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# Face Recognition-Based Attendance System

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## ABSTRACT

***This research paper is about the creation of a program for attendance marking using face recognition, which takes the concepts of the Haar Cascade algorithm created by Viola and Jones and the LBPH classifier developed by Timo Ahonen et al. Each student's data was collected by a program interface that also took photos of each student for face detection and recognition to take place. The success of the program was it was able to detect each student correctly with an accuracy of 91%. This program has been successfully implemented in the last 12 months.***

**Keywords:** *Face Detection, Face Recognition, Haar-Cascade algorithm, LBPH classifier, Attendance Marking*

## Introduction

In the modern world, computer technology has become deeply intertwined with daily life, transforming how individuals interact with systems and automating numerous processes. One such innovation is face recognition technology, which has emerged as a crucial tool for identifying individuals based on facial features. This technology holds vast potential for applications in security, attendance systems, and beyond, due to its non-intrusive and efficient nature.

The traditional methods of attendance management, such as manual entry, RFID cards, and fingerprint systems, often suffer from various issues like human error, susceptibility to manipulation, and inefficiency. Face recognition-based systems offer a more reliable solution by leveraging the distinct and immutable characteristics of the human face, thus enhancing accuracy and reducing fraudulent practices.

The field of face recognition has evolved significantly over the years, with pioneering contributions from researchers who sought to address challenges such as image blur, posture variations, and occlusion in video-based face recognition (VFR). These challenges are particularly prevalent in surveillance video, where faces often appear distorted or obscured, complicating the task of reliable recognition.

The Haar Cascade algorithm, introduced by Viola and Jones, revolutionized real-time object detection by utilizing Haar-like features. These features are computed as differences in pixel intensities between rectangular regions and are highly effective in detecting edges, lines, and other critical patterns in images. The algorithm employs a cascaded classifier approach, allowing it to rapidly discard non-facial regions and focus computational resources on promising areas, thereby enhancing detection speed and accuracy. (Viola & Jones, 2001). Meanwhile, the Local Binary Patterns Histogram (LBPH) classifier, based on the Local Binary Pattern (LBP) method introduced by Ojala et al. (1996), was designed to analyze texture in images through pixel comparisons in a local neighborhood. The LBP operator compares the intensity of a central pixel with its surrounding pixels, encoding the relationship into a binary pattern, which is then converted into a decimal value, called the LBP code (Ojala et al., 1996, p. 53).

The LBPH method, later applied to face recognition by (Pietikäinen et al), works by dividing the face image into multiple regions. For each region, LBP codes are computed, and a histogram is created that reflects the distribution of local patterns. These histograms are concatenated to form a feature vector representing the face. This approach provides robustness to variations in lighting and facial expressions, making it suitable for face recognition in dynamic environments. (Pietikäinen et al., 2004, 470)

This research aims to leverage the strengths of the Haar Cascade algorithm and LBPH classifier to develop a face recognition-based attendance system capable of handling real-time video processing. By integrating these technologies, the system seeks to improve the accuracy and efficiency of attendance tracking, providing a scalable solution for various applications.

The integration of the Haar Cascade algorithm and LBPH classifier addresses key challenges in video-based face recognition, offering a powerful combination that enhances the reliability of face detection and recognition. This research not only contributes to the advancement of face recognition technology but also demonstrates its practical utility in streamlining attendance processes and improving organizational efficiency.

By exploring the potential of these innovative algorithms, the study lays the groundwork for future developments in biometric systems, positioning face recognition technology as a critical component of modern digital infrastructure.

**Haar Cascade Algorithm for Object Detection**

The Haar Cascade algorithm, introduced by Viola and Jones in 2001, is widely used for real-time object detection, particularly face detection. It operates through three main stages: feature extraction using Haar-like features, efficient computation using an integral image, and object detection via a cascade of classifiers.

**1. Haar-like Feature Extraction**

Haar-like features are rectangular patterns that capture intensity differences between regions of an image. These features are used to detect edges, lines, and patterns. Unlike pixel-based methods, Haar-like features use adjacent rectangular regions to capture the contrast between light and dark areas. While the original paper does not provide a formula, it describes the features as a combination of simple rectangular structures (e.g., edge and line features) applied to different areas of the image (Viola & Jones, 2001)

**2. Integral Image for Fast Calculation**

Rectangle features can be computed very rapidly using an intermediate representation of the image which we call the integral image.2 The integral image at location *x, y* contains the sum of the pixels above and to the left of *x, y*, inclusive

$$ii(x,y) = \sum_{x' \leq x, y' \leq y} i(x', y'),$$

where *ii(x, y)* is the integral image and *i(x, y)* is the original image. Using the following pair of recurrences:

$$\begin{aligned} s(x,y) &= s(x,y-1) + i(x,y) \\ ii(x,y) &= ii(x-1,y) + s(x,y) \end{aligned}$$

(where *s(x, y)* is the cumulative row sum, **s(x, -1) = 0**, and **ii(-1, y) = 0**) the integral image can be computed in one pass over the original image. (Viola & Jones, 2001). This enables real-time performance.

