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A Multi-Camera Automated Attendance System Using LBPH-Based Face Recognition

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Abstract

This study presents the development and evaluation of a Multi-Camera Automated Attendance System employing Local Binary Patterns Histograms (LBPH) for face recognition. Traditional single-camera solutions struggle in large classrooms with occlusion, lighting variability, and limited viewpoints. All these challenges are addressed by the Multi-Camera Automated Attendance System Using LBPH-Based Face Recognition (MCAAS-LBPH). This system integrates three IP cameras with LBPH and Haar Cascade Classifier algorithms to achieve real-time, accurate student identification. It provides daily reporting and stores attendance in Comma Separated Value (CSV) format for quick conversion to Excel or PDF.

Keywords: *Face detection, Feature Extraction, Face Recognition, LBPH, Haar Cascade algorithms, Python, OpenCV, IP Camera*

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1. Introduction

With the rise of digital integration, automatic attendance monitoring has become a vital component across various sectors, including education, corporate environments, and security-sensitive fields. Recent attendance systems, often reliant on manual entry or single-camera facial recognition, encounter challenges such as occlusions, varying lighting conditions, and inconsistencies in facial orientation. These limitations underscore the necessity for multi-camera-based face recognition systems to enhance accuracy and reliability for real-time attendance verification.

This paper explores the development of a multi-camera face recognition attendance system that employs Local Binary Patterns Histograms (LBPH)—an established algorithm known for its resilience to environmental variations and computational speed. By strategically positioning three cameras in the classroom, one in front and two on the sides. The system captures several angles of an individual's face, thereby enhancing recognition accuracy and minimizing errors caused by occlusions or unfavorable angles. Furthermore, the approach utilizes both decision-level fusion and feature-level fusion, allowing the system to consolidate data from multiple views to reinforce identification reliability.

One of the key benefits of applying LBPH compared to holistic methods like Eigenfaces is that it can identify local texture patterns, making it well-suited for real-world applications where facial variations in expression and lighting are common. Secondly, compared to deep learning-based systems such as Convolutional Neural Networks (CNNs), which require extensive training, synchronization, and complex resource management, LBPH offers a lightweight alternative that significantly reduces development time while maintaining reliable performance. Leveraging OpenCV's strong framework, the implementation makes development simpler while maintaining flexibility across environments.

2. Literature Review

2.1 Brief Statistics of the Face Recognition System

Facial recognition is highlighted as one of the top three biometric methods for identifying individuals by analyzing aspects of their physiology or anatomy. The global facial recognition market size is estimated at USD 7.68 billion in 2025 and is expected to reach USD 16.27 billion by 2030, at a CAGR of 16.2% during the forecast period 2025-2030 (https://www.mordorintelligence.com/industry-reports/facial-recognition-market) (Intelligence, 2025). This rapid growth is due to the technology's versatility in commercial applications and its ease of setup, making it useful for purposes ranging from surveillance to targeted advertising.

2.2 Related Work

Rakshe et al. (2023) developed a deep learning-based attendance system that utilized multi-face recognition for better accuracy and efficiency in attendance marking. The system utilizes VGG16 in a Siamese network architecture with a triplet loss function, enabling the real-time detection of multiple individuals without the requirement for sequential scanning. Developed to be contactless and efficient with a particular application in post-pandemic situations, the system applies one-shot learning methods to function efficiently with small datasets. Built on the Flask framework alongside SQL Alchemy for database incorporation, the system was found to be very accurate with a variety of CNN models. The authors indicated a limitation in the recognition of occluded faces, highlighting possible avenues for future optimization.

Haldar et al. (2023) propose a technology-based attendance automation framework based on the use of multiple face detection and recognition approaches. This new system seeks to rectify the flaws found in traditional attendance record-keeping by taking advantage of live video streams obtained with strategically placed cameras, which are processed with the aid of computer vision and deep learning algorithms like Haar cascades and convolutional neural networks (CNN). By matching the detected facial features with pre-established templates, the system promises effective, fast, and secure recording of attendance. Key advantages include minimizing the administrative burden, giving real-time feedback, error reduction, and increased ability to prevent identity forgery. The authors mention the system's real-time processing and scalability features, making it suitable for use in schools and professional setups where tracking attendance for large groups is critical.

