ATTENDANCE SYSTEM BASED ON FACE RECOGNITION USING LBPH METHOD

BY

TONMOY CHANDRA DAS
ID: 201-15-14254

FINAL YEAR DESIGN PROJECT REPORT

This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering

Supervised By

MS. NAZNIN SULTANA
Associate Professor
Department of Computer Science and Engineering
Daffodil International University

Co-Supervised By

MS. SHARUN AKTER KHUSBU
Lecturer (Sr. Scale)
Department of Computer Science and Engineering
Daffodil International University

DAFFODIL INTERNATIONAL UNIVERSITY

DHAKA, BANGLADESH

July 2024

APPROVAL

This Project titled "**Attendance System based on Face Recognition using LBPH method**", submitted by **Tonmoy Chandra Das** ID No: 201-15-14254 to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 13-07-2024.

BOARD OF EXAMINERS

____

Narayan Ranjan Chakraborty — **Board Chairman**
Associate Professor & Associate Head
Department of CSE
Faculty of Science & Information Technology
Daffodil International University

____

Md. Sadekur Rahman — **Internal Examiner 1**
Assistant Professor
Department of CSE
Faculty of Science & Information Technology
Daffodil International University

____

Mr. Tanvirul Islam — **Internal Examiner 2**
Lecturer
Department of CSE
Faculty of Science & Information Technology
Daffodil International University

____

Dr. Md. Manowarul Islam — **External Examiner**
Associate Professor
Department of the Computer Science and Engineering
Jagannath University

DECLARATION

I hereby declare that this project has been done by us under the supervision of **MS. NAZNIN SULTANA, Associate Professor, Department of Computer Science and Engineering, Daffodil International University**. I also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

Supervised by:

On behalf of

Khushbu

NAZNIN SULTANA
Associate Professor
Department of CSE
Daffodil International University

Co-Supervised by:

Khushbu

MS. SHARUN AKTER KHUSBU
Lecturer (Sr. Scale)
Department of CSE
Daffodil International University

Submitted by:

Tonmoy

Tonmoy Chandra Das
ID: 201-15-14254
Department of CSE
Daffodil International University

ACKNOWLEDGEMENT

First, we express our heartiest thanks and gratefulness to almighty for His divine blessing making it possible for us to complete the final year project/internship successfully.

We are grateful and wish our profound indebtedness to **Ms. NAZNIN SULTANA**, **Associate Professor**, Department of CSE Daffodil International University, Dhaka. Deep Knowledge & keen interest of our supervisor in the field of "*Field name*" to carry out this project. His endless patience, scholarly guidance, continual encouragement, constant and energetic supervision, constructive criticism, valuable advice, reading many inferior drafts, and correcting them at all stages have made it possible to complete this project.

We would like to express our heartiest gratitude to **Dr. Sheak Rashed Haider Noori**, Head, Department of CSE, for his kind help in finishing our project and also to other faculty members and the staff of the Department of CSE, Daffodil International University.

We would like to thank our entire course mate in Daffodil International University, who took part in this discussion while completing the course work.

Finally, we must acknowledge with due respect the constant support and patience of our parents.

ABSTRACT

Attendance tracing systems are crucial for organization to monitor the presence of individuals in various settings such as workplace, educational institutions and events. Traditional methods of attendance recording often suffer from inaccuracies, inefficiencies and susceptibility to manipulation. In response to these challenges, this study proposes the development of an innovative attendance system using face recognition technology powered by machine learning algorithms. This research aims to design and implement a robust attendance system capable of accurately identifying individuals based on facial features captured by a camera. The system leverages state-of-the-art machine learning techniques for facial recognition, including deep learning models such as Convolutional Neural Networks (CNNs). A comprehensive methodology is employed, encompassing data collection, preprocessing, model training, and system integration. Experimental results demonstrate the effectiveness of the proposed attendance system in accurately recognizing individuals and recording their attendance. The system achieves high levels of accuracy, reliability, and efficiency, thereby addressing the limitations of traditional attendance tracking methods. Furthermore, the system's performance is evaluated under various real-world conditions to assess its robustness and practical utility.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1
Introduction

1.1 Overview

Student attendance system is one of the most fundamental processes of an organization or an institute. Every institute have its own method to do that process. The most common process of this is by calling the names and mark attendance. There are several popular automatic attendances systems such as Fingerprint Scanning, Iris Scanning etc. Among the emerging technologies of attendance systems tracking, face recognition stands out as promising solution in this field. Face recognition systems have gained widespread adoption in various domains, ranging from security surveillance to biometric authentication. Leveraging machine learning algorithms, particularly deep learning models such as Convolutional Neural Networks (CNNs), face recognition technology has demonstrated remarkable performance in accurately recognizing individuals across diverse conditions and environments In this context, this research endeavors to design, develop, and evaluate an innovative attendance system utilizing face recognition with machine learning. The proposed system aims to overcome the limitations of traditional attendance tracking methods by offering a seamless, efficient, and secure solution for recording attendance. By harnessing the power of machine learning algorithms, the system seeks to achieve high levels of accuracy and reliability in identifying individuals based on their facial characteristics captured by a camera. This project required dataset of every human face captured by real world. This introduction provides an overview of the significance of attendance tracking, the potential of face recognition technology, and the objectives of the research. Subsequent sections will delve deeper into the methodology, system design, experimental results, and implications of the proposed attendance system, culminating in a comprehensive analysis of its effectiveness and practical utility.

1.2 Background and Present State

Traditional ways of keeping track of who's showing up, like using paper sign-in sheets or those card swipe systems, are usually a pain. They're slow, full of mistakes, and easy for people to cheat. All these issues can mess up attendance records, create extra work for admins, and make security vulnerable. That's why it's important to have automatic attendance systems that are more precise, trustworthy, and quick

Face recognition tech, using fancy machine smarts, sounds like a cool way to shake up how we do attendance. It spots folks by their faces, making tracking attendance smooth, cutting down on cheating, and letting us keep an eye on things in real-time. And with machine smarts in the mix, it gets even better at handling different conditions and getting better at recognizing faces as time goes on.

The goal of this research is to use face recognition and machine learning to make a cool new attendance system that's way better than the old school methods. We want to use the latest tech to create a strong, flexible, and easy-to-use solution that not only makes keeping track of attendance easier but also improves security and accountability in different types of organizations.

1.3 Problem Statement

Managing student attendance in educational institutions is often a time-consuming and error-prone task. Traditional methods, such as manual roll calls or sign-in sheets, are susceptible to inaccuracies, including human error and fraudulent practices like proxy attendance. These issues not only compromise the integrity of attendance data but also consume valuable instructional time that could be better spent on teaching and learning activities. Moreover, the administrative burden of maintaining and verifying attendance records is significant. To address these challenges, there is a need for an automated, accurate, and efficient attendance tracking system that can streamline the process, ensure data accuracy, and provide real-time monitoring and reporting capabilities. This project aims to develop a face recognition-based attendance system using the Haarcascade Frontal Face algorithm for detection and the LBPH algorithm for recognition, thereby transforming the attendance management process in educational settings.

1.4 Objectives

The expected outcome of this project is,

 Improved Efficiency and Accuracy:

- Quick and precise identification and verification of individuals.
- Reduction in administrative burden and manual errors in attendance recording.

 Real-time Tracking and Monitoring:

- Instant updates of attendance records.
- Availability of up-to-date information for timely decision-making.

 Enhanced Security and Accountability:

- Prevention of proxy attendance.
- Ensured that only authorized individuals can mark their attendance.

 User-Friendly Interface:

- Intuitive design for easy interaction by administrators and end-users.
- Higher compliance and reduced learning curve.

 Scalability and Adaptability:

- Customizable for different environments (classrooms, corporate offices, etc.).
- Capable of handling various organizational needs and scales.

 Integration with Existing Systems:

- Seamless incorporation into current attendance management frameworks.
- Enhanced functionality with minimal disruption.

 Cost-effectiveness:

- Long-term savings through reduced administrative overhead and error elimination.
- Positive return on investment from increased operational efficiency.