**3. Adaboost and Cascade of Classifiers**

Adaboost selects the most important Haar features, combining them into strong classifiers. The cascade of classifiers starts with simple classifiers to reject unlikely regions quickly, applying more complex classifiers in later stages. Each stage $h_i(x)$ is defined as:

$$h_j(x) = \begin{cases} 1 & \text{if } p_j f_j(x) < p_j \theta_j \\ 0 & \text{otherwise} \end{cases}$$

Regions passing all stages are classified as containing the object. (Viola & Jones, 2001)

## Local Binary Patterns Histogram (LBPH) Algorithm

The Local Binary Patterns Histogram (LBPH) algorithm, adapted from the Local Binary Pattern (LBP) method introduced by Ojala et al. is widely used for face recognition due to its effectiveness in capturing local texture information. It is particularly robust against changes in lighting conditions and facial expressions by focusing on local patterns of pixel intensity rather than absolute values (Pietikäinen et al., 2004, 469). The LBPH algorithm proceeds as follows:

***1. Grayscale Conversion:***

- The input image is first converted to grayscale, as LBP operates on intensity values rather than colour information.

***2. Image Division:***

- The grayscale image is divided into non-overlapping regions (referred to as "blocks" in (Pietikäinen et al., 2004), not necessarily 3x3 pixels as mentioned earlier. These regions can vary in size depending on the implementation.

***3. Local Binary Pattern Calculation:***

- For each pixel in a block, the LBP operator compares the intensity of the central pixel with its neighbouring pixels (typically 8 neighbours in a 3x3 grid). A binary code is assigned based on whether each neighbour's intensity is greater than or equal to the centre pixel's intensity.
- The resulting binary pattern is then converted into a decimal value, referred to as the LBP code. (Ojala et al., 1996, p. 52).

***4. Histogram Computation:***

- For each region, a histogram of LBP codes is computed, capturing the frequency of each unique LBP pattern within that block. This histogram represents the texture information for that specific region (Pietikäinen et al., 2004,470 ).

***5. Feature Vector Formation:***

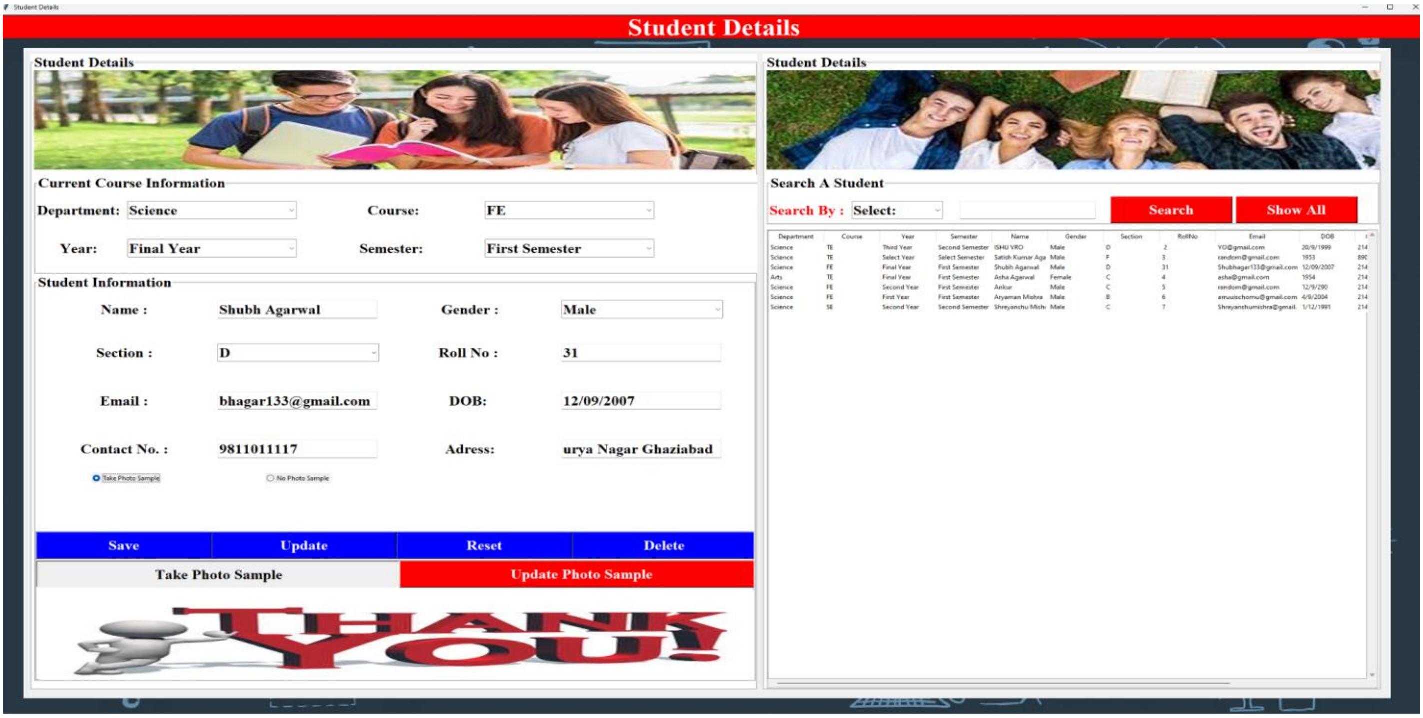
- The histograms from all regions are concatenated into a single feature vector that describes the texture distribution across the entire face image. This feature vector is used to represent the face for recognition purposes. (Pietikäinen et al., 2004, 470)