Raj and Vadivel (2023) presented an economically feasible, cloud-based attendance system using facial recognition technology, built with Python, OpenCV, and Dlib, for real-time facial detection and identification. This novel system overcomes the challenges of conventional manual attendance systems by using the Python library, face recognition, for automatic detection of students and marking their attendance. Upon successful facial identification, the system records attendance data in both a local CSV file and a Google Sheet through the Google Sheets API, thereby enabling combined cloud and local storage without incurring the usual expenses of commercial services. The authors highlight the system's remarkable accuracy,

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evidenced by a 99.38% recognition rate on the Labeled Faces in the Wild benchmark as evaluated by Dlib, and its economic feasibility and ease of use for institutions. This method improves the operational efficiency of administrators, minimizes the possibility of user errors, and supports real-time attendance tracking and reporting through an integrated interface. Overall, this method presents a scalable and feasible improvement over existing systems, especially for small organizations with limited infrastructural capabilities.

Kolaki et al. (2022) proposed a smart attendance system utilizing a multiple face detection technique to automate the process of student attendance recording in schools. The system applies the Haar Cascade Classifier for face detection and the Local Binary Pattern Histogram (LBPH) algorithm for the identification of faces, leveraging the aid of OpenCV for real-time computer vision capabilities. Included in the proposed methodology are the preprocessing of images, conversion of images into grayscale, detection of faces through Haar features, and identification of faces by matching extracted features with those in a pre-trained database through LBPH. The authors claim this methodology demonstrates greater precision, lesser error susceptibility, and increased efficiency over traditional attendance systems. Empirical evidence showed the effective implementation of login operations, student enrollment, training sessions, and the taking of attendance with the aid of a user interface, with the attendance details stored effectively in an Excel file. One of the most important features of the proposed system is the identification of multiple faces, thus qualifying it as a valuable classroom implementation option.

3. Proposed System and Novel Contributions

The proposed attendance system is developed as a standalone solution that runs entirely on a local computer, ensuring ease of deployment and operation without external dependencies. The main innovation lies in the use of a multi-camera setup, with a uniquely placed set of three IP cameras, one facing the front of the class and two placed side-by-side, used for facial capture from multiple angles. This setup significantly improves recognition accuracy by minimizing occlusion and maximizing facial feature visibility.

Additionally, the system combines feature-level and decision-level fusion, a rare integration within non-deep learning-based systems. In the feature-level fusion approach, features extracted using the Local Binary Pattern Histogram (LBPH) are extracted from images captured using all cameras and combined into a single descriptor during training. This combined representation provides increased reliability of recognition under different viewing angles. At the same time, decision-level fusion is achieved during real-time attendance monitoring through the application of a voting scheme or confidence-based evaluation of the output of each individual recognizer, further increasing the system's tolerance to errors in recognition or occurrences of false positives.

