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A real-time intruder detection and notification system using the LBPH facial recognition method via the LINE application

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ABSTRACT

Face detection and recognition in images and videos is a widely studied topic in the field of biometrics, with increasing importance in security and surveillance applications. This paper presents the development of a real-time face recognition system designed to enhance security and automation. The system utilizes a Haar-cascade classifier for initial face detection and the Local Binary Pattern Histogram (LBPH) algorithm for face recognition, based on a locally generated training dataset. It operates in two main stages: detecting human faces and identifying individuals. In cases where an unrecognized face is detected, the system sends an immediate alert via the LINE application. Key components of the system include real-time processing, identity verification, and access control. The proposed system shows strong potential for practical deployment in areas such as crowd monitoring and personal security in sensitive environments like airports. Experimental results demonstrate a recognition accuracy ranging from 90% to 93.45%, validating the effectiveness of the approach.

Keywords: Real Time, LINE Alert, Face-Recognition, Image Processing, LBPH Bold.

1. INTRODUCTION

Facial recognition has emerged as a widely studied topic in recent years due to growing security demands and the rapid advancement of portable computing devices. It has proven to be highly effective across multiple applications, including access control, identity verification, security systems, surveillance, smartphone unlocking, and social media platforms. Access control use cases span offices, computers, mobile devices, ATMs, and more. However, most current implementations have yet to fully standardize facial recognition as a primary method for granting access. With advancements in computer vision and the development of robust algorithms, facial recognition is increasingly being considered as a potential replacement for traditional authentication methods such as passwords and fingerprint scanners. Manual attendance systems are time-consuming for both faculty and students. When attendance is taken manually, students often experience delays, and such methods are prone to human error and inefficiency. These drawbacks can lead to administrative overhead and decreased productivity. Since facial recognition is a natural and universally understood method of identification, automating the attendance process can significantly enhance accuracy and operational efficiency.

Human Face Recognition (HFR) is a well-established biometric authentication technique used primarily for identity verification. It plays a key role in applications such as video surveillance, human-computer interaction, door access control, and network security. For instance, some studies have proposed automated classroom attendance systems using Discrete Wavelet Transform (DWT) and Discrete Cosine Transform (DCT) to extract facial features, followed by classification using a Radial Basis Function (RBF) neural network.

In this paper, we present a real-time face recognition system running on a PC equipped with a built-in webcam. Facial images are captured by the webcam and detected using Haar Cascade classifiers. The system creates a dataset with ID-labeled images, and face recognition is performed using pre-trained data via Local Binary Patterns (LBP) classification. Upon successful identification, attendance records are generated and stored. The proposed system includes a camera that transmits captured images to a Raspberry Pi, which is programmed to execute face recognition using the LBP algorithm. If a student's image matches an entry in the trained dataset (e.g., a master door access image), a servo motor is triggered to open the door. Attendance results are stored in a MySQL database connected to the Attendance Management System (AMS), allowing real-time access to attendance data through a web interface. In this system, face detection is implemented using the Viola-Jones algorithm, while feature extraction is performed using the Local Binary Pattern Histogram (LBPH) method. Final classification is carried out using a Euclidean distance classifier. The overall process includes dataset creation, face capture, feature extraction, and classification—all implemented using OpenCV in Python.

2. RELATED WORK

In 2018, Ahmed, Aftab, et al. [1] designed an improved face recognition system based on Local Binary Pattern Histogram (LBPH) for low-resolution images, titled "LBPH-Based Improved Face Recognition at Low Resolution." While automatic face recognition has been a longstanding challenge in computer vision, law enforcement agencies still struggle to effectively identify individuals via video surveillance. Factors such as blurriness, poor lighting, low resolution, and exposure significantly affect accuracy. The proposed system in their study performed effectively even at a minimum resolution of 35 pixels, enabling recognition from various angles, including side profiles, and allowing for continuous face tracking during motion. Also in 2018, Yohanes, Banu Wirawan, Reva Diaz Airlangga, and Iwan Setyawan [14] introduced a study titled "Real-Time Face Recognition Comparison Using Fisherfaces and Local Binary Pattern." This research compares two popular methods: Fisherfaces, which enhances the traditional Eigenfaces approach through Fisher's Linear Discriminant for improved classification accuracy, and LBP, which relies on local pixel neighborhood textures. Both algorithms were tested across three different datasets and in real-time video applications. Their performance was evaluated based on accuracy, training time, and testing time using a k-fold cross-validation technique. In 2020, Ahsan, Md. Manjurul, et al. [2] presented a study titled "Face Recognition in an Unconstrained and Real-Time Environment Using Novel BMC-LBPH Methods Incorporating DJI Vision Sensor." This research addressed the problem of face recognition under challenging conditions such as low lighting, varying illumination, and adverse weather. Although algorithms like Eigenfaces, Fisherfaces, and LBPH