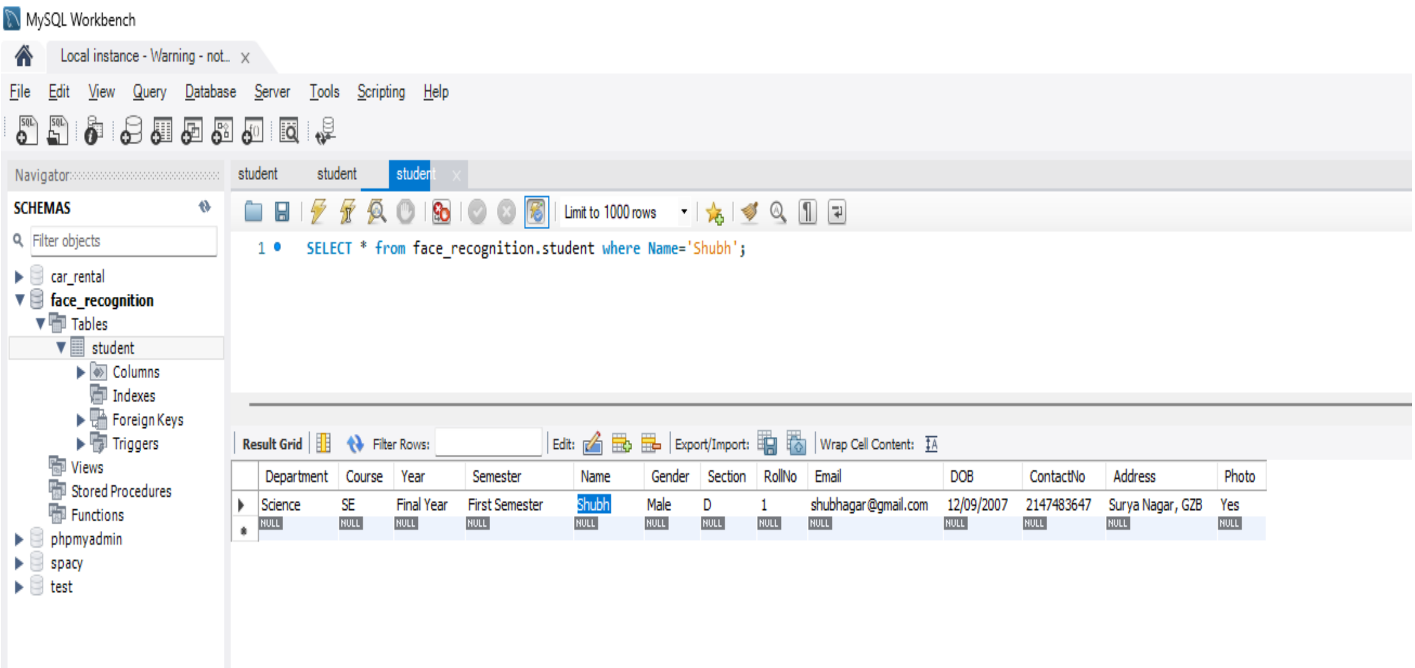
***6. Face Recognition:***

- The feature vector of the input image is compared to feature vectors in the database using a distance metric, such as the Chi-square or Euclidean distance, to identify the closest match (Pietikäinen et al., 2004, 472).

## Methodology

1. **Data Collection and Storage**:
   - The process began by collecting detailed information about each student, including stream, year, semester, name, gender, section, roll number (as the primary key), email, date of birth, contact number, and address.
   - This data was stored in a **MySQL database** to manage student records efficiently and to use it for fetching student information during the attendance process.