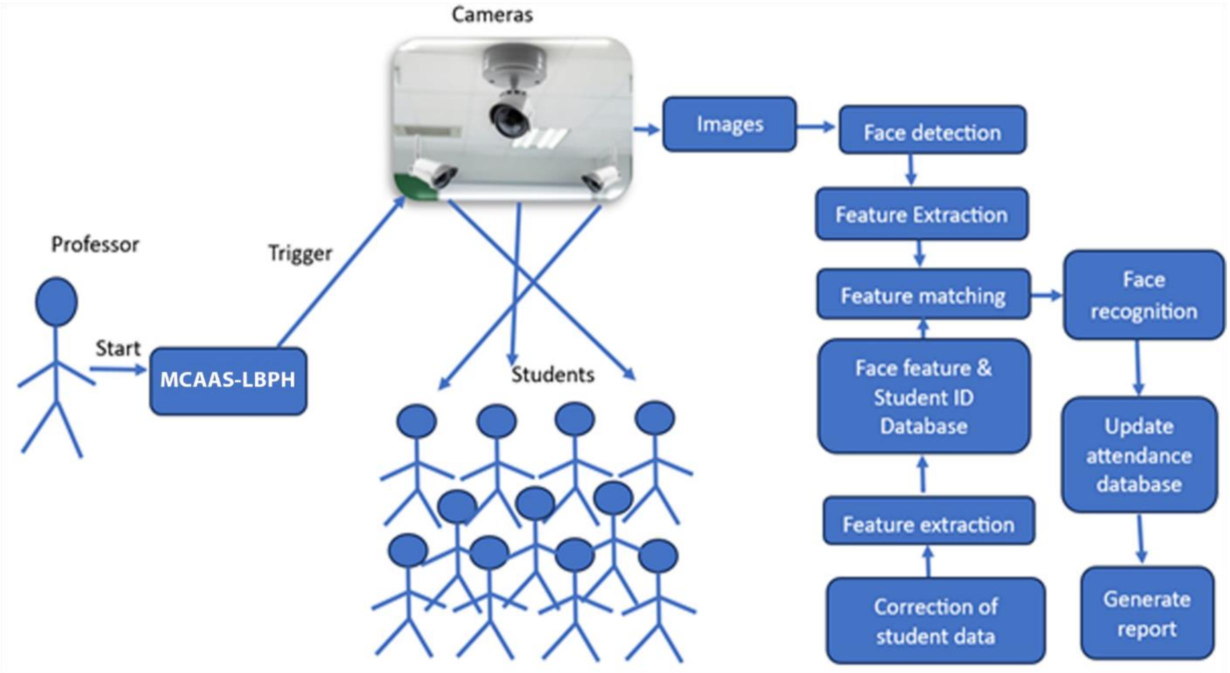

Figure 1: System design of MCAAS-LBPH

Unlike deep neural network-based approaches, the method introduced here achieves real-time performance through the use of computationally efficient algorithms, namely LBPH and Haar Cascade classifiers. These make it especially suitable for resource-constrained environments where GPU-accelerated computing is not a viable option.

The system features operational features that greatly enhance the user experience, such as automated generation of CSV reports. These features successfully bridge the gap between the development of prototypes and real-world use, providing a complete and effective attendance tracking system with scalability and cost savings for schools.

4. Methodology

4.1 Feature-Level and Decision-Level Fusion

a. Feature-Level Fusion (During Training Phase)

A series of facial images is captured from different angles (left, middle, right) for every student through the use of three cameras.

Each image is processed by LBPH, which extracts a feature vector (a histogram representing facial textures).

In feature-level fusion, these multiple feature vectors are combined or compiled into a single comprehensive image for each student.

b. Decision-Level Fusion (During the Recognition/Testing Phase)

Each camera captures a face and runs LBPH-based recognition independently.

This generates an expected identifier (student ID and name), and a confidence score indicates how close the match is.

During decision-level fusion, the three camera outputs are combined using logical operations like:

Majority voting: If 2 out of 3 cameras predict the same student ID, it is accepted.

Weighted voting: More confident predictions are given more influence.

Thresholding: Accepting a match only when confidence values drop below a given threshold, indicating a high similarity.

4.2 Research methodology

Development of the Multi-Camera Automated Attendance System Using LBPH-Based Face Recognition (MCAAS-LBPH) followed the Waterfall Software Development Model, with its methodical and linear approach to following through with the different steps of system requirement analysis, design, implementation, testing, deployment, and maintenance. The choice of the Waterfall model mainly followed because of its benefits in documentation, sequential process, and quality assurance in the context of a controlled project environment.

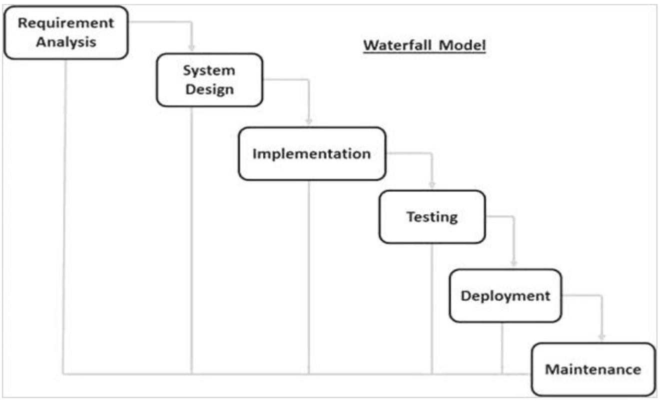

Figure 1: Waterfall model steps

4.3 Data Collection Methods

Primary Data

• Observation: The prototype system was implemented in a school environment. It was evaluated based on its operational effectiveness, user interaction, camera placement, and response times.

• System Testing: Real-time performance indicators, such as face detection rate, recognition accuracy, and time for attendance recording, were recorded under various environmental conditions.

Secondary Data

A thorough review of the literature was conducted, including previous systems of student attendance, facial recognition technology, and biometric applications in schools. The sources examined included academic journals, conference papers, and established technology-oriented publications.

4.4 System Architecture and Design

As shown in Figure 1, the system consists of three core elements:

1. The Image Capture Module uses three IP cameras placed at different angles in a classroom environment to capture the faces of students simultaneously.