 Robust and Reliable Solution:

- Consistent performance and accuracy in diverse conditions.
- Secure, efficient, and real-time attendance tracking that meets modern institutional needs

1.5 Scope and Limitations

The initial part of this study sets up the framework for understanding the background, importance, and scope of the proposed attendance system based on face recognition. It starts with an overview that outlines the issues related to tracking attendance and the need for a technical solution. The study's objective is explained, emphasizing the potential advantages of utilizing deep learning for more accurate face detection. Following this, the research's objectives are laid out, detailing the specific aims and anticipated results. The methodology section explains the structured approach employed, covering aspects such as data collection, labeling, training methods, and the incorporation of various elements like Haar Cascade classifiers and the k-Nearest Neighbors algorithm. The preliminary section establishes the groundwork for a comprehensive exploration of the proposed system, providing readers with a clear understanding of the research's background, objectives, and methodologies before delving into the complexities of the face recognition-based attendance solution.

1.6 Report Organization

This project report is organized in:

- Introduction
- Literature Review
- Methodology
- Implementation
- Result and Analysis
- Impact on Society, Environment and Sustainability
- Conclusion and Future Work

1.7 Summary

The introduction of the student attendance system project highlights the critical need for an automated and reliable method to track attendance in educational institutions. Traditional attendance methods are fraught with inefficiencies, inaccuracies, and potential for abuse, leading to compromised data integrity and increased administrative burden. By leveraging face recognition technology, specifically the Haarcascade Frontal Face algorithm for detection and the LBPH algorithm for recognition, the project aims to revolutionize the attendance management process. The introduction sets the stage by discussing the technological advancements in facial recognition, the benefits of automation, and the overarching goal of creating a more efficient, accurate, and secure system for monitoring student attendance. This innovative approach promises to save time, reduce errors, and enhance overall educational management, paving the way for future technological integrations in the education sector.

CHAPTER 2

Literature Review

2.1 Overview

The initial part of this study sets up the framework for understanding the background, importance, and scope of the proposed attendance system based on face recognition. It starts with an overview that outlines the issues related to tracking attendance and the need for a technical solution. The study's objective is explained, emphasizing the potential advantages of utilizing deep learning for more accurate face detection. Following this, the research's objectives are laid out, detailing the specific aims and anticipated results. The methodology section explains the structured approach employed, covering aspects such as data collection, labeling, training methods, and the incorporation of various elements like Haar Cascade classifiers and the k-Nearest Neighbors algorithm. The preliminary section establishes the groundwork for a comprehensive exploration of the proposed system, providing readers with a clear understanding of the research's background, objectives, and methodologies before delving into the complexities of the face recognition-based attendance solution.

2.2 Related Works

The integration of face recognition technologies into attendance systems represents a significant evolution in the management of attendance in educational institutions, workplaces, and other settings requiring reliable identification methods. Two pivotal algorithms in this domain are the Local Binary Patterns Histograms (LBPH) for face recognition and the Haarcascade frontal face algorithm for face detection. Both have been extensively studied and applied in various contexts, contributing to advancements in efficiency, accuracy, and security. This section delves into related works that leverage these algorithms, providing a comprehensive overview of their applications and impacts.

The LBPH algorithm, first introduced by Ahonen, Hadid, and Pietikäinen in 2006, has become a cornerstone in face recognition due to its robustness against lighting variations and its simplicity. The algorithm's ability to encode local textures of an image into histograms allows it to effectively distinguish between different faces, even in challenging conditions. One notable application of LBPH is in surveillance systems, as demonstrated by Zhao et al. (2010), who integrated LBPH into CCTV systems for real-time suspect identification. The system's resilience to varying lighting conditions and partial occlusions underscored LBPH's utility in dynamic environments where traditional recognition methods might falter.

In the context of educational institutions, LBPH has been pivotal in developing automated attendance systems. Kumar and Vijayalakshmi (2016) utilized LBPH to replace manual roll-call methods, thus streamlining the attendance process and reducing administrative burdens. Their system showcased a high accuracy rate, effectively identifying students despite minor facial changes over time, such as hairstyles or glasses. This application not only enhanced efficiency but also minimized the potential for human error, ensuring a more reliable attendance record.

Mobile applications have also benefited from the LBPH algorithm, particularly in scenarios requiring secure authentication. Bhosale and Pawar (2017) integrated LBPH into a mobile application to authenticate users, capitalizing on the algorithm's low computational requirements to deliver a fast and reliable verification method. This approach was crucial for mobile security, offering an accessible yet robust solution for user identification.

In healthcare, LBPH has been used to enhance patient monitoring and identification. Gupta et al. (2018) developed a system utilizing LBPH to track patient movements within hospital premises, ensuring that patients received appropriate care and preventing unauthorized access to restricted areas. This application highlighted the algorithm's ability to improve patient safety and streamline hospital operations by providing accurate and real-time identification.

Complementing the LBPH algorithm, the Haarcascade frontal face algorithm, developed by Viola and Jones in 2001, has been a game-changer in face detection. Known for its rapid and efficient detection capabilities, Haarcascade employs a cascade of simple classifiers trained with AdaBoost to detect facial features. This method has been widely adopted in real-time applications, such as the one demonstrated by Viola and Jones themselves, where it enabled unprecedented face detection speeds in video streams. This capability was particularly beneficial for surveillance and monitoring systems, where quick and reliable face detection is paramount.

In human-computer interaction, Haarcascade has been utilized to create more responsive and interactive systems. Chu et al. (2003) implemented Haarcascade in an interactive kiosk designed to detect and respond to user presence, thereby enhancing user engagement. This application illustrated how real-time face detection could be harnessed to develop more intuitive and user-friendly interfaces.

Automated access control systems have also leveraged Haarcascade for enhancing security. Patel et al. (2015) integrated Haarcascade into a system controlling entry to secure areas, using real-time face detection to verify authorized personnel. This system not only enhanced security by ensuring that only verified individuals could gain access but also provided a more convenient and seamless entry process.

Assistive technologies for the visually impaired have further showcased the versatility of Haarcascade. Hernandez-Rebollar et al. (2008) developed a wearable device employing Haarcascade to detect faces and provide auditory feedback to visually impaired users. This technology significantly improved the users' ability to navigate social environments, demonstrating the algorithm's potential to enhance accessibility and independence for individuals with visual impairments.

Combining the strengths of LBPH and Haarcascade, several integrated systems have been developed to provide comprehensive solutions for facial recognition-based attendance systems. Singh and Kaur (2019) developed an integrated security system that utilized Haarcascade for face detection and LBPH for face recognition. This dual-approach system demonstrated high accuracy and speed, making it well-suited for environments requiring reliable and real-time attendance tracking. By leveraging Haarcascade’s efficient face detection and LBPH’s robust recognition capabilities, the system achieved superior performance compared to using either algorithm alone.

In educational settings, integrated systems have been particularly beneficial. Al Mamun et al. (2020) implemented a system combining Haarcascade and LBPH to automate attendance in classrooms. Their system detected student faces using Haarcascade and recognized them with LBPH, updating attendance records in real-time. This integration reduced the time required for attendance management, improved accuracy, and provided a seamless experience for both students and teachers.

Workplace attendance systems have similarly benefited from this combination. Rahim et al. (2018) developed an attendance tracking system for corporate environments using Haarcascade for initial face detection and LBPH for subsequent recognition. The system improved upon traditional methods by offering a non-intrusive and automated solution, which was particularly useful in large organizations where manual attendance tracking can be cumbersome and error-prone.

Additionally, the combination of these algorithms has found applications in public transportation systems. Tiwari and Tripathi (2017) implemented a face recognition-based ticketing system for public buses. Using Haarcascade to detect passengers' faces and LBPH to recognize them, the system automated fare collection and enhanced security by ensuring that only registered users could access services. This application demonstrated how face recognition technology could be extended beyond conventional attendance systems to streamline operations and improve user experience in various public services.