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have been tested in such environments, LBPH demonstrated the highest robustness. However, the study noted that detailed analysis is lacking regarding the optimal configuration of LBPH's four key parameters—radius, neighbors, grid size, and threshold—for balancing accuracy and computational efficiency. In 2022, Chen, Yeong-Chin, et al. [3] proposed "An Enhanced LBPH Approach to Ambient-Light-Affected Face Recognition Data in Sensor Networks." The study emphasized the importance of algorithms that can maintain facial recognition accuracy despite fluctuations in lighting. It compared LBPH with OpenFace, a deep learning-based model, by measuring performance in terms of accuracy and error rates under different lighting conditions. Most recently, in 2024, Shukla, Ratnesh Kumar, Arvind Kumar Tiwari, and Ashish Ranjan Mishra [11] introduced a hybrid approach titled "Face Recognition Using LBPH and CNN." Their method combines LBPH with Convolutional Neural Networks (CNN) for enhanced preprocessing and histogram balancing. The study found that as the number of training epochs increases, the model's feature extraction improves significantly, with vector-based similarity comparison delivering the highest accuracy.

3. THE PROPOSED METHOD

The LINE application, utilizing facial recognition through the Local Binary Patterns Histogram (LBPH) method with a webcam device, consists of four main components:

1. Face Detection Module: Captures facial images using a webcam and stores them as training data. The Local Binary Patterns Histogram (LBPH) algorithm is used to extract relevant features during this process.

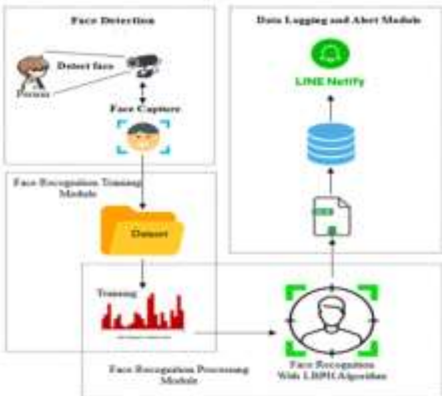

FIGURE 1. The Proposed Methods Diagram.

2. Face Recognition Training Module: Trains the system to recognize faces using the collected data. An LBP cascade classifier is employed to extract and differentiate facial features for use in the recognition process.
3. Face Recognition Processing Module: Detects and compares faces from input images with the trained dataset to identify individuals. Unrecognized faces are flagged for further processing.

4. Data Logging and Alert Module: Stores unrecognized facial images in a MySQL database for future review, logs all detected faces in an Excel file, and sends an alert via the LINE application when an unknown face is detected.

3.1 OBJECTIVE OF THE STUDY

The Local Binary Patterns Histogram (LBPH) is a simple yet effective algorithm used for labeling pixels in an image based on their local texture. It operates by comparing each pixel to its surrounding neighbors and encoding the result as a binary pattern. These binary values are then converted into decimal values, which collectively form a histogram that describes the local features of the image. Unlike global feature-based methods, LBPH emphasizes local texture information, making it particularly suitable for distinguishing fine-grained facial characteristics. One of the key advantages of LBPH is its robustness to variations in lighting, making it a reliable approach for facial recognition in diverse environmental conditions.

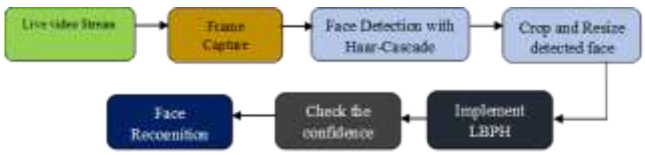

Figure 2. Steps of Real Time Facial Recognition.

