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Face Recognition Attendance System Using Local Binary Pattern Histogram Algorithm

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Abstract

Maintaining accurate and tamper-proof attendance records in educational and corporate environments has long been a challenge due to the limitations of manual and biometric systems. This study introduces the development and deployment of a contactless, automated attendance system that utilizes facial recognition through the local binary pattern histogram (LBPH) algorithm. The primary goal is to offer a secure and efficient substitute for conventional attendance methods by harnessing the power of computer vision and machine learning technologies. The system is developed using Python and OpenCV and employs Haar cascade classifiers for face detection, followed by the LBPH algorithm for facial recognition. A graphical user interface (GUI) is integrated using Tkinter to manage enrollment, training, and real-time attendance logging. The system securely stores attendance records in a MySQL database, with unrecognized faces being identified and managed accordingly. It is designed to be lightweight, functioning efficiently without the need for graphics processing unit (GPU) acceleration, and performs well on typical desktop computers. The system was tested under various lighting conditions and facial changes, including the presence of glasses and facial hair. The system achieved an average recognition accuracy of approximately 90% and was able to correctly reject unregistered faces, minimizing false positives. Real-time response and high accuracy make this system suitable for institutional deployment. This project demonstrates how a well-trained facial recognition model, when paired with a simple user interface and optimized backend, can significantly improve attendance tracking. The solution is scalable, cost-effective, and provides a foundation for further enhancements such as cloud integration, anti-spoofing, and mobile platform support.

Keywords: Face recognition, attendance system, local binary pattern histogram (LBPH), Haar cascade, automation

INTRODUCTION

Automation has transformed numerous sectors by enhancing efficiency and reducing the likelihood of human mistakes. One significant area in which automation can be leveraged is attendance management systems. Traditional attendance recording methods, such as manual signing or calling out names, are not only time-consuming but also prone to inaccuracies and frauds such as proxy attendance.

Biometric systems provide an effective approach for accurately recognizing individuals based on their unique physical characteristics. Among various biometric techniques, face recognition stands out as non-intrusive and user-friendly [1].

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However, achieving reliable face recognition in dynamic environments presents challenges, such as lighting variations, pose changes, and appearance modifications, such as glasses or facial hair.

This study introduces a face recognition attendance system that utilizes the local binary pattern histogram (LBPH) algorithm, known for its reliability and low computational requirements for facial recognition tasks. Combined with Haar cascade face detection, the system offers a reliable real-time attendance recording mechanism. The proposed system is easy to deploy, scalable, and requires minimal hardware, primarily a webcam and computer.

LITERATURE REVIEW

Numerous approaches have been suggested in existing research for the automation of attendance systems. In [2], radio frequency identification (RFID) was used for attendance tracking; however, RFID tags are susceptible to loss and unauthorized usage. Fingerprint-based systems [3] offer higher security but require physical interaction, posing hygiene concerns, particularly in the post-pandemic world.

Face recognition-based systems have emerged as superior alternatives. Early systems using Eigenfaces [4] and Fisherfaces [5] struggled with changes in illumination and facial variations. The LBPH has been proposed as a better alternative because of its robustness against monotonic grayscale transformations and its ability to handle different expressions and minor occlusions [6].

Recent studies have integrated the Haar cascade for face detection with LBPH for recognition, yielding good performance in controlled settings. In contrast, our system was designed to improve real-world applicability in environments such as classrooms or offices, where lighting conditions and facial appearances may vary.

PROPOSED SYSTEM

The proposed face recognition attendance system was designed to automate the attendance process by detecting and recognizing faces in real time. The system integrates two major computer vision techniques: a Haar cascade classifier for face detection, and a LBPH for face recognition.

The complete flow of the system is shown in Figure 1. It consists of four primary modules.

1. Image acquisition
2. Pre-processing and face detection
3. Face recognition and identification
4. Attendance marking and storage

Figure 1. System architecture of the face recognition attendance system.

System Architecture

- *Image acquisition:* Real-time video feed is captured using a webcam. Each frame is extracted for processing.
- *Pre-processing and face detection:* Each frame is converted to grayscale to simplify the processing. The Haar cascade classifier [7] was applied to detect the facial region.
- *Face recognition:* Detected face regions are fed into the LBPH face recognizer. The model predicts the identity based on the trained features.
- *Attendance marking:* Recognized faces were cross-checked against the database. If matched, attendance was marked automatically and stored in a comma-separated values (CSV) file and SQL database.

DATASET AND METHODOLOGY

Dataset Collection

Due to the absence of a standardized attendance dataset, a custom dataset was created for this project [8, 9].