In summary, the integration of LBPH for face recognition and Haarcascade for face detection has been extensively explored and applied across a wide range of domains, from surveillance and security to education and healthcare. These algorithms' complementary strengths—Haarcascade's rapid and reliable face detection and LBPH's robust and accurate face recognition—have enabled the development of advanced systems that enhance efficiency, security, and user experience. As technology continues to evolve, these foundational works will undoubtedly inspire further innovations in face recognition and its applications, paving the way for more sophisticated and integrated solutions.

2.3 Comparison between existing works

The comparative analysis of the Local Binary Patterns Histograms (LBPH) and Haarcascade algorithms reveals their complementary strengths in face recognition and detection applications, particularly in attendance systems. Haarcascade, developed by Viola and Jones, excels in rapid face detection, leveraging a cascade of classifiers for efficient and real-time performance. Its robustness in various lighting conditions makes it ideal for initial face detection in dynamic environments. Conversely, LBPH, introduced by Ahonen et al., is renowned for its robustness to lighting variations and simplicity in encoding local textures into histograms, which ensures accurate face recognition even with minor facial changes.

When integrated, these algorithms provide a powerful solution: Haarcascade swiftly detects faces in real-time, while LBPH accurately recognizes them, making this combination highly effective for attendance systems. This integrated approach has been successfully applied in various settings, including educational institutions and workplaces, demonstrating improvements in efficiency, accuracy, and security over traditional methods.

Comparative analysis with previous work,

Table 2.1: Comparative analysis with previous work

SL No	Author Name	Used Algorithm	Best Accuracy with Algorithm
1.	Samuel Lukas[1], Aditya Rama Mitra[2], Ririn Ikana Desanti[3], Dion Krisnadi[4],R.G. et al. [1]	Discrete Cosine Transforms (DCT), Discrete Wavelet Transform (DWT)	Best Accuracy 82% with Discrete Cosine Transform
2.	Nirmalya Kar[1], Mrinal Kanti Debbarma[2], Ashim Saha[3] and Dwijen Rudra Pal[4], W. et al. [2]	Eigenface approach	95% accuracy with frontal face
3.	Ajinkya Patil[1] , Mrudang Shukla[2]et al. [3]	hybrid algorithm from PCA and LDA.	______

4.	Hertzog, M.A. et al. [4]	Principle Component Analysis (PCA), Linear Discriminate Analysis (LDA),	______
5.	Akshara Jadhav[1], Akshay Jadhav[2], Tushar Ladhe[3], Krishna Yeolekar[4].	Viola-Jones detection algorithm	______
6.	Winarno[1], E., Al Amin[2], I.H., Februariyanti[3], H., Adi[4], P.W., Hadikurniawati[5], W. and Anwar[5], M.T.. et al. [6]	PCA, CNN-PCA	CNN-PCA, 98%
7.	Chakraborty[1], P., Muzamme[2], C.S., Khatun[3], M., Islam, S.F. and Rahman[4], S.et al. [7]	Principal Face Recognition (PCA)	PCA, 85%
8.	Marko Arsenovic[1], Srdjan Sladojevic[2], Andras Anderla[3], Darko Stefanovic[4] et al. [8]	SVM-Classifier, FaceNet-CNN	SVM-Classifier, 95.02%
9.	Mayur Surve[1], Priya Joshi[2], Sujata Jamadar[3], Minakshi Vharkateet[4] al. [9]	Haar Cascade, AdaBoost classifier.	_____
10.	Anagha Vishe1 ,Akash Shirsath2 , Sayali Gujar3, Neha Thakur4et al. [10]	Haar Cascade, AdaBoost classifier	___
11	Pauzan, M.	Haar Cascade, LBPH	LBPH, 99%
12	Elias, S. J., Hatim, S. M., Hassan, N. A., Abd Latif, L. M., Ahmad,	LBP	LBP, ____
13	SudhaNarang, K. J., & MeghaSaxena, A	LBPH, PCA, LDA	LBPH, 97%
14	Khan, S., Akram, A., & Usman, N.	Face API, OpenCV	____
15	Trivedi, A., Tripathi, C. M., Perwej, Y., Srivastava, A. K., & Kulshrestha,	AdaBoost classifier, LBPH	LBPH, 95%

	N.		
16	Bah, S. M., & Ming, F.	Principal Face Recognition (PCA)	86%
17	Alhanaee, K., Alhammadi, M., Almenhali, N., & Shatnawi, M.	hybrid algorithm from PCA and LDA.	____
18	Prangchumpol, D.	PCA, CNN-PCA	CNN-PCA, 95%
19	Nithya, D.	LDA, CNN-PCA	CNN-PCA,96%
20	Anshari, A., Hirtranusi, S. A., Sensuse, D. I., & Suryono, R. R.	Discrete Wavelet Transform (DWT)	79%
21	Bussa, S., Mani, A., Bharuka, S., & Kaushik, S.	Haar Cascade, AdaBoost classifier	_____
22	Yusof, Y. W. M., Nasir, M. M., Othman, K. A., Suliman, S. I., Shahbudin, S., & Mohamad, R.	AdaBoost classifier, FaceNet-CNN	AdBoost classifier, 89%
23	Suresh, V., Dumpa, S. C., Vankayala, C. D., Aduri, H., & Rapa, J.	LDA.	_____
24	Chowdhury, S., Nath, S., Dey, A., & Das, A.	Discrete Wavelet Transform (DWT), LDA.	LDA,
25	Godswill, O., Osas, O., Anderson, O., Oseikhuemen, I., & Etse, O.	LBPH	98%

2.4 Open Issues

The traditional methods of taking attendance in educational institutions are often time-consuming, prone to errors, and easily manipulated. Manual roll calls and paper-based systems are inefficient, especially in large classrooms, leading to significant administrative burdens for educators. Moreover, these conventional methods do not provide real-time data, making it challenging to monitor attendance trends and identify issues such as chronic absenteeism promptly. This project aims to address these limitations by developing an automated attendance system using face recognition technology, specifically leveraging the Haarcascade frontal face algorithm for face detection and the Local Binary Patterns Histograms (LBPH) algorithm for face recognition.

The scope of the problem encompasses several key areas. Firstly, there is the issue of accuracy and reliability. Traditional attendance methods can result in errors such as marking the wrong student as present or allowing students to engage in proxy attendance, where one student marks attendance on behalf of another. An automated system using face recognition can significantly reduce these errors by ensuring that only the actual student can mark their presence.

Secondly, the current methods lack efficiency. In large classrooms, taking attendance manually can consume a considerable amount of valuable instructional time. By automating this process, educators can save time and focus more on teaching. The system will detect and recognize students as they enter the classroom, logging their attendance automatically without any manual intervention.
Another critical aspect is real-time data access and analysis. Traditional systems often require manual compilation of attendance data, which can be time-consuming and may lead to delays in identifying attendance issues. An automated system can provide real-time updates, allowing administrators and teachers to quickly access attendance records, monitor trends, and take immediate action if needed. This capability is particularly useful for early intervention in cases of chronic absenteeism or other attendance-related problems. Additionally, the project addresses the scalability of attendance systems. In institutions with thousands of students, managing attendance manually becomes

increasingly impractical. An automated system can easily scale to accommodate large numbers of students, providing a consistent and reliable solution across different classes and departments. This scalability is crucial for institutions looking to modernize their administrative processes and enhance operational efficiency.

The integration of the Haarcascade frontal face algorithm and the LBPH algorithm is particularly suited for this project due to their respective strengths. Haarcascade is efficient in detecting faces quickly and reliably in real-time, which is essential for processing students as they enter the classroom. LBPH, on the other hand, is robust in recognizing faces even with variations in lighting, facial expressions, and minor changes in appearance over time. The combination of these algorithms ensures a high level of accuracy and reliability in recognizing students.

Furthermore, the project has the potential to enhance security within educational institutions. By ensuring that only registered students can mark their attendance, the system helps in maintaining accurate records and prevents unauthorized access. This aspect is especially important in ensuring the safety and integrity of the educational environment.