Figure 2 illustrates the workflow of the LBPH algorithm, where a 3×3 sliding window is used to scan the entire image. At each position, the center pixel is compared with its eight neighboring pixels. A threshold is determined by the intensity value of the center pixel. Each neighboring pixel is then assigned a binary value: 1 if its intensity is greater than or equal to the center pixel, or 0 if it is lower. These binary values are read in a specified order—typically clockwise—to form a binary pattern, such as 001111110. This binary pattern is then converted into a decimal value, which represents the local texture of that region. A more detailed visualization of this process is shown in Figure 3.

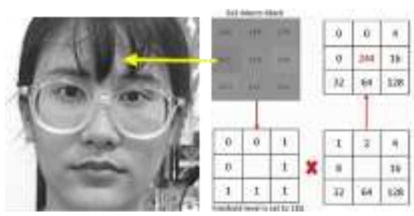

Figure 3. Block Representation of Image Thresholding in LBPH.

The Local Binary Patterns Histogram (LBPH) operator is designed to capture the contrast between a central pixel and its surrounding neighbors. Operating within a 3×3 window, it uses the intensity of the center pixel as a threshold. Each of the eight neighboring pixels is compared to this threshold: if the neighbor's intensity is greater than or equal to that of the center pixel, it is assigned a value of 1; otherwise, it is

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assigned 0. This comparison generates a binary pattern that encodes the local texture information. The transformation is defined mathematically in Equation (1).

$$s(x) = \begin{cases} 1, x \geq 0 \\ 0, x < 0 \end{cases} \quad (1)$$

3.2 LINE NOTIFY PROCESS

Notifications via the LINE application are triggered when individuals are detected in the computer room outside of scheduled class hours. The process begins with a motion sensor that detects movement, followed by a camera that captures an image of the detected user. An alert is then immediately sent to the administrator’s mobile device via the LINE application.

This alert mechanism is implemented using the LINE Notify service, which allows notifications to be sent exclusively to registered accounts or users who have subscribed to the service. Notifications cannot be delivered to unregistered chat rooms or general LINE groups. To enable this functionality, an API request must first be registered with LINE, which then issues a unique Access Token. This token, generated only once per registration, serves as the authentication key for sending messages via the LINE API. The token is embedded into the system’s source code and configured to operate on a Raspberry Pi board, ensuring that alert messages are transmitted correctly and securely.

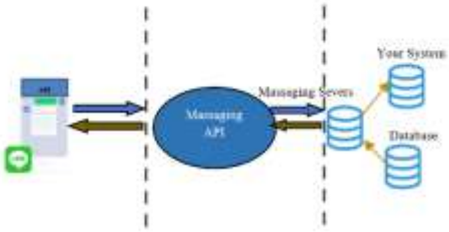

FIGURE 4. Line Notify Process.

3.3 PERFORMANCE CALCULATION

Numerous performance evaluation metrics for image classification have been explored in previous studies [25, 26]. To evaluate the effectiveness of the classifiers in identifying skin conditions, we employed Equations (2)–(5). In these equations:

$$Accurancy = \frac{True\ Positive + True\ Negative}{Total\ Number\ of\ images} \times 100\% \quad (2)$$

$$Precision = \left(\frac{TP}{TP + FP}\right) \times 100\% \quad (3)$$

$$F1\ Score = \left(2 \times \frac{Precision \times Recall}{Precision + Recall}\right) \times 100\% \quad (4)$$

$$Recall = \frac{TP}{(TP + FN)} \times 100\% \tag{5}$$

Where TP represents true positives, FP denotes false positives, TN refers to true negatives, and FN stands for false negatives.

4. RESULTS AND DISCUSSION

In this study, the model was trained using individual images of each subject. Two datasets were employed. The first dataset was created using a laptop camera by recording videos of individuals facing various directions. From these videos, facial regions were detected, and frames were extracted—resulting in approximately 500 images per class. Each image was resized to 50×50 pixels to meet computational constraints. The second dataset used was the publicly available ORL face dataset.

The system was implemented on a machine equipped with an Intel® Core™ i5-10210U quad-core CPU, 8 GB of RAM, and a 1-megapixel camera. Development was carried out using PyCharm as the integrated development environment, with the Django framework employed to build a web-based application that includes an interactive user interface. Furthermore, the web application can be embedded into Microsoft Teams channels to facilitate automated attendance tracking.