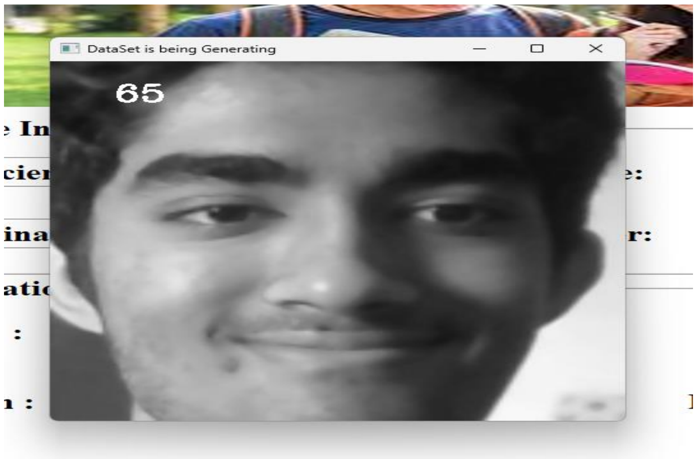




2. **Face Detection Using Haar Cascade**:

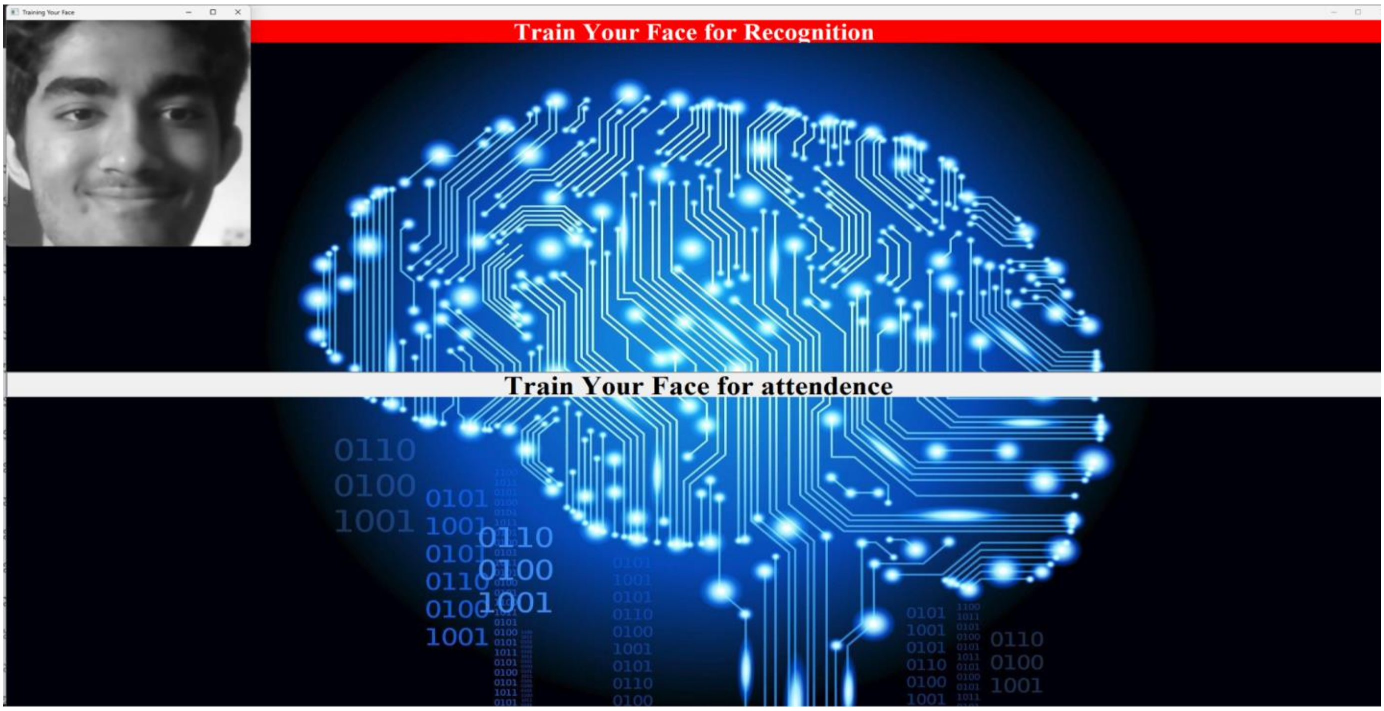
- The **Haar Cascade algorithm** was used to detect faces in the 100 photos taken of each student. Haar-like features were used to scan each image and detect regions where a face was likely present, using rectangular regions to identify features such as edges and lines.
- The face region was then cropped from the image for further processing, discarding other irrelevant parts.

3. **Grayscale Conversion for LBPH Classifier**:
   - After detecting the face, the images were converted to grayscale, as LBPH (Local Binary Patterns Histogram) works on intensity patterns rather than colour.
   - This conversion helped simplify the image data and prepared it for training the classifier.