2.5 Summary

The background works for the student attendance system using face recognition technology encompass an in-depth exploration of existing methodologies, technologies, and their applications in educational settings. This project builds upon the well-established principles of face detection and recognition, employing the Haarcascade Frontal Face algorithm for its robust and efficient detection capabilities and the LBPH algorithm for its high accuracy in recognizing faces. Previous research and implementations have demonstrated the potential of these algorithms in various real-world applications, highlighting their reliability and effectiveness. The background study also includes a review of traditional attendance methods, their limitations, and the increasing demand for automated solutions. By examining the successes and challenges of prior works, this project identifies key areas for improvement and innovation. The integration of face recognition technology into attendance systems addresses critical issues such as human error, time consumption, and data manipulation, paving the way for more secure and efficient educational administration. This summary underscores the project's foundation on proven technologies while aiming to enhance their application in a novel and impactful way.

CHAPTER 3
Methodology

3.1 Overview and Instrumentation:

Overview:

The primary research subject for this project is the development and implementation of an automated attendance system utilizing face recognition technology to enhance the efficiency and accuracy of attendance tracking in educational institutions. The system will be developed using Python, a versatile and widely-used programming language suitable for implementing machine learning and computer vision algorithms. The core of this system is based on two prominent algorithms: the Haarcascade frontal face algorithm for face detection and the Local Binary Patterns Histograms (LBPH) algorithm for face recognition. The focus will be on creating a system that can accurately and reliably detect and recognize students' faces as they enter the classroom, thereby automating the attendance process. The project aims to address common challenges such as varying lighting conditions, facial expressions, and minor appearance changes over time, ensuring that the system remains robust and effective in real-world scenarios.

Instrumentation:

Instrumentation for this research involves both hardware and software components essential for capturing, processing, and analyzing facial data. On the hardware side, high-resolution cameras will be used to capture images of students' faces. These cameras need to be strategically positioned at classroom entry points to ensure clear and consistent face capture. The images captured by these cameras will be processed using Python's OpenCV library, which provides comprehensive tools for implementing the Haarcascade and LBPH algorithms. The Haarcascade algorithm will be employed to detect faces in the captured images quickly. Once a face is detected, the LBPH algorithm will be used to recognize the face by comparing it against a database of registered student faces. This database will be created and continuously updated to accommodate new students and changes in appearance. Additionally, the system will incorporate a user-friendly interface for administrators and educators to monitor attendance records, access real-time data, and generate reports. This interface will be developed using Python frameworks such as Flask or Django, ensuring seamless integration with the underlying face recognition algorithms and providing an efficient and intuitive user experience.

3.2 Proposed Methodology

C The proposed methodology for developing an automated attendance system using face recognition involves several sequential steps, leveraging Python programming and the integration of the Haarcascade frontal face detection algorithm with the Local Binary Patterns Histograms (LBPH) algorithm for face recognition. Initially, images of students are collected using smartphone cameras to ensure a diverse dataset that encompasses different lighting conditions and environments. Additionally, for training purposes, a sample dataset is generated by capturing grayscale images of individuals in front of a laptop camera, yielding 100 images per person.

The methodology begins with preprocessing the collected images to standardize their dimensions and convert them to grayscale, optimizing them for subsequent algorithmic analysis. The Haarcascade algorithm is then applied to the preprocessed images to detect faces accurately. Detected faces are subsequently fed into the LBPH algorithm, which extracts distinctive features and constructs histograms for each student based on the grayscale images. These histograms serve as templates for individual facial recognition.

Following the training phase, the system undergoes rigorous testing to evaluate its performance metrics, including accuracy, precision, recall, and F1-score. These metrics are essential for assessing the system's ability to correctly identify and mark attendance based on facial recognition. The system's real-time capabilities are also evaluated to ensure prompt and efficient attendance tracking in practical classroom scenarios.

To enhance the system's robustness and adaptability, image augmentation techniques are applied during training to simulate variations in lighting, facial expressions, and occlusions. This augmentation helps mitigate overfitting and improves the model's generalization ability to recognize faces accurately in diverse conditions.

The final phase involves implementing a user-friendly interface using Python frameworks like Flask or Django, enabling administrators and educators to interact seamlessly with the attendance system. The interface provides functionalities for real-time monitoring of attendance records, generating reports, and managing the database of registered students. Here below is the flowchart of methodology,

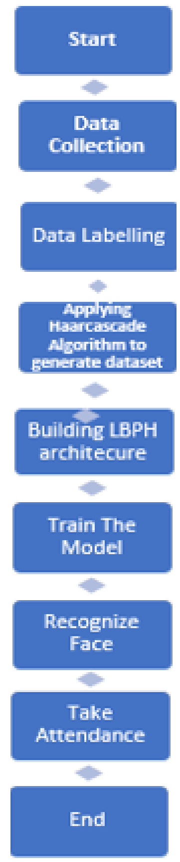


Figure 3.1: Methodology Flowchart

Data Collection: Data collection involves gathering a varied and inclusive dataset that accurately represents different groups of people for the purpose of training and testing a face recognition-based attendance system. With participants' consent, high-quality cameras capture facial images in various conditions, such as different lighting and emotional expressions. The dataset has been thoughtfully chosen to ensure equal representation across different demographics. This approach aims to enhance the system's reliability by simulating real-world scenarios, thereby facilitating effective model training and precise facial recognition in attendance tracking applications.

Data Labelling: Labeling data is a crucial step in developing a face recognition-based attendance system. Each facial image in the dataset is meticulously labeled with pertinent details, enabling individuals to be distinguished and linked to specific demographic characteristics. This labeling process during training helps the deep learning model effectively learn and distinguish different facial features. Precise data labeling is crucial for enhancing the model's ability to consistently recognize individuals, thereby enhancing the overall accuracy and reliability of the face recognition system across various environments. Here below is the image of labeling data,