Accuracy testing was conducted by comparing face recognition performance across different image scales—specifically 70%, 60%, and less than 50% of the original image size (see Table 1). The results indicate that the LBPH face recognition algorithm achieves higher accuracy when facial regions occupy approximately 70% of the total image size. This is attributed to the increased visibility of distinctive facial features in larger face regions, which enhances the system's ability to recognize and differentiate individuals accurately. In contrast, recognition performance declined when the facial region was reduced to 60% or below, due to the loss of finer feature details necessary for precise classification.

4.1. PERFORMANCE TESTING OF FACE RECOGNITION USING THE LBPH ALGORITHM

The performance of face recognition was evaluated using the Local Binary Patterns Histogram (LBPH) algorithm implemented in OpenCV. For face detection, the LBP Cascade classifier was used, while recognition was carried out by loading a pre-trained model from the trainer.yml file. The image analysis function processes selected images by detecting faces, identifying individuals, and reporting both the recognition confidence and the average accuracy for each recognized face. Upon completion, the system summarizes the number of correctly recognized and unrecognized images.

Using a dataset containing 300 diverse images per individual, the system achieved strong results (see Table 2), with an average recognition rate of 93.45%. In repeated testing (10 iterations), the system maintained a consistent classification accuracy of 90.0%, correctly matching names with detected faces.

Despite the overall robustness, certain misclassifications highlight areas for further refinement. The LBPH algorithm classifies faces by encoding pixel neighborhoods into binary patterns, generating histograms across facial regions, and comparing them against stored templates. High classification accuracy indicates strong visual

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similarity between known and detected faces, contributing to precise identification results (see Table 3).

In Figure 5, part (A) illustrates a chart comparing recognition rates relative to the number of individuals in the dataset, serving as an indicator of overall system performance. Part (B) demonstrates that the proposed LBPH algorithm achieves higher recognition accuracy and confidence levels compared to alternative algorithms. While other algorithms lack the same level of precision and confidence in their outputs, LBPH was selected due to its consistently superior performance across various test conditions.

TABLE 1.
The Comparison of The Accuracy of Human Faces when Image Sizes are Different.

Face detection test image	**Size of the face in the image**	**Accuracy**
	70%	66.28%
	60%	53.35%
	<50%	20.23%

Table 2.
The Face Recognition Accuracy Results using LBPH Algorithm.

Dataset	**Image data 300 images**		**Accuracy**
Image 1	300	0	89.33 %
Image 2	150	150	92.11 %
Image 3	56	244	96.72 %
Image 4	120	180	95.52 %
Image 5	80	220	97.21 %
Image 6	250	50	88.22%
Image 7	150	150	93.37%
Image 8	50	250	97.55%
Image 9	200	100	87.67%
Image 10	70	230	96.86%

Table 3
The Face Classification Results of Face Recognition using LBPH Algorithm.

Times	**Person 1**	**Person 2**	**Person 3**	**Person 4**	**Person 5**	**Person 6**	**Person 7**	**Person 8**	**Person 9**	**Person 10**
1	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes
2	Yes	Yes	Yes	Yes	No	No	Yes	Yes	Yes	Yes
3	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
4	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes
5	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes
6	Yes	Yes	Yes	Yes	No	No	Yes	Yes	Yes	Yes
7	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
8	Yes	Yes	Yes	Yes	No	No	Yes	Yes	Yes	Yes
9	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
10	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes
Accuracy	100 %	100 %	100 %	100 %	50 %	70 %	80 %	100 %	100 %	100 %
Average accuracy = 90.0 %										

