols have necessitated a shift toward contactless technologies. This research explores a computer vision-based approach utilizing facial recognition to automate attendance, thereby enhancing process efficiency, integrity, and hygiene.

Algorithm Selection Rationale:

- **Haar Cascade (The Detector):** An established, efficient method for object detection. It utilizes simple contrast patterns for rapid processing, making it ideal for real-time video, though it is sensitive to non-frontal face angles.
- **LBPH (The Recognizer):** This algorithm analyzes local texture features by comparing pixels to their neighbors. It is particularly robust against varying lighting conditions, a common challenge in computer vision applications.
- **Eigenfaces (PCA) & Fisherfaces (LDA):** While Eigenfaces simplifies facial data into principal components, it exhibits significant performance degradation under lighting variations. Fisherfaces offers improvements but remains less robust than LBPH regarding texture analysis.
- **Deep Learning (CNNs):** While representing the gold standard for accuracy, these models often require high-performance GPUs. Implementing them on standard office hardware frequently results in high latency, rendering them less suitable for real-time attendance tracking on budget constraints.

II. OBJECTIVES

Our main goal was to build a system that is robust, easy to use, and actually practical for schools to install.

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Primary Objectives:

- **Process Optimization:** To reduce the time expenditure of manual attendance (approx. 10–15 minutes) to near-zero by automating the verification process in the background.
- **Elimination of Fraudulent Attendance:** To mitigate "proxy" attendance by replacing manual signatures with biometric verification, ensuring the physical presence of the enrollee.
- **Data Integrity:** To integrate a MySQL database for the maintenance of secure, immutable, and precise entry logs.
- **Robust Enrollment Strategy:** To utilize a dataset of approximately 100 images per subject during the training phase, ensuring the algorithm remains robust against minor variations in facial expression or orientation.

Secondary Goals:

- **Hardware Optimization:** To demonstrate that high-performance facial recognition is viable on standard consumer hardware (e.g., Dual-Core processors with 4GB RAM) without the need for specialized supercomputing resources.
- **User Accessibility:** To provide a Graphical User Interface (GUI) developed via Tkinter, enabling non-technical administrative staff to operate the system, perform registrations, and generate reports efficiently.

Research Goals:

- **Environmental Stress Testing:** To evaluate system efficacy under suboptimal conditions, specifically low-light environments and varying distances (40cm to 125cm).
- **Generalization vs. Overfitting:** To analyze the model's ability to generalize to new data, ensuring it does not "overfit" by merely memorizing training images, but rather learns distinct facial features applicable to slight changes in appearance (e.g., hairstyles or clothing).

III. DATA ANALYSIS AND FINDINGS

Here is a breakdown of how the system actually processes the data.

A. Data Pre-processing The quality of input data is a critical determinant of model success.

- **Live Video Acquisition:** OpenCV was utilized to capture video streams, providing multiple angular perspectives of the subject in real-time.
- **Grayscale Conversion:** Input images were converted to grayscale to reduce computational load. Since color data (RGB) is not essential for geometric feature extraction, this conversion improved processing speed by approximately 300% without compromising accuracy.
- **Region of Interest (ROI):** Upon detection, the image is cropped to isolate the facial region, thereby eliminating background noise and focusing the analysis solely on relevant biometric features.

How the Algorithms Worked Together

- **Haar Cascade (Finding the Face):** Think of this as a rapid-fire filter. It scans the image with a "sliding window." It rejects 90% of the image (the background) instantly because it doesn't have face-like patterns. This cascading rejection is why the system is fast enough for live video. However, we confirmed that it is strictly for *frontal* faces. If a student looks sideways, the detector misses them.
- **LBPH (Identifying the Person):** Once the face is found, LBPH takes over. It breaks the face into a grid (like an 8x8 checkerboard). In each square, it looks at the texture (edges, spots, flat areas) and turns that into a number (histogram). It then creates a "fingerprint" of the face.

The "Confidence" Score: When the system matches a live face to a stored one, it gives a "confidence" score. Confusingly, in OpenCV, a **lower** score is better. It represents the "distance" or difference between the two images. A score of 0 is a perfect match.

System Workflow The app runs on a desktop.