**Original image:** **Cropped Image:**



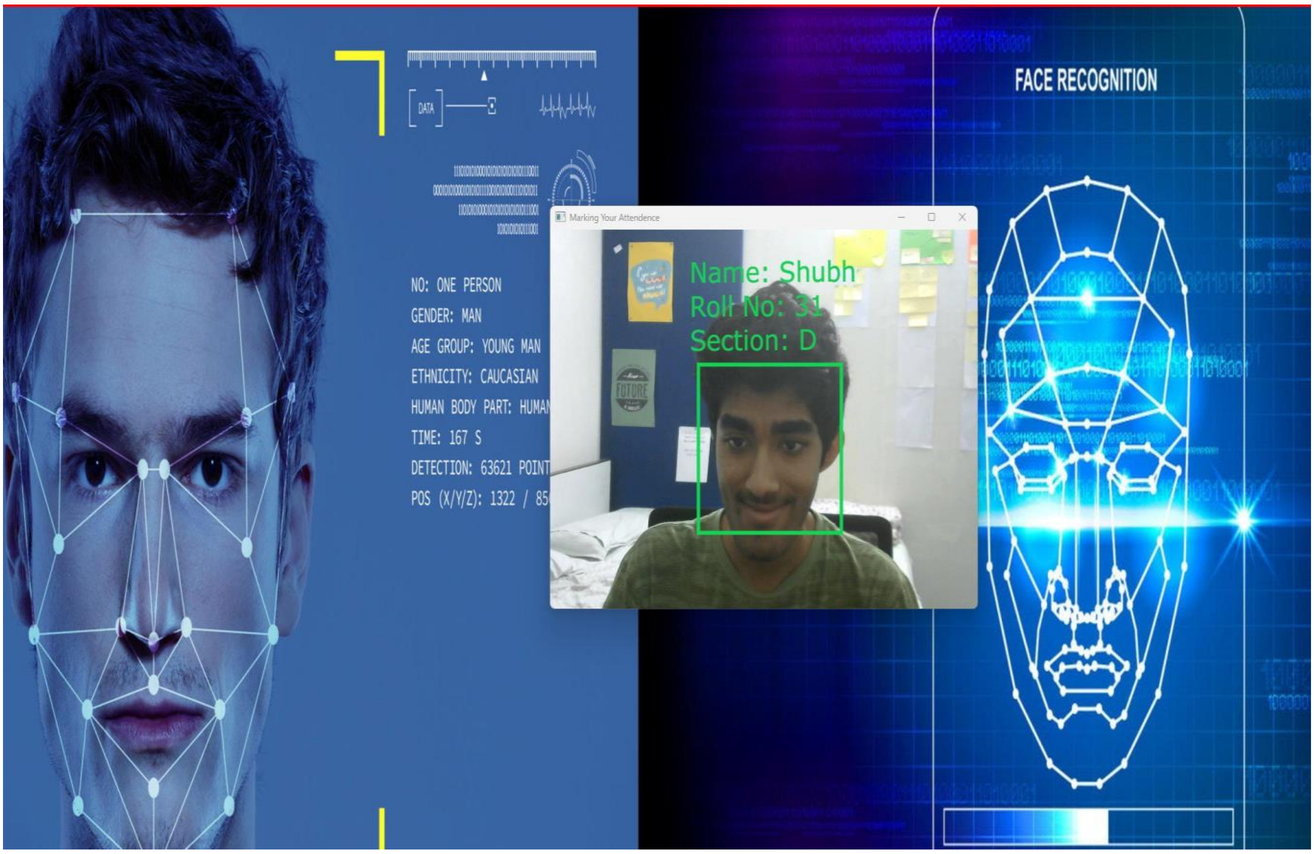

4. **Training the Classifier**:
   - The **LBPHFaceRecognizer_create()** function from OpenCV was used to train the classifier on the grayscale images of each student's face.
   - The classifier was trained using the 100 grayscale photos of each student and stored as an XML file for future real-time use.