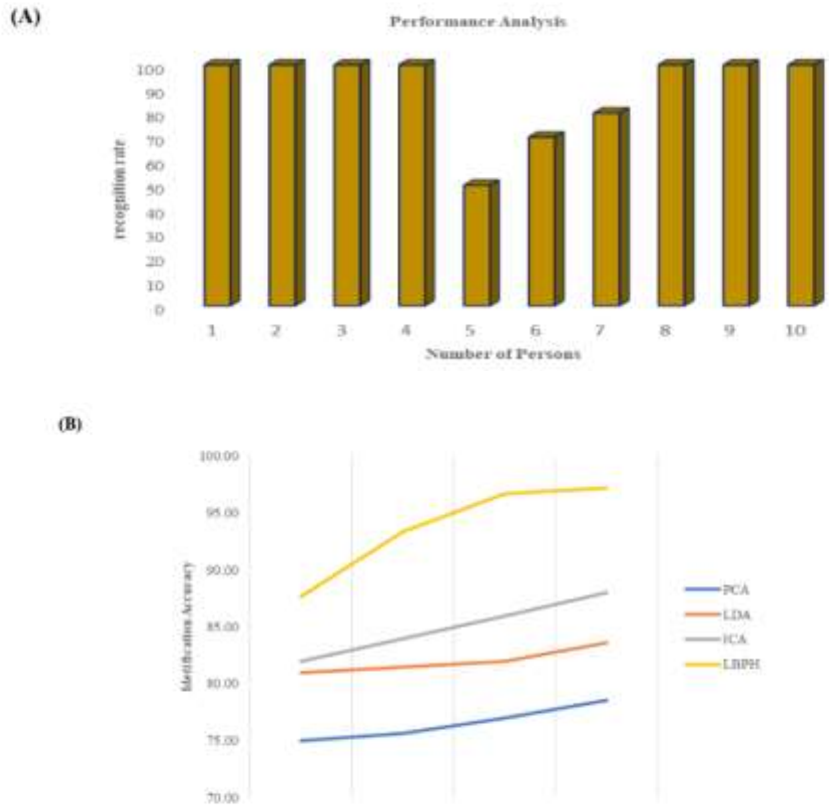

FIGURE 5. (A) Recognition rate vs. number of individuals chart, (B) Comparison chart of different algorithms.

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4.2 NOTIFICATION TESTING

The notification system integrated into the developed face detection program was tested for its effectiveness in identifying and classifying faces. The system employs the Haar Cascade method for face detection and Local Binary Patterns Histograms (LBPH) for facial recognition, enabling it to distinguish between known and unknown individuals. When an unknown face is detected, the system automatically sends an alert via LINE Notify, including both a text message and an image of the detected face with a timestamp. This allows the administrator to be promptly informed of any unauthorized presence.

The criterion for labeling a person as "Unknown" is based on the confidence value produced by the LBPH classifier. Specifically, if the confidence score exceeds 70 (noting that in LBPH, lower values indicate higher certainty), the individual is classified as unknown. The system presents this information in a user-friendly format, as illustrated in Figure 6. Testing confirmed that the system functions as intended: upon detecting an unknown face, it successfully sends an alert through LINE Notify along with the captured image. This makes the system well-suited for real-time monitoring and tracking in security applications.

FIGURE 6. Notification message via LINE Notify

5. CONCLUSION AND FUTURE SCOPE

In this paper, face detection is performed using established algorithms, specifically employing the Haar Cascade method for detecting faces and Local Binary Patterns Histogram (LBPH) for feature extraction. Classification is carried out using the Euclidean distance classifier, and alerts are sent via LINE Notify. The system is developed using OpenCV and Anaconda.

Based on the results illustrated in the graph, the combination of LBPH and the Euclidean distance classifier yields superior recognition performance, achieving an accuracy rate between 90% and 93.45%. These findings highlight the effectiveness of the proposed approach under various conditions.

The system has been tested and adapted to accommodate diverse challenges such as variations in lighting, the presence of eyeglasses or beards, and even identical twins, using a minimum distance classifier. Additionally, it has been fine-tuned to account for genetic traits and facial expression variations, enhancing its adaptability to dynamic environments and different security requirements.

The proposed system demonstrates strong potential for applications such as securing sensitive government databases and criminal identification. Future work will focus on improving overall accuracy and extending system capabilities to handle a broader range of facial expressions, environmental conditions, and demographic diversity.

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AUTHORS' CONTRIBUTIONS

Author 1 conducted the literature review, devised the study plan, performed the data analysis, and drafted the initial version of the manuscript. Author 2 contributed to protocol development and data analysis. All authors reviewed, revised, and approved the final version of the manuscript.

CONFLICT OF INTEREST

This unique manuscript is not under consideration for publication elsewhere and has not been previously disseminated. The authors declare no conflicts of interest.

DATA AVAILABILITY

All data were gathered from simulation reports generated by the authors' program and tools. The authors are currently working on extending the study using real-world data, pending appropriate permissions

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