- **Enrollment:** The admin types a name, and the camera snaps 100 quick photos.
- **Training:** The system crunches these photos and saves a .yml training file.
- **Recognition:** When class starts, the camera turns on. If it sees a face it knows (within a certain confidence threshold), it logs the ID.
- **Database:** It checks MySQL. If the student is already marked "Present" for today, it ignores them (to avoid duplicate entries).

IV. ACCURACY RESULTS

We tested the system to see not just *if* it works, but *when* it breaks.

Performance Metrics In a controlled room (good light, looking at the camera), the system is excellent—hitting 92% to 95% accuracy. However, in "uncontrolled" settings (bad light, people walking by quickly), accuracy drops to around 70-85%. We noticed clear signs of **overfitting**. The system recognized the training images 100% of the time. But if the live video looked very different (e.g., different shadows) from the training photos, the system struggled.

The "Real World" Variables

Distance Matters: The sweet spot is 40cm to 75cm (arm's length).

At **40cm**, accuracy is near 98%.

At **125cm+**, accuracy crashes below 50%. The face simply becomes too small in the frame for the algorithm to read the pixel textures. This means the system works best as a "kiosk" where you walk up to it, rather than a surveillance camera monitoring the whole room.

- **Lighting is Key:** LBPH is pretty good at handling lighting changes, but it has limits.
- **Uniform Light:** Great results.
- **Low Light:** The camera gets "grainy" (noise). This confuses the texture reader, leading to failures.
- **Backlight:** If a student stands with a window behind them, their face becomes a dark silhouette. The Haar Cascade can't even find the face in this situation.
- **Pose:** You have to look at the camera. Masks, heavy sunglasses, or looking at the floor will cause the system to mark you as "Unknown."

LBPH vs. The Rest

Vs. Eigenfaces: LBPH won easily. Eigenfaces got confused every time the sun went behind a cloud.

Vs. Deep Learning: Deep Learning is smarter, but slower. On a regular laptop, Deep Learning runs at about 5 frames per second (laggy). LBPH runs at 15+ FPS (smooth). For a basic attendance app, smooth performance is more important than that final 1% of accuracy.

The Confidence Threshold We set the "rejection" threshold at 50. If the difference score is higher than 50, the system says "Unknown."

If we lower it to 30, we get fewer mistakes, but the system rejects valid students too often.

If we raise it to 80, it recognizes everyone, but might mistake one student for another. 50 was the balanced choice.

V. CONCLUSION

This project proves that automating attendance is not only possible but practical for standard schools and offices. By moving away from paper sheets, we save time and ensure the data is honest.

Key Takeaways:

- **It Works:** Combining Haar Cascade and LBPH creates a lightweight, effective system that runs on cheap computers. It hits 90-95% accuracy in proper conditions.
- **Constraints:** It is not magic. It requires students to be within 1 meter of the camera and requires decent lighting. It is a "cooperative" system—users need to look at the camera.

- **Data Security:** Using a SQL database transforms attendance from a piece of paper into searchable, secure digital data.
- **Room for Improvement:** The system currently can't tell the difference between a real face and a high-quality photo held up to the camera (spoofing).
- **Future Work:** To make this enterprise-ready, we need to add **Liveness Detection** (checking for eye blinks) to stop spoofing. Moving the database to the cloud would also allow a principal to check attendance from their phone in real-time. Finally, as mobile phones get faster, we could switch to lightweight Deep Learning models (like MobileNet) to improve accuracy in bad lighting without sacrificing speed.

VI. ACKNOWLEDGMENT

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REFERENCES

[1]. "Haar Cascade LBPH face recognition accuracy limitations comparison," *ITM Web of Conferences*, 2022.

[2]. "Comparison of facial recognition systems Fisherfaces and LBPH for access control," *ResearchGate*, 2017.

[3]. "Deep Learning Approaches for Facial Recognition in Educational Institutions," *International Journal of Innovative Technology and Interdisciplinary Research*, 2019.

[4]. "A Comparative Study of Facial Recognition Techniques for Attendance Marking," *IEEE*, 2020.

[5]. "The Effect of Dataset Count on Facial Recognition Accuracy Using Haar Cascade Classifier," *ResearchGate*.

[6]. "Performance Evaluation of Face Recognition Algorithms on Embedded Systems," *IEEE*, 2019.