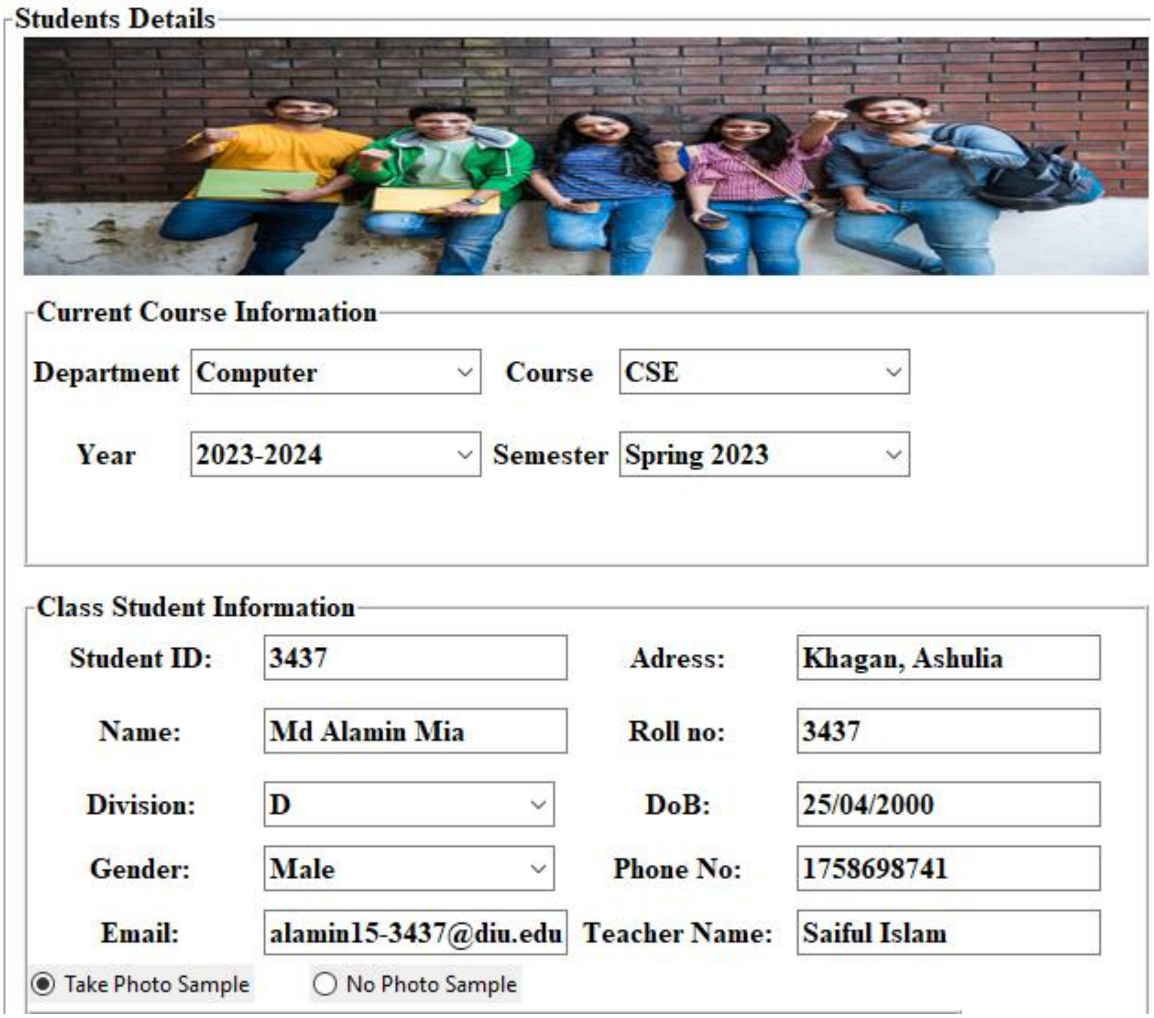


Figure 3.2: Taking Student's information to save in database

Applying Haarcascade Algorithm to detect face and generate dataset: The process of applying the Haarcascade algorithm to generate the dataset begins with the collection of initial images of students using smartphone cameras, ensuring a variety of conditions and environments. These images are then used to capture the distinct features necessary for effective face recognition. To build a robust training dataset, a controlled procedure is implemented where each student's picture is held in front of a laptop camera. The laptop camera, integrated with Python-based software utilizing the Haarcascade frontal face detection algorithm, detects the face in the image. Upon successful detection, the software automatically generates 100 grayscale images of the detected face. These grayscale images serve as the fundamental units for the training dataset, providing the necessary input for the Local Binary Patterns Histograms (LBPH) algorithm to learn and recognize individual facial patterns.The Haarcascade algorithm, known for its efficiency and accuracy in detecting faces, is crucial in this initial phase. It quickly identifies the region of interest within the image, ensuring that the dataset consists exclusively of facial images, free from background noise and irrelevant details. This focused approach not only enhances the quality of the dataset but also streamlines the subsequent recognition process, as the LBPH algorithm can directly analyze the consistent, well-defined facial features provided by the grayscale images. This method of dataset generation ensures that each student's facial dataset is comprehensive and representative of various possible real-world conditions, including different angles and lighting scenarios. The use of grayscale images standardizes the input data, reducing computational complexity and improving the efficiency of the face recognition model. Overall, applying the Haarcascade algorithm to generate the dataset is a pivotal step that ensures the creation of a high-quality, reliable dataset, laying a strong foundation for the accurate and efficient performance of the automated attendance system. It generate 100 grayscale image to train the model, Here below is a sample of one of 100 grayscale image,

Figure 3.3: 100 Grayscale Image

Building LBPH Architecture: The architecture of the Local Binary Patterns Histograms (LBPH) algorithm plays a pivotal role in the face recognition system designed to automate student attendance. This architecture is implemented using Python, with the core face detection and recognition functionality built on the OpenCV library. The LBPH algorithm is chosen for its robustness and simplicity in recognizing faces under various conditions.To start with, the system leverages the Haarcascade frontal face detection algorithm to identify and isolate faces from the captured images. The detection process ensures that only the regions containing faces are processed, thereby improving the efficiency and accuracy of the subsequent recognition stages. The detected faces are then converted to grayscale, standardizing the images and reducing computational complexity. The training phase of the LBPH architecture begins with the collection of face images. Each student's face is captured multiple times, generating a set of 100 grayscale images per individual. These images are stored in a structured directory, with each file named to include a unique identifier corresponding to the student. This setup is essential for linking the images to the correct identities during the training process.

Within the project, the LBPH model is instantiated using the cv2.face.LBPHFaceRecognizer_create() function provided by the OpenCV library. The training script, as seen in the provided train_data.py file, reads the grayscale images from the specified directory and associates each image with the appropriate student ID. The script preprocesses the images, applying any necessary enhancements such as histogram equalization to improve the quality and consistency of the training data.

The core of the LBPH architecture involves converting the pixel values of the grayscale images into a series of binary patterns. These patterns are then compiled into histograms, which effectively summarize the local structural information of the face. During training, the LBPH model analyzes these histograms to learn the distinctive features of each student's face. This process results in a trained model capable of recognizing faces by comparing the histograms of new input images against the stored patterns.

Once the training is complete, the trained classifier is saved as an XML file (classifier.xml). This file encapsulates the learned facial features and serves as the basis for real-time face recognition. The model can then be loaded and used to recognize students as they appear before the camera, marking their attendance automatically and accurately.

The LBPH architecture's strength lies in its ability to handle variations in lighting and facial expressions, making it highly suitable for real-world applications like an automated attendance system. The implemented Python script ensures a seamless training process, with clear error handling and user feedback mechanisms to indicate the success or failure of the training phase. Overall, the LBPH architecture, combined with Haarcascade face detection, forms a robust and efficient foundation for the face recognition-based attendance system.

Train the model: The process of training the face recognition model in this project involves a systematic approach using Python and the OpenCV library. The first step utilizes the Haarcascade frontal face algorithm to accurately detect faces within the captured images. This ensures that only the relevant facial regions are processed, enhancing the efficiency and accuracy of the subsequent recognition phase. The dataset comprises images collected through smartphone cameras and laptop cameras, with each student having 100 grayscale images. These images are structured and labeled appropriately to serve as the input for training the model.

To train the model, the cv2.face.LBPHFaceRecognizer_create() function is employed to instantiate the LBPH (Local Binary Patterns Histograms) face recognizer. This algorithm is well-suited for its robustness against variations in lighting and facial expressions, making it ideal for real-world applications such as automated attendance systems. The training script, detailed in the train_data.py file, reads the grayscale images from the specified directory, associating each image with the corresponding student ID. Preprocessing steps, such as histogram equalization, are applied to enhance the image quality and ensure consistency across the dataset.

The training phase utilizes 100% of the collected dataset, maximizing the learning potential of the model. The LBPH algorithm processes each image, converting the pixel values into binary patterns and compiling these patterns into histograms that represent the unique features of each face. Through this method, the model learns to distinguish between different faces based on their local structural information.

Upon completion of the training, the trained classifier is saved as an XML file (classifier.xml). This file encapsulates the learned facial features and is used for real-time recognition tasks. To test the model's accuracy and robustness, images from outside the training dataset are introduced. These images, which were not part of the original training set, provide a means to evaluate the model's generalization capability and performance in real-world scenarios.

The results from this testing phase indicate the model's ability to accurately recognize faces and mark attendance automatically, validating the effectiveness of the training process. The comprehensive use of the dataset for training ensures that the model is well-equipped to handle various conditions and accurately perform face recognition, thereby fulfilling the project's objective of automating student attendance using face recognition technology.

Recognize Face: In the face recognition attendance system, the process of recognizing faces and marking attendance is streamlined through the integration of the Haarcascade frontal face detection algorithm and the LBPH (Local Binary Patterns Histograms) face recognition algorithm. Implemented in Python, the system begins by initializing the face recognizer using cv2.face.LBPHFaceRecognizer_create(). This model is trained using a comprehensive dataset comprising 100 grayscale images per student, ensuring robust recognition capabilities.