2. Face Detection and Recognition Module uses the Haar Cascade Classifier for initial detection of faces and uses Local Binary Patterns Histograms (LBPH) for recognition.

3. The Attendance Management Module systematically stores known faces in a secure database, and creates CSV file logs.

System design conceptualization was done by using Data Flow Diagrams (DFD) to map the processes' paths, whereas the overall system implementation was done in Python using OpenCV with the support of a relational database (MySQL or SQLite) for storing attendance records.

4.5 Tools and Technologies

Python: A Core programming language for backend logic and model integration.

Tkinter: User Interface development.

OpenCV: For face detection, feature extraction, and recognition.

Haar Cascade Classifier: Used for the detection of objects to instantly recognize faces.

LBPH: Selected due to its efficiency and robustness in conducting facial recognition under changing lighting conditions.

Visual Studio Code: Used as the code editor.

IP Cameras: For time-lapse, multi-angle picture capture

Database: MySQL or SQLite to store student profiles, attendance logs, and reports.

4.6. System Implementation Procedure

1. Student Registration: Admin registers students and assigns unique IDs.

2. Image Capture: Cameras capture images of students' faces during registration.

3. Training Stage: The model is trained using the LBPH method with many face images of each student.

4. Real-Time Detection: During the sessions, the system detects faces using Haar Cascade and then recognizes them using LBPH.

5. Attendance Documentation: Recognized students are marked as present, and their information is stored in the database.

6. Generation of Reports: Attendance summaries are generated and kept in CSV form.

4.7. Evaluation Standards

Although the system was tested with a sample of 50 students, only one participant's photograph is included in this paper, by prior consent, to respect privacy and institutional data-sharing agreements. 10 images per student were gathered, including slight differences in the posture and expression to ensure better recognition. All the images were grouped under a single directory with filenames following the order of the student ID (e.g., User.1.1.jpg), thereby easing labeling and the ensuing training of the LBPH face recognizer from the dataset.

"Local Binary Patterns Histogram (LBPH) functionality:

- Suppose we have an image having dimensions N x M.
- We divide it into regions of the same height and width, resulting in an m x m dimension for every region.

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Figure 2: LBPH demonstration

- A local binary operator is used for every region. The LBP operator is defined in a window of 3x3.

$$LBP(X_{C,}Y_C) = \sum_{p=0}^{p-1} 2^p\, s(i_p - i_c) \qquad (1)$$

Here '(Xc, Yc)' is the central pixel with intensity 'Ic'. And 'In' being the intensity of the neighbor pixel.

- Using the median pixel value as a threshold, it compares a pixel to its 8 closest pixels using this function.

$$s(x) = \begin{cases} 1, x \geq 0 \\ 0, x < 0 \end{cases} \qquad (2)$$

- If the value of the neighbor is greater than or equal to the central value, it is set as 1; otherwise, it is set as 0.
- Thus, we obtain a total of 8 binary values from the 8 neighbors.
- After combining these values, we get an 8-bit binary number, which is translated to a decimal number for our convenience.
- This decimal number is called the pixel LBP value, and its range is 0-255.

Table 1*:* Local Binary Pattern Operator

1	2	2
9	5	6
5	3	1

Threshold

	0	0
1		1
1	0	0

Binary: 00010011

- Later, it was noted that a fixed neighborhood fails to encode details varying in scale. The algorithm was improved to use different numbers of radius and neighbors, now it was now known as circular LBP.

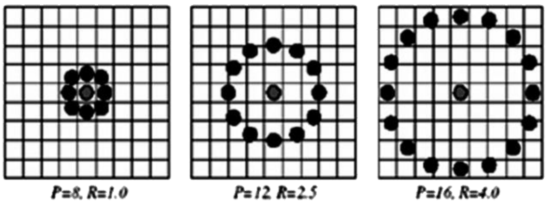

Figure 3: Circular LBP

- The idea here is to align an arbitrary number of neighbors on a circle with a variable radius. This way, the following neighborhoods are captured:

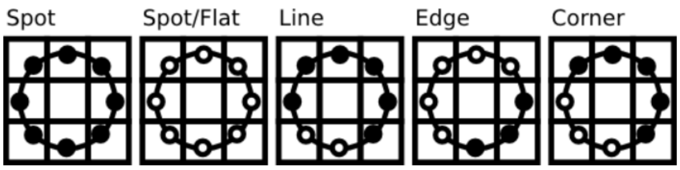

Figure 4: Circular with a variable radius

- For a given point (Xc, Yc), the position of the neighbor (Xp, Yp), p belonging to P, can be calculated by:

$$x_p = x_c + R\cos\left(\frac{2\pi p}{p}\right) \tag{3}$$

$$y_p = y_c - R\sin\left(\frac{2\pi p}{p}\right) \tag{4}$$

Here, R is the radius of the circle, and P is the number of sample points.