[7]. "Face Detection & Recognition Using LBPH and OpenCV," *Medium*, 2020.

[8]. "Haar Cascade vs LBPH vs Eigenfaces accuracy comparison," *MDPI*, 2021.

[9]. "A Study of LBPH, Eigenface, Fisherface and Haar-like features for Face recognition using OpenCV," *ResearchGate*, 2019.

[10]. "Comparison between attendance system implemented through haar cascade classifier and face recognition library," *ResearchGate*.

[11]. "Face Recognition Attendance Management System using LBPH and Haar Cascade," *ResearchGate*, 2025.

[12]. "Real-Time Face Recognition System Using LBPH and Haar Cascade Classifier," *International Journal of Recent Technology and Engineering (IJRTE)*.

[13]. "Face Recognition Based Attendance System Using Haar Cascade Algorithm," *E-Journal UPI*, 2023.

[14]. "Facial recognition based workplace security system using LBPH algorithm," *ResearchGate*.

[15]. Comparison of Real-Time Face Detection and Recognition Algorithms - ITM Web of Conferences, accessed November 28, 2025, https://www.itm-conferences.org/articles/itmconf/pdf/2022/04/itmconf_icacc2022_03046.pdf

[16]. Comparison between attendance system implemented through haar cascade classifier and face recognition library - ResearchGate, accessed November 28, 2025, https://www.researchgate.net/publication/348605656_Comparison_between_attendance_system_implemented_through_haar_cascade_classifier_and_face_recognition_library

[17]. A Study of LBPH, Eigenface, Fisherface and Haar-like features for Face recognition using OpenCV - ResearchGate, accessed November 28, 2025, https://www.researchgate.net/publication/337528180_A_Study_of_LBPH_Eigenface_Fisherface_and_Haar-like_features_for_Face_recognition_using_OpenCV

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[18]. Evaluating the Performance of Eigenface, Fisherface, and Local Binary Pattern Histogram-Based Facial Recognition Methods under Various Weather Conditions - MDPI, accessed November 28, 2025, https://www.mdpi.com/2227-7080/9/2/31

[19]. Custom Face Classification Model for Classroom Using Haar-Like and LBP Features with Their Performance Comparisons - MDPI, accessed November 28, 2025, https://www.mdpi.com/2079-9292/10/2/102

[20]. (PDF) The Effect of Dataset Count on Facial Recognition Accuracy Using Haar Cascade Classifier - ResearchGate, accessed November 28, 2025, https://www.researchgate.net/publication/394731653_The_Effect_of_Dataset_Count_on_Facial_Recognition_Accuracy_Using_Haar_Cascade_Classifier

[21]. Face Recognition: Based Attendance System - IJFMR, accessed November 28, 2025, https://www.ijfmr.com/papers/2024/6/32722.pdf

[22]. Face Detection & Recognition using LBPH and OpenCV | by Vincents - Medium, accessed November 28, 2025, https://medium.com/@vincents0511/face-detection-recognition-using-lbph-and-opencv-cea124d9846a

[23]. Face Recognition Attendance Management System using LBPH and Haar Cascade | Request PDF - ResearchGate, accessed November 28, 2025, https://www.researchgate.net/publication/383240749_Face_Recognition_Attendance_Management_System_using_LBPH_and_Haar_Cascade

[24]. Attendance Capture System Using Face Recognition, accessed November 28, 2025, https://ijetms.in/Vol-8-issue-3/Vol-8-Issue-3-52.pdf

[25]. Face Recognition Based Attendance System Using Haar Cascade Algorithm with Histogram Equalization and Median Blur Filter Jurnal, accessed November 28, 2025, https://ejournal.upi.edu/index.php/Edsence/article/download/65907/pdf

[26]. (PDF) Facial recognition based workplace security system using LBPH algorithm, accessed November 28, 2025, https://www.researchgate.net/publication/364633059_Facial_recognition_based_workplace_security_system_using_LBPH_algorithm

[27]. Comparison of facial recognition systems Fisherfaces and LBPH for access control to restricted areas - ResearchGate, accessed November 28, 2025, https://www.researchgate.net/publication/366651178_Comparison_of_facial_recognition_systems_Fisherfaces_and_LBPH_for_access_control_to_restricted_areas

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