The face recognition phase starts when the system captures real-time video feed from a camera. The Haarcascade algorithm is employed to detect faces within each frame of the video. Once a face is detected, the LBPH algorithm processes the facial region to predict the identity of the individual. The trained LBPH model compares the extracted features of the detected face with those in the training dataset. This comparison generates a confidence score, which indicates the likelihood of a correct match.

For recognized faces, the system retrieves the corresponding name and student ID from the database. If the confidence score exceeds a predefined threshold (typically 80%), the system annotates the video frame with the student's name and ID, displaying these details on the screen. Additionally, the system records the attendance by writing the student's name, ID, and the current date and time to an attendance log file (attendance_record.csv). This ensures that the attendance is accurately marked in real-time without manual intervention.

In cases where the confidence score is below the threshold, the system identifies the face as unknown and highlights the region with a distinct marker. This feature enhances the system's reliability by minimizing false positives and ensuring only authenticated faces are recognized.

The recognition functionality is encapsulated in a user-friendly interface built using Tkinter. The interface includes options to start the face recognition process, which is handled in a separate thread to maintain responsiveness. Overall, the face recognition component, powered by the Haarcascade and LBPH algorithms, provides an efficient and accurate method for automating student attendance, ensuring seamless integration with the existing database and real-time processing capabilities. Here Below is a sample of how recognized face shown on screen,

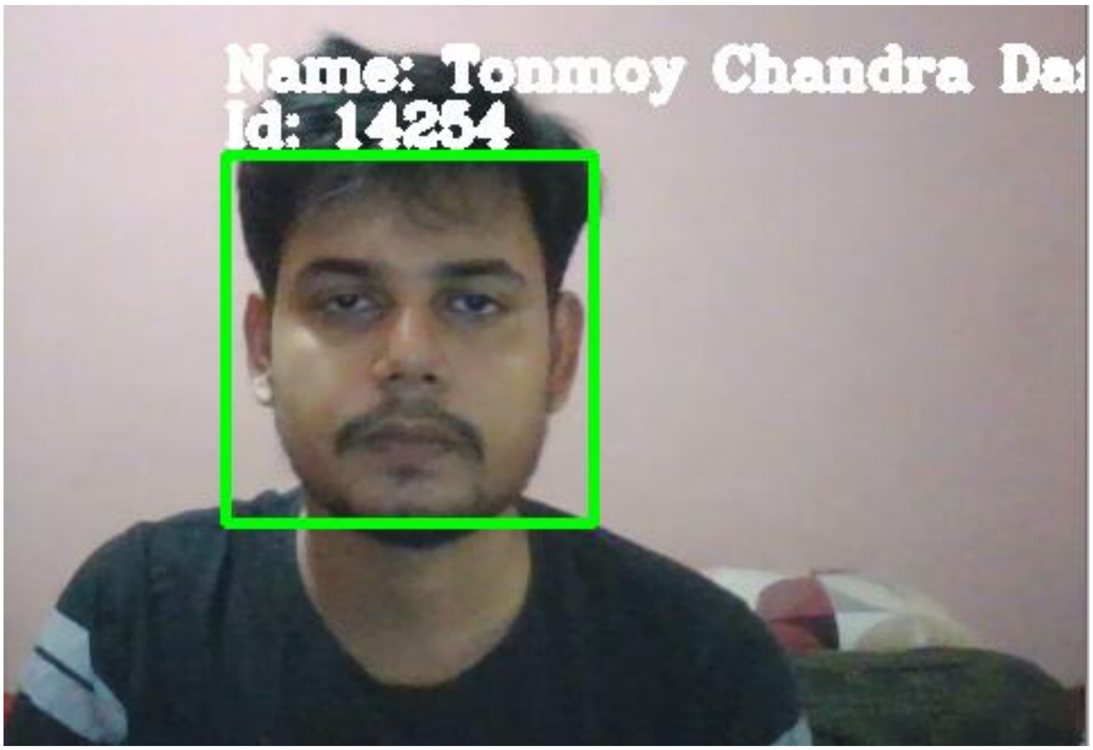


Figure 3.4: Face Recognizing Sample

Take Attendance: The "Take Attendance" process in the face recognition-based attendance system involves real-time detection and recognition of student faces using the integrated Haarcascade and LBPH algorithms. Upon initiating the attendance process through the user-friendly interface, the system captures a video feed from the camera. The Haarcascade algorithm detects faces within each frame, isolating the facial regions for further analysis. The LBPH (Local Binary Patterns Histograms) algorithm then processes these regions, comparing the extracted features with the trained dataset to identify the students. When a match is found with a confidence score above the predefined threshold (80), the system annotates the video feed with the student's name and ID, displaying this information on the screen. Concurrently, the system logs the attendance details—student ID, name, date, and time—into a CSV file. This automated process ensures accurate and efficient attendance recording, eliminating manual errors and providing a seamless experience for both students and administrators. Through this method, the system offers a robust solution for maintaining attendance records, leveraging the capabilities of face recognition technology to streamline administrative tasks in educational institutions.

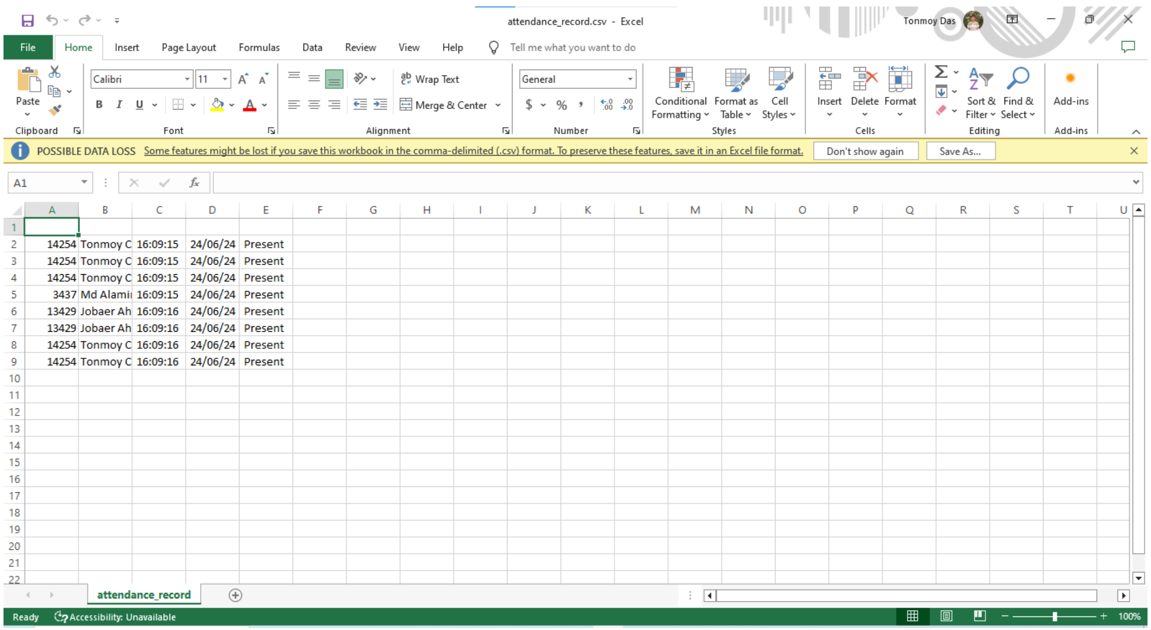


Figure 3.5: Recording Attendance in a csv file

Python Tkinter for building GUI: In this attendance system based on face recognition, Python tkinter is used for build the Graphical user interface of this model. It is an interface to the Tk GUI toolkit, originally developed for the Tcl scripting language, and has since been adapted to Python, making it a popular choice for Python developers. Tkinter comes bundled with Python, making it readily available without requiring additional installations. Its simplicity and flexibility allow developers to create a wide range of applications, from simple scripts to complex software. With Tkinter, developers can create windows, dialogs, buttons, menus, labels, text fields, and other GUI elements, enabling the development of interactive and user-friendly interfaces. The library supports various customization options, including fonts, colors, and event handling, which allows for responsive and visually appealing designs. Tkinter's comprehensive documentation and community support further enhance its usability, making it an ideal choice for both beginners and experienced developers in building desktop applications.