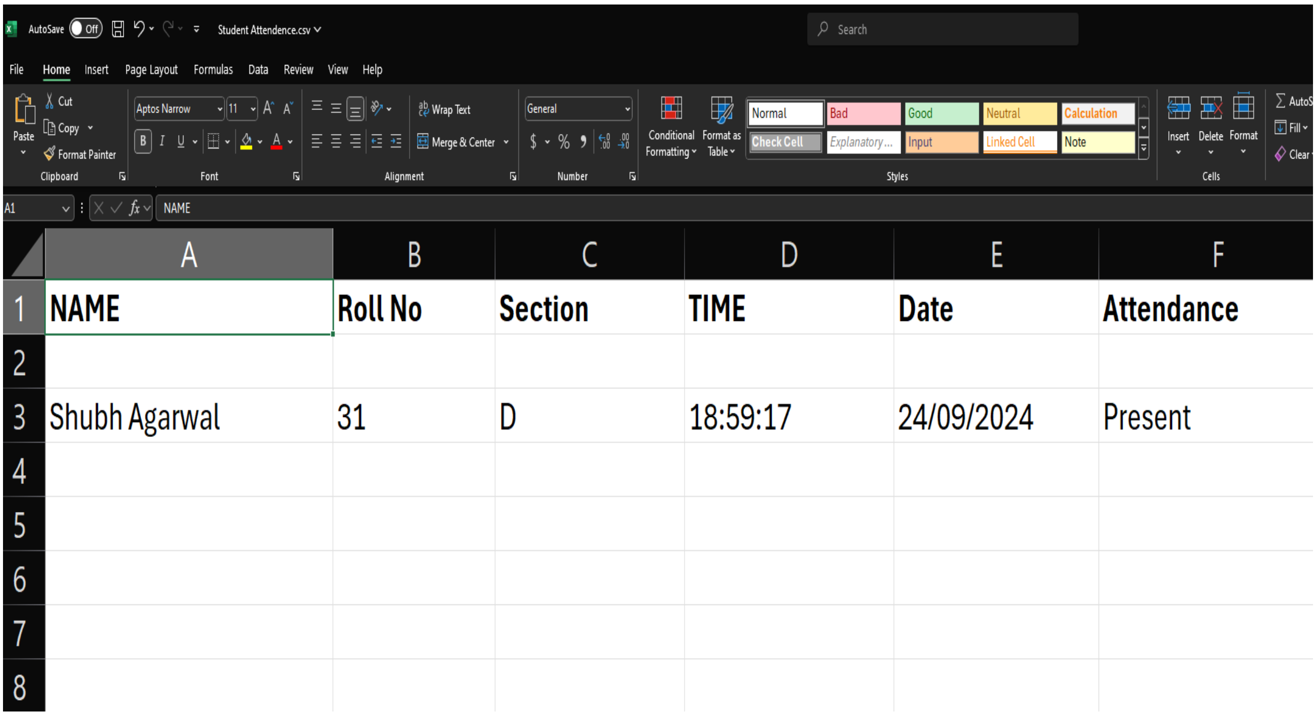

5. **Real-Time Face Detection and Grayscale Conversion**:
   - During the attendance marking process, the **detectMultiScale()** function from the Haar Cascade algorithm was used to find rectangular regions in the live camera feed, which might contain a face.
   - The captured image was converted to grayscale in real time, and this grayscale face was fed into the classifier.
   - Simultaneously, the live feed of the student's face was shown, with a bounding box drawn around the detected face.

6. **Face Recognition Using LBPH Classifier**:
    - The LBPH classifier, which had been trained earlier, identified the student based on the grayscale image fed in real time. The classifier breaks the image into local patterns and compares these to the stored model of each student's face, identifying the student if a match is found.

7. **Fetching Student Info and Displaying**:
    - Once the student's identity is recognized by the LBPH classifier, the primary key (roll number) is used to fetch additional student information from the MySQL database, such as name and section.
    - This information, along with a bounding box around the face, is displayed on the screen.




8. **Attendance Logging in Excel**:
    - The student's attendance is marked in an **Excel sheet**, recording the name, section, time, and date of attendance marking.



| NAME | Roll No | Section | TIME | Date | Attendance |
|---|---|---|---|---|---|
| | | | | | |
| Shubh Agarwal | 31 | D | 18:59:17 | 24/09/2024 | Present |