- If a point coordinate on the circle doesn't correspond to image coordinates, it gets interpolated generally by bilinear interpolation:

$$f(x,y) \approx \begin{bmatrix} 1-x & x \end{bmatrix} \begin{bmatrix} f(0,0) & f(0,1) \\ f(1,0) & f(1,1) \end{bmatrix} \begin{bmatrix} 1-y \\ y \end{bmatrix} \tag{5}$$

- The LBP operator is robust against monotonic gray scale transformations.

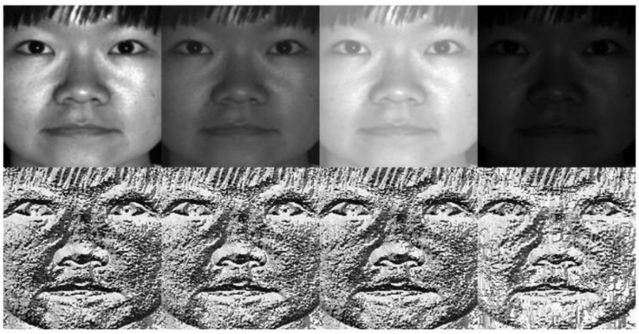

Figure 5: **LBP operator result**

- After the generation of the LBP value histogram of the region is created by counting the number of similar LBP values in the region.
- After the creation of a histogram for each region, all the histograms are merged to form a single histogram, and this is known as the feature vector of the image.

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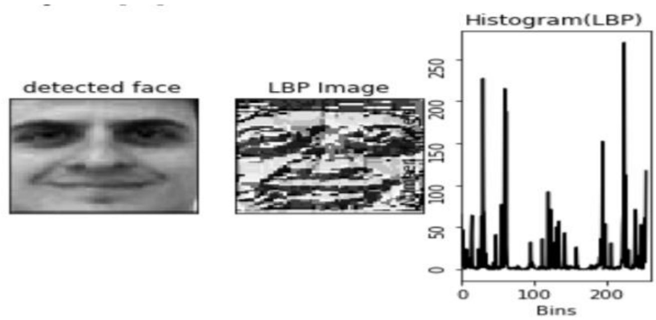

Figure 6: Feature vector of the image

- Now we compare the histograms of the test image and the images in the database, and then we return the image with the closest histogram.

(This can be done using many techniques like Euclidean distance, chi-square, absolute value, etc)

- The Euclidean distance is calculated by comparing the test image features with features stored in the dataset. The minimum distance between the test and original image gives the matching rate.

$$d(a,b) = \sqrt{\sum_{i=1}^{n} |a_i - b_i|^2} \tag{6}$$

- As an output, we get an ID of the image from the database if the test image is recognized." (Saini, 2024).

5. Results

The system was evaluated in a real-classroom setting, involving a group of 50 participants, to test its effectiveness in the detection, recognition, and marking of attendance using face images. Images were taken by using three strategically mounted IP cameras placed at the front, left, and right sides of the room. Both feature-level and decision-level fusion schemes were used by the system, which was able to achieve accurate recognition regardless of changes in the position of the head and lighting conditions. On average, the whole attendance process, including image acquisition, real-time recognition, decision fusion, and CSV file, took around 3 to 6 minutes for all participants. With regard to the participants' privacy, this report releases one participant's subject face image, taken under prior consent, while keeping the other participants' dataset confidential.

Login

Admin and Lecturer have the same login interface; they differ in their credentials according to their role registered in the database.