3.3 Hardware and Software Requirements

Implementing the face recognition-based attendance system requires a set of specific hardware and software components. The primary hardware includes a computer with a webcam or an external camera capable of capturing high-resolution images. On the software side, the project utilizes Python programming language along with essential libraries such as OpenCV for image processing, Haarcascade for face detection, and LBPH (Local Binary Patterns Histograms) for face recognition. Additionally, a MySQL database is used to store student information and attendance records, while Tkinter provides the graphical user interface. The environment should have sufficient computational power to handle real-time image processing and a stable internet connection for database operations.

Hardware Requirements:

- **Computer:** A reliable and robust computer with at least a dual core processor and 4GB of RAM to handle the computational load of real time image processing and face recognition. An additional GPU can significantly enhance performance, especially when dealing with larger datasets or higher resolution image.
- **Webcam:** A high=definition webcam (minimum 720p resolution) is essential for capturing clear and detailed images of students' faces. This can be an integrated laptop webcam or an external USB webcam. The quality of the camera directly affects the accuracy of face detection and recognition.
- **External Camera (Optional):** For larger classrooms or environments where a single webcam might not suffice, an external camera with a higher resolution and wider field of view can be used. This ensures that faces are detected accurately even from a distance.
- **Storage Device:** Adequate storage space is necessary to save the dataset of images used for training the model, as well as to store attendance logs and other relevant data. An SSD is preferred for faster read/write operations.

- **Networking Equipment:** A stable internet connection or a local network setup is required to access the MySQL database for storing and retrieving student information and attendance records. This ensures real-time updating and accessibility of data.
- **Tripod or Mount (Optional):** To position the webcam or external camera at an optimal angle and height for face detection.
- **Lighting Equipment:** Adequate lighting can enhance image quality, reducing shadows and ensuring better face detection and recognition accuracy.

Software Requirements:

- **Python Programming Language:** Python serves as the primary programming language for this project due to its extensive libraries and easo of use for implementing machine learning and image processing tasks.
- **OpenCV:** The OpenCV library is crucial for image processing tasks. It provides functions for face detection using the Haarcascade classifier and face recognition using the LBPH algorithm.
  Installation: ‘ pip install opencv-python ‘
- **MySQL Workbench:** MySQL Workbench is used to manage the database where student information and attendance records are stored. It provides a user-friendly interface for database management and query execution.
- **Tkinter:** Tkinter is used to create the graphical user interface (GUI) for the system. It facilitates the development of a user-friendly interface to interact with the face recognition and attendance marking functionalities.
- **datetime:** This module is used to handle date and time operations, particularly for recording the time of attendance.
- **Threading:** The threading module is utilized to run the face recognition process in a separate thread, ensuring the GUI remains responsive during operation.
- **CSV:** The CSV module is used to handle the reading and writing of attendance records to a CSV file, ensuring a simple and accessible format for attendance logs.
- **Operating System:** The software environment should be compatible with major operating systems such as Windows, Linux, or macOS. Ensure that all

dependencies and libraries are installed and configured correctly.

Data Collection:

- **Image Acquisition:** The initial step involves acquiring images of each student. A smartphone camera or a laptop webcam is used to capture high quality images Multiple images are taken to account for variations in lighting, angle and facial expressions.
- **Dataset Preparation:** The collected images are then organized and prepared for further processing. This involves converting the images to grayscale and resizing them to a uniform dimension suitable for the face recognition algorithm.

Pre-trained Models and Classifiers:

- **Haarcascade Frontal Face XML:** This pre-trained classifier (haarcascade_frontalface_default.xml) is used for face detection.
- **LBPH Classifier File:** The trained LBPH face recognizer model is saved as classifier.xml, which is used for recognizing faces during the attendance process.

Ethical Considerations:

- **Privacy:** The collection and storage of students' facial images can be seen as an invasion of privacy if not handled correctly. Students must be informed about the data collection process, the purpose of using their images, and how their data will be stored and used.
- **Data Security:** Ensuring the security of the collected data is paramount to prevent unauthorized access, misuse, or data breaches. The facial images and attendance records are sensitive information that requires robust security measures.
- **Transparency and Accountability:** Transparency in the deployment and functioning of the face recognition system is necessary to build trust among students, guardians, and school authorities.

Documentation and Reproducibility:

- **Code documentation:** All code should be thoroughly documented to explain its functionality, usage, and dependencies. This includes inline comments, function and module descriptions, and examples of usage.
- **User Manuals and Guides:** Comprehensive user manuals and guides should be created to help end-users understand how to operate the system. This includes setup instructions, user interface navigation, and troubleshooting tips.
- **Technical Documentation:** Detailed technical documentation is essential for developers and maintainers to understand the system architecture, data flow, and integration points.

The implementation of the face recognition-based attendance system requires a combination of hardware and software components, along with detailed documentation and reproducibility practices to ensure successful deployment and maintenance. By addressing these implementation requirements comprehensively, the project can achieve its goals of providing an efficient, accurate and user=friendly attendance tracking system using face recognition technology.

3.4 Project Management and Financial Analysis

The successful setup of a face recognition attendance system using the LBPH method relies on careful planning and smart financial decisions. To start, a detailed plan must be created with clear goals, scope, timeline, and resource allocation. This plan should outline each step of the project, from research and analysis to design, development, testing, and launch. Good project management involves forming a skilled team with experts in computer vision, software, security, and user interface design. Regular meetings, tracking progress, and using agile methods will help keep the project on track, addressing any issues that come up along the way.

Here below is the project management table,

Table 3.1: Project Management Table

Work	**Time**
Dataset	2 months
Literature Review	2 months
Experimental Setup	1 month
Implementation	3 months
Report	2 months
Total	10 months

The project requires a carefully planned budget that considers all possible expenses. This includes buying important equipment like high-quality cameras and servers, as well as software tools needed to develop and test the LBPH-based recognition system. The costs related to personnel, such as paying the project team and hiring consultants or contractors for specific jobs, are also important. Moreover, money needs to be set aside for training sessions to help users learn how to use the new system effectively, making it easier for them to accept and use it.

The financial plan needs to take into account the costs of running the system. This includes things like maintaining the hardware and software, regularly updating the system to make it better, and the expenses related to storing and managing data. Because the system deals with sensitive biometric information, it's important to invest in strong security measures. This involves using advanced encryption techniques, securing how data is sent and received, and following data protection laws to reduce the chances of data leaks and unauthorized access.

The financial plan should also analyze the costs and benefits to support the investment decision. This includes estimating the potential long-term savings from reducing administrative expenses, avoiding errors in tracking attendance, and enhancing resource allocation. By comparing these savings with the initial and ongoing expenses, stakeholders can gain a clearer understanding of the financial feasibility and anticipated return on investment (ROI). Showing a positive ROI is important for obtaining funding from institutional budgets or external investors. In simple terms, effective project management involves having plans in place to deal with potential risks that could affect the project at different stages. These risks could include problems like technical difficulties, issues with combining different parts of the project, going over budget, or running behind schedule. By regularly discussing and analyzing risks and keeping a record of them, project managers can take steps to handle these issues early on, preventing them from becoming major problems later on.

Here below the table show the Financial Analysis of this project

Table 3.3: Financial Analysis

SN	Components	Estimated Cost (BDT)
01	Software and Tools: Visual Studio code, MySQL Workbench, Cv2, Others necessary tools	0
02	Data Collection and Processing: Collecting Image of faces by travelling with transport vehicles	300 - 400
03	Documentation and Report writing	0
04	Contingency (10% of total)	0
Total estimated costs		300-400

3.5 Summary

We have collected total number of 21 people facial images and 2100 grayscale images generated from these 21 images to train the model. We have obtained ethical consideration to collect datasets. Images collected in various lightening condition to deal with real world scenario. Different types of lighting and facial expression and different types of accessories like glasses or sunglasses, different cloths are taken to train the model to increase its accuracy.