- *Total individuals enrolled:* 25
- *Images per individual:* 80 to 100
- *Environment:* Different lighting conditions, slight pose variations, and facial expressions.

Images were captured using the webcam of the system in controlled indoor environments. Each image is labeled with a unique identifier for each user.

Pre-Processing

Captured images undergo the following pre-processing steps:

1. Conversion to grayscale
2. Noise reduction
3. Histogram equalization (to enhance contrast)
4. Face detection using Haar cascade classifier

The detected facial regions (region of interest (ROI)) were cropped and resized to a standard dimension, as shown in Figure 2.

Face Detection Using Haar Cascade

The Haar cascade classifier proposed by Viola and Jones [7] uses Haar-like features for rapid object detection. This method employs integral images and AdaBoost to improve the detection speed and accuracy. It efficiently detects frontal faces, even under partial occlusions.

Face Recognition Using LBPH Algorithm

A LBPH [6] is a texture descriptor that encodes facial features by comparing neighboring pixels.

- For each pixel, neighbors are thresholded.
- Binary patterns were created (1 for higher and 0 for lower than the center pixel).
- Local histograms are generated and concatenated into a feature vector.

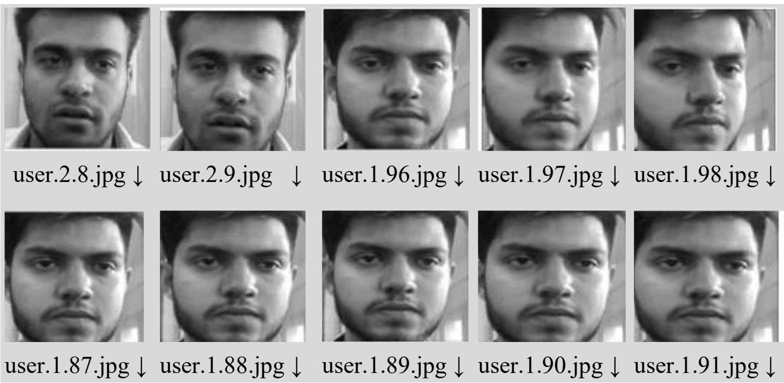

Figure 2. Sample images of students' faces.

The LBPH is robust to changes in illumination and slight pose variations, making it ideal for real-world attendance systems.

Pseudocode for Recognition Process

Input: Grayscale face image.
Output: Predicted identity or "Unknown."

1. Apply the LBP operator to the input face.
2. Compute histogram features.
3. Compare with the trained model using Euclidean distance.
4. If the confidence score was less than the threshold (50%), the mark was recognized.
5. Else label as "Unknown."

Attendance Marking

Once a face is recognized:

- The individual's name and ID are retrieved from the database.
- Attendance is marked only once per session to avoid duplicates.
- If a person is labeled as "Unknown," their image is saved separately for security audits.

An example of a real-time recognition window and an attendance sheet is shown in Figure 3.

RESULTS AND ANALYSIS

The proposed system was evaluated based on various real-world scenarios, such as varying lighting conditions, facial orientation changes, and accessories, such as glasses and masks. The evaluation results validated the robustness and practical feasibility of the LBPH-based face recognition attendance system [10–12].

Experimental Setup

- *Hardware:* Intel Core i5 CPU, 8GB RAM, HD Webcam
- *Software:* Python 3.10, OpenCV library, MySQL database
- *Testing dataset:*
    - 25 registered users
    - 10 additional unregistered (unknown) users
    - Each user had~100 images captured under various conditions.

Recognition Performance

The system was tested using live real-time video. It demonstrated high accuracy in correctly identifying registered users and appropriately labeling unknown individuals (Table 1).

Sample Outputs

Figure 3 shows a live recognition frame where the student is correctly identified and attendance is marked.

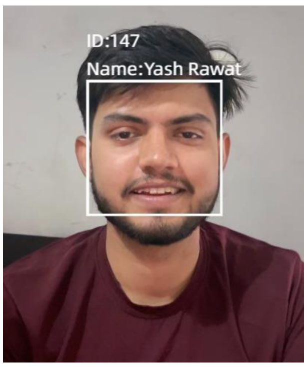

Figure 3. Real-time face recognition during attendance marking.

Table 1. Performance evaluation of the proposed system.

Metric	Result
Student recognition rate (registered)	92%
False positive rate (registered)	8%
Unknown person recognition rate	85%
False positive rate (unknown)	12%

Table 2. The attendance sheet was generated after successful recognition.