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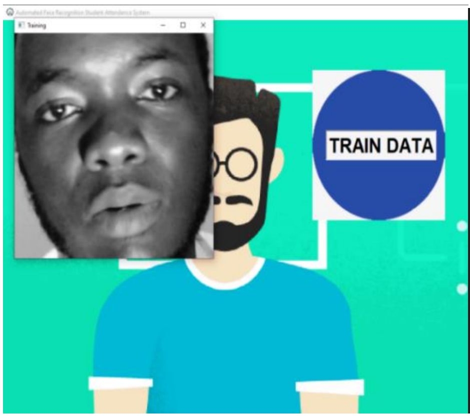
Figure 7: Login interface

Train data

The system is capable of training all faces simultaneously with high accuracy in a few seconds. Below is a screenshot and sample code.




```python
def train_classifier(self):
    data_dir=("data")
    path=[os.path.join(data_dir,file) for file in os.listdir(data_dir)]

    faces=[]
    ids=[]

    for image in path:
        img=Image.open(image).convert('L') #Gray scale image
        imageNp=np.array(img,'uint8')
        id=int(os.path.split(image)[1].split('.')[1])

        faces.append(imageNp)
        ids.append(id)
        cv2.imshow("Training",imageNp)
        cv2.waitKey(1)==13
    ids=np.array(ids)

    #****************** Train the classifier and save ****************

    clf=cv2.face.LBPHFaceRecognizer_create()
    clf.train(faces,ids)
    clf.write("classifier.xml")
    cv2.destroyAllWindows()
    messagebox.showinfo("Result","Training datasets completed!")
```

Figure 8: **Dataset model training**

Face detection

While the cameras capture an unregistered student, they will show an **"unknown face"** highlighted by a red rectangle around the face.

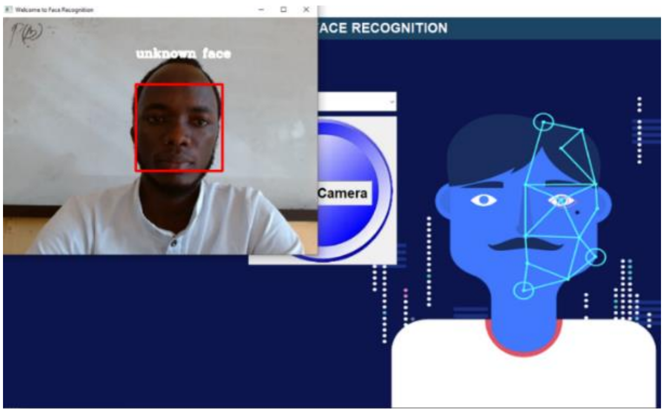


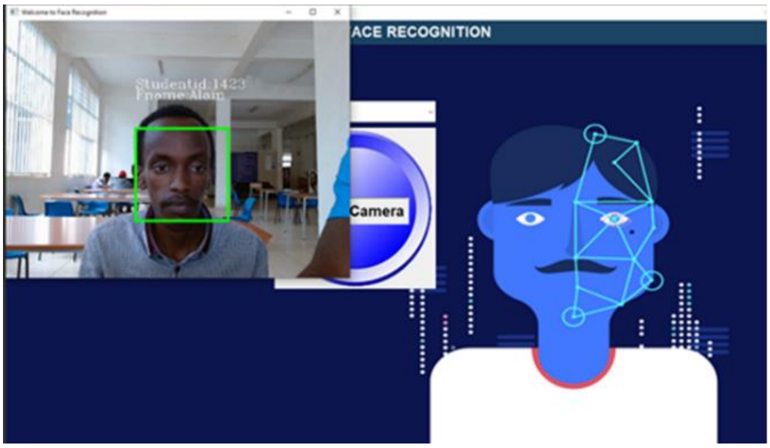
Figure 9: Unregistered student

The Lecturer starts the system and records attendance while students are present in the classroom, with immediate feedback to the system administrators. The attendance was stored safely in a relational database for analysis and retrieval.

The system generated detailed attendance reports, including daily, weekly, and monthly summaries, and attendance trends student-wise. The reports were displayed through the admin interface on demand.

Attendance Marking

When the face is recognized, it shows the basic student information with a green rectangle. The system takes attendance automatically and saves it in the database as well as in a CSV file, which can be printed as a PDF.



6. Conclusion

The Multi-Camera Automated Attendance System Based on LBPH Face Recognition (MCAAS-LBPH) is an effective way to enhance how student attendance is taken in schools. Three strategically positioned cameras capture facial images from multiple angles. It effectively handles challenges such as occluded faces and varying head orientations. The system is accurate and well-suited to be operated in real time through feature fusion and options.

It operates as an independent desktop application without the necessity of external servers or high-end hardware, which is convenient for institutions such as schools that have fewer resources to spend on hardware. Overall, MCAAS-LBPH offers an effective, privacy-preserving, and cost-efficient approach to attendance management, and it can be further enhanced by integration with cloud services, mobile devices, or deep learning systems.

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