## Proof of Result

| | A | B | C | D | E | F |
|---|---|---|---|---|---|---|
| 1 | NAME | Roll No | Section | TIME | Date | Attendance |
| 2 | Raunit Malhotra | 7 | C | 08:08:13 | 2024-09-23 | Present |
| 3 | Rahul Tiwari | 87 | A | 11:30:26 | 2024-09-22 | Present |
| 4 | Harshit Malhotra | 23 | D | 10:36:06 | 2024-09-20 | Present |
| 5 | Om Tyagi | 85 | A | 11:41:54 | 2024-09-20 | Present |
| 6 | Shanaya Goyal | 22 | C | 09:08:55 | 2024-09-19 | Present |
| 7 | Pratham Maheshwari | 81 | D | 10:46:23 | 2024-09-19 | Present |
| 8 | Sukriti Jain | 43 | D | 11:35:44 | 2024-09-18 | Present |
| 9 | Rohan Gupta | 74 | D | 09:18:14 | 2024-09-18 | Present |
| 10 | Ridhimma Jain | 57 | C | 10:28:25 | 2024-09-17 | Present |
| 11 | Shubh Agarwal | 31 | D | 09:09:13 | 2024-09-16 | Present |
| 12 | Rahul Attri | 94 | D | 08:19:19 | 2024-09-15 | Present |
| 13 | Vishesh Kumar | 28 | D | 08:03:27 | 2024-09-15 | Present |
| 14 | Himanshu Mehta | 21 | D | 10:09:14 | 2024-09-15 | Present |
| 15 | Varun Pandey | 16 | C | 09:25:23 | 2024-09-14 | Present |
| 16 | Karan Sharma | 75 | D | 09:48:41 | 2024-09-14 | Present |
| 17 | Akash Mehta | 51 | D | 09:49:01 | 2024-09-14 | Present |
| 18 | Diya Kapoor | 70 | D | 09:33:47 | 2024-09-13 | Present |
| 19 | Yasharth Saxena | 92 | C | 09:44:35 | 2024-09-12 | Present |
| 20 | Naman Jha | 67 | C | 11:55:53 | 2024-09-11 | Present |
| 21 | Radhika Baisoya | 24 | D | 11:52:26 | 2024-09-10 | Present |
| 22 | Vineet Chauhan | 54 | A | 08:08:35 | 2024-09-09 | Present |
| 23 | Rohit Kapoor | 77 | D | 11:23:55 | 2024-09-08 | Present |
| 24 | Raveena Bansal | 12 | A | 11:51:41 | 2024-09-07 | Present |
| 25 | Geetika Malhotra | 32 | B | 10:08:02 | 2024-09-07 | Present |
| 26 | Satvik Pandey | 91 | D | 09:19:11 | 2024-09-06 | Present |
| 27 | Raj Tandon | 98 | C | 08:02:21 | 2024-09-04 | Present |
| 28 | Vivek Singh | 4 | A | 11:15:02 | 2024-09-04 | Present |
| 29 | Siddharth Bhatt | 6 | C | 11:48:08 | 2024-09-04 | Present |
| 30 | Neha Mehta | 13 | D | 09:14:28 | 2024-09-04 | Present |
| 31 | Tarun Patel | 44 | A | 10:10:25 | 2024-09-04 | Present |
| 32 | Ankit Gupta | 82 | B | 08:37:29 | 2024-09-03 | Present |
| 33 | Kunal Bhargava | 48 | C | 08:35:32 | 2024-09-02 | Present |
| 34 | Preeti Sharma | 25 | A | 10:16:14 | 2024-08-31 | Present |
| 35 | Bhavya Rathi | 64 | C | 10:16:44 | 2024-08-28 | Present |
| 36 | Shalini Raj | 40 | C | 11:47:27 | 2024-08-27 | Present |
| 37 | Anjali Sinha | 41 | A | 08:43:39 | 2024-08-27 | Present |
| 38 | Deepak Soni | 66 | A | 10:21:42 | 2024-08-26 | Present |
| 39 | Pankaj Choudhary | 78 | D | 09:48:33 | 2024-08-26 | Present |
| 40 | Rachna Goyal | 90 | A | 09:11:29 | 2024-08-25 | Present |
| 41 | Sameer Mathur | 80 | B | 10:21:46 | 2024-08-22 | Present |
| 42 | Jatin Khurana | 3 | B | 11:09:33 | 2024-08-22 | Present |
| 43 | Priyanka Chawla | 71 | A | 10:57:10 | 2024-08-20 | Present |
| 44 | Nitin Sharma | 37 | D | 10:57:25 | 2024-08-18 | Present |
| 45 | Lakshay Gupta | 63 | A | 11:38:32 | 2024-08-18 | Present |
| 46 | Zoya Qureshi | 79 | A | 09:56:54 | 2024-08-16 | Present |
| 47 | Lakshmi Tiwari | 72 | D | 08:54:01 | 2024-08-16 | Present |
| 48 | Sonia Kapoor | 46 | D | 09:15:20 | 2024-08-15 | Present |
| 49 | Ishaan Sood | 14 | D | 08:31:59 | 2024-08-15 | Present |
| 50 | Sakshi Malhotra | 30 | A | 10:54:27 | 2024-08-14 | Present |
| 51 | Sanjay Bansal | 42 | A | 11:34:24 | 2024-08-13 | Present |
| 52 | Usha Rathi | 29 | B | 09:59:27 | 2024-08-13 | Present |
| 53 | Raman Negi | 58 | B | 11:05:51 | 2024-08-13 | Present |
| 54 | Monika Raj | 19 | B | 11:58:12 | 2024-08-11 | Present |
| 55 | Nilesh Bhatt | 1 | B | 09:19:57 | 2024-08-10 | Present |
| 56 | Anil Verma | 35 | C | 09:52:39 | 2024-08-10 | Present |
| 57 | Tina Bhatia | 59 | D | 11:13:28 | 2024-08-09 | Present |
| 58 | Devika Chawla | 2 | D | 11:13:07 | 2024-08-06 | Present |
| 59 | Naman Raj | 69 | A | 11:49:14 | 2024-08-05 | Present |
| 60 | Hridank Agarwal | 88 | B | 10:12:49 | 2024-08-05 | Present |
| 61 | Samaira Bansal | 26 | C | 09:37:15 | 2024-08-05 | Present |
| 62 | Pooja Mishra | 38 | C | 10:43:01 | 2024-08-05 | Present |
| 63 | Aishwarya Chauhan | 83 | D | 11:08:35 | 2024-08-03 | Present |