ID	Name	Department	Time	Date
48	Harsh Tongar	Computer Science and Engineering	11:23:54	08/04/2025
52	Hemant	Computer Science and Engineering	11:25:43	08/04/2025
147	Yash Rawat	Computer Science and Engineering	11:29:32	08/04/2025

A snapshot of the generated attendance report in CSV format (Table 2).

Analysis

- *Lighting conditions:* The system remained highly accurate under normal indoor lighting and slightly dim conditions but showed a minor drop (~5%) under very bright or low-light settings.
- *Facial accessories:* Students wearing spectacles or with facial hair (e.g., beard growth) were still recognized with minimal errors.
- *Unknown detection:* The system successfully separated unknown individuals, minimizing false entries through threshold tuning (confidence >50% was considered unrecognized).
- *Processing speed:* The system processed approximately 10–15 frames per second, which is adequate for real-time classroom or office applications.

CONCLUSION AND FUTURE WORK

The development of a face recognition-based attendance system using the LBPH algorithm addresses the critical challenges faced by traditional attendance methods, such as manual errors, proxy entries, and time inefficiencies. By integrating computer vision techniques with a real-time recognition engine and user-friendly interface, this system provides a reliable and contactless method for marking attendance.

Through practical testing, the system demonstrated strong performance under various lighting and facial appearance conditions, achieving consistent recognition accuracy without the need for high-end hardware. Its lightweight architecture makes it suitable for deployment in institutions with a limited technical infrastructure.

Overall, the project proved that a well-implemented facial recognition model can significantly enhance attendance management. This study lays a solid foundation for future upgrades, including cloud synchronization, mobile access, and security features such as liveness detection, further improving usability and scope in real-world environments.

Limitations

- Slight accuracy drop in extreme lighting conditions.
- Slight delay observed when processing multiple faces simultaneously.

Future Work

- Integrate deep-learning-based detection (e.g., DNN face detectors) to improve detection under complex conditions.
- Expand the dataset for larger class sizes.
- Introduce real-time notification alerts (e.g., SMS or email) when unknown individuals are detected.
- Implement cloud synchronization to manage attendance data securely over multiple branches.

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REFERENCES

1. Joseph J, Zacharia KP. Automatic attendance management system using face recognition. Int J Sci Eng Res. 2013;2(11):327–330.
2. Ononiwu GC, Okorafor GN. Radio frequency identification (RFID) based attendance system with automatic door unit. Acad Res Int. 2012 Mar;2(2):168–181.
3. Shoewu O, Idowu OA. Development of attendance management system using biometrics. Pac J Sci Technol. 2012;13(1):300–307.
4. Turk M, Pentland A. Eigenfaces for recognition. J Cogn Neurosci. 1991;3(1):71–86. doi:10.1162/jocn.1991.3.1.71.
5. Belhumeur PN, Hespanha JP, Kriegman DJ. Eigenfaces vs. fisherfaces: Recognition using class-specific linear projection. IEEE Trans Pattern Anal Mach Intell. 1997;19(7):711–720. doi:10.1109/34.598228.
6. Ahonen T, Hadid A, Pietikäinen M. Face description with local binary patterns: Application to face recognition. IEEE Trans Pattern Anal Mach Intell. 2006;28(12):2037–2041. doi:10.1109/TPAMI.2006.244.
7. Viola P, Jones MJ. Robust real-time face detection. Int J Comput Vis. 2004;57(2):137–154. doi:10.1023/B:VISI.0000013087.49260.fb.
8. Salton K. (2017). Face recognition: understanding LBPH algorithm. [Online] Medium. TDS Archive. Available from: https://medium.com/data-science/face-recognition-how-lbph-works-90ec258c3d6b
9. Dubey SR, Singh SK, Chaudhuri BB. Activation functions in deep learning: A comprehensive survey and benchmark. Neurocomputing. 2022;503:92–108. doi:10.1016/j.neucom.2022.06.111.
10. Ahmed A, Guo J, Ali F, Deeba F. LBPH based improved face recognition at low resolution. 2018 International Conference on Artificial Intelligence and Big Data (ICAIBD), Chengdu, China. 2018. p. 144–147. doi: 10.1109/ICAIBD.2018.8396183.
11. Ariffin NABM, Gimba UA, Musa A. Face detection based on Haar cascade and convolution neural network (CNN). J Adv Res Comput Appl. 2025;38(1):1–11.
12. Singhal N, Ganganwar V, Yadav M, Chauhan A, Jakhar M, Sharma K. Comparative study of machine learning and deep learning algorithm for face recognition. Jordanian J Comput Inf Technol. 2021;7:1. doi:10.5455/jjcit.71-1624859356.