| 64 | Sachin Mahajan | 56 | C | 10:48:16 | 2024-08-03 | Present |
| 65 | Vedika Jain | 33 | B | 08:16:11 | 2024-08-01 | Present |
| 66 | Ravi Mishra | 11 | D | 08:28:09 | 2024-08-01 | Present |
| 67 | Surbhi Rajput | 5 | B | 08:10:08 | 2024-07-31 | Present |
| 68 | Arjun Kapoor | 55 | A | 08:29:23 | 2024-07-31 | Present |
| 69 | Uday Singh | 36 | A | 08:31:58 | 2024-07-30 | Present |
| 70 | Ashish Goel | 39 | B | 11:12:12 | 2024-07-27 | Present |
| 71 | Aarav Singh | 65 | B | 08:01:31 | 2024-07-27 | Present |
| 72 | Abhishek Sharma | 18 | A | 08:45:56 | 2024-07-27 | Present |
| 73 | Nilansh Bhatt | 99 | B | 10:42:03 | 2024-07-26 | Present |
| 74 | Yash Tandon | 86 | A | 09:12:47 | 2024-07-25 | Present |
| 75 | Manish Oberoi | 60 | D | 08:58:30 | 2024-07-25 | Present |
| 76 | Esha A | 95 | B | 10:36:36 | 2024-07-24 | Present |
| 77 | Ritika Chopra | 61 | B | 11:49:17 | 2024-07-23 | Present |
| 78 | Ayush Gupta | 20 | A | 10:22:37 | 2024-07-22 | Present |
| 79 | Ravi Sharma | 96 | D | 10:14:12 | 2024-07-22 | Present |
| 80 | Manisha Chaudhary | 17 | B | 10:09:28 | 2024-07-20 | Present |
| 81 | Poonam Gupta | 10 | A | 09:35:42 | 2024-07-20 | Present |
| 82 | Aayush Dutta | 34 | D | 08:21:13 | 2024-07-19 | Present |
| 83 | Shivani Narang | 89 | C | 10:07:38 | 2024-07-19 | Present |
| 84 | Kabir Bhushan | 8 | D | 10:30:45 | 2024-07-18 | Present |
| 85 | Vidhur Mahajan | 47 | A | 11:59:58 | 2024-07-15 | Present |
| 86 | Sana Bansal | 53 | B | 10:20:49 | 2024-07-13 | Present |
| 87 | Vivek Aggarwal | 68 | B | 08:35:06 | 2024-07-13 | Present |
| 88 | Tanvi Agarwal | 84 | D | 09:13:24 | 2024-07-13 | Present |
| 89 | Meghna Kella | 15 | A | 08:50:30 | 2024-07-13 | Present |
| 90 | Priya Patel | 50 | B | 08:10:27 | 2024-07-13 | Present |
| 91 | Devika Chawla | 100 | B | 08:03:59 | 2024-07-12 | Present |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 92 | Isha Singh | 76 | D | 10:52:09 | 2024-07-11 | Present | | |
| 93 | Kartik Sharma | 97 | B | 08:13:01 | 2024-07-10 | Present | | |
| 94 | Divya Singh | 27 | D | 10:43:33 | 2024-07-08 | Present | | |
| 95 | Aditi Singh | 93 | B | 10:41:20 | 2024-07-07 | Present | | |
| 96 | Nisha Jain | 73 | A | 09:21:24 | 2024-07-06 | Present | | |
| 97 | Satakshi Dhaneja | 49 | D | 11:47:36 | 2024-07-05 | Present | | |
| 98 | Amit Verma | 52 | A | 10:53:20 | 2024-07-04 | Present | | |
| 99 | Riya Malhotra | 62 | D | 09:42:38 | 2024-07-03 | Present | | |
| 100 | Vinay Kapoor | 9 | A | 09:57:34 | 2024-07-02 | Present | | |
| 101 | Ankita Ahuja | 45 | A | 09:32:39 | 2024-07-01 | Present | | |
| 102 | | | | | | | | |
| 103 | | | | | | | | |
| 104 | | | | | | | | |
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| 109 | | | | | | | | |

Student Attendance

This program was implemented in school around August 2023. This program was further tested on a personal device between the period July 2024 to September 2024. The attendance of 110 students was checked but only the correct attendance of 100 students was marked correctly. The 10 students were not recognized by the program hence their attendance was not marked. **This gives us an accuracy of roughly 91%**.

## Conclusion

This paper detailed the development of a Face Recognition-Based Attendance System using the LBPH algorithm and Haar Cascade classifier. The system automates the attendance process by recognizing students' faces in real-time, making it accurate and efficient. By using grayscale images and the LBPH algorithm, the system can handle varying lighting conditions, while Haar Cascade ensures quick and effective face detection.

The system integrates with MySQL for managing student data and logs attendance in Excel, making it user-friendly and scalable. It reduces the need for manual attendance, cuts down errors, and prevents proxy attendance.

In summary, the face recognition system offers a reliable, automated solution for attendance tracking, improving both accuracy and convenience. Future improvements could focus on handling more complex scenarios like partial face coverage or diverse environments.

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