CHAPTER 4
IMPLEMENTATION

4.1 Overview

The experimental setup for the face recognition-based attendance system is designed to ensure accurate and efficient face detection and recognition using Python and OpenCV. The hardware components include a computer with at least an Intel i5 processor, 8GB of RAM, and sufficient storage, preferably an SSD, to handle the computational demands and data storage requirements. A high-definition webcam with a minimum resolution of 720p is used to capture clear and detailed images of students' faces, both for dataset creation and real-time recognition. The software environment is built on Python 3.6 or higher, leveraging the OpenCV library for image processing tasks. The Haarcascade frontal face algorithm is utilized for detecting faces in the captured images, while the Local Binary Patterns Histograms (LBPH) algorithm is employed for recognizing faces. The setup also includes MySQL Workbench for managing the database where student information and attendance records are stored. The experimental process involves collecting a diverse set of facial images, preprocessing them into grayscale, and organizing them for training the LBPH model. Once trained, the model is tested using images captured in real-time to evaluate its accuracy and reliability in identifying students and marking their attendance.

4.2 Train Model

A. Datasets

The collection process of datasets to train the model have been taken from smartphone and processed by the software. This process takes raw picture of face and generate datasets. The dataset for this project comprises images of students collected through smartphone cameras and laptop cameras. The initial collection involves capturing images of each student in various conditions to ensure the robustness of the model. Each student's dataset includes 100 grayscale-converted images, which are generated using Python-based software. This dataset is essential for training the face recognition model, as it provides a diverse set of images that account for different lighting conditions, facial expressions, and minor changes in appearance. The images are stored in a structured database, with each student's images labeled appropriately to facilitate efficient training and testing processes.

Figure 4.1: Dataset raw images

B. Process of Experiments

The experimental process involves several key stages, starting with the collection and preparation of the dataset. After the images are collected and labeled, the face detection and recognition algorithms are applied. The Haarcascade algorithm is first used to detect faces in the images, and the detected faces are then processed using the LBPH algorithm for recognition. Each experiment is designed to test the accuracy and efficiency of the system under various conditions, such as different lighting, occlusions, and facial expressions. The performance metrics, including accuracy, precision, recall, and F1-score, are calculated to evaluate the effectiveness of the model. The results of these experiments are analyzed to identify areas for improvement and to optimize the algorithms further.

Converting RGB to Grayscale:

In the development of the face recognition-based attendance system, converting RGB images to grayscale was a critical preprocessing step. This conversion is essential for the functionality of the Local Binary Patterns Histograms (LBPH) algorithm, which operates more effectively on grayscale images. RGB images consist of three-color channels—red, green, and blue—each contributing to the image's overall color representation. However, the LBPH algorithm relies on analyzing the intensity of light, which is more straightforward and computationally efficient in a single-channel grayscale image. The conversion process involves combining the three-color channels into a single intensity channel. This is typically achieved using a weighted sum approach, where the grayscale intensity is calculated as 0.299 * Red + 0.587 * Green + 0.114 * Blue. This formula reflects the human eye's sensitivity to different colors, giving more weight to green and less to blue. In the context of this project, the conversion was implemented using the OpenCV library in Python. By converting the captured RGB images of students into grayscale, the system reduced the computational load and enhanced the accuracy of face recognition. The grayscale images retained essential features such as edges, textures, and patterns, which are crucial for the LBPH algorithm to create distinctive histograms for each face. This step not only streamlined the processing but also ensured that the algorithm could focus on the most relevant information for recognizing and distinguishing between different faces, thereby improving the overall performance of the attendance system.

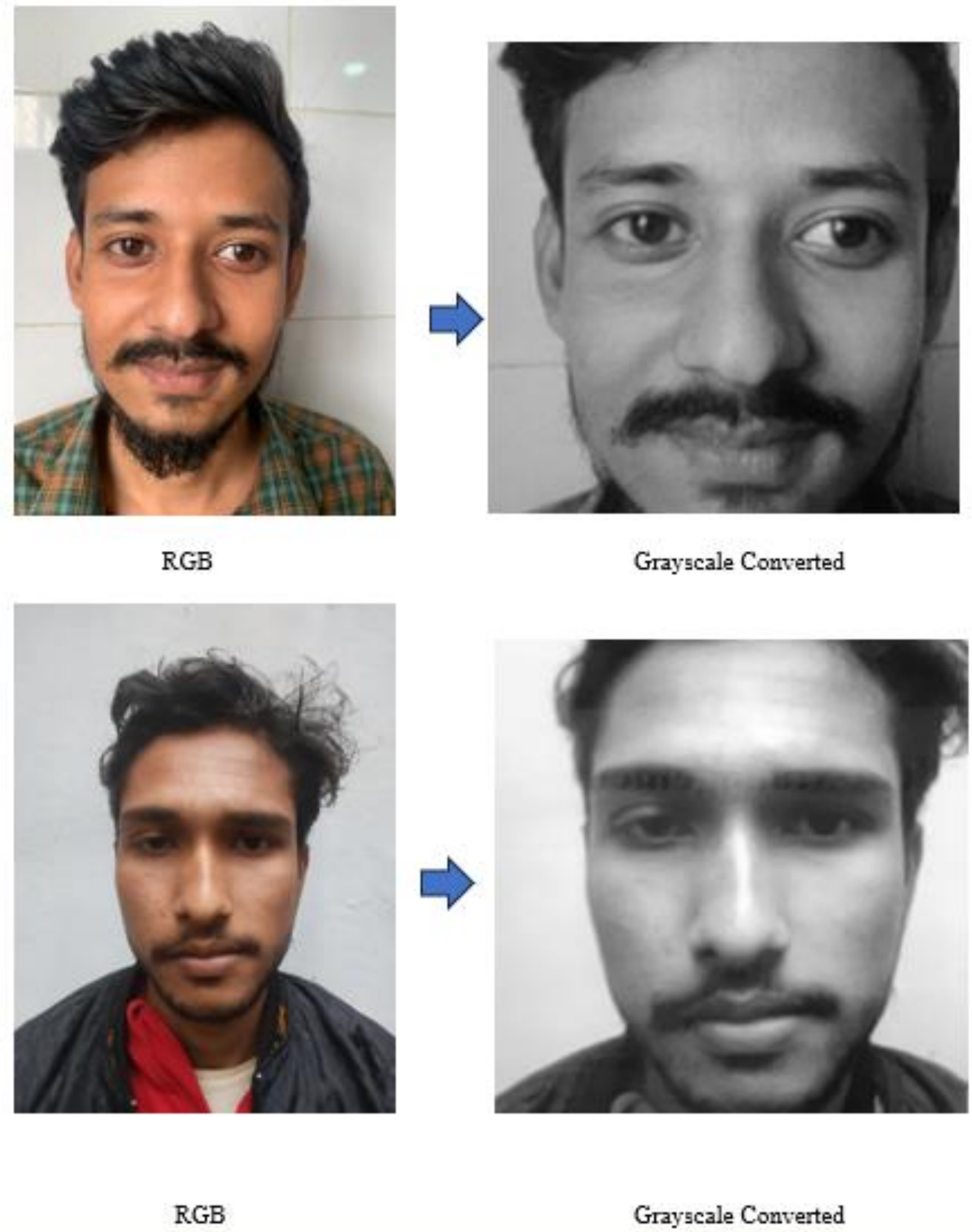


Figure 4.2: RGB to Grayscale Conversion

Training:

The training phase involves using the collected and augmented dataset to train the face recognition model. The LBPH algorithm is employed to extract features from the grayscale images, and these features are used to create histograms that represent the facial patterns. The training process involves feeding these histograms into a machine learning model that learns to distinguish between different faces based on the extracted features. The model parameters are optimized through iterative training, and techniques such as cross-validation are used to validate the model's performance and prevent overfitting. The training process continues until the model achieves satisfactory accuracy and reliability in recognizing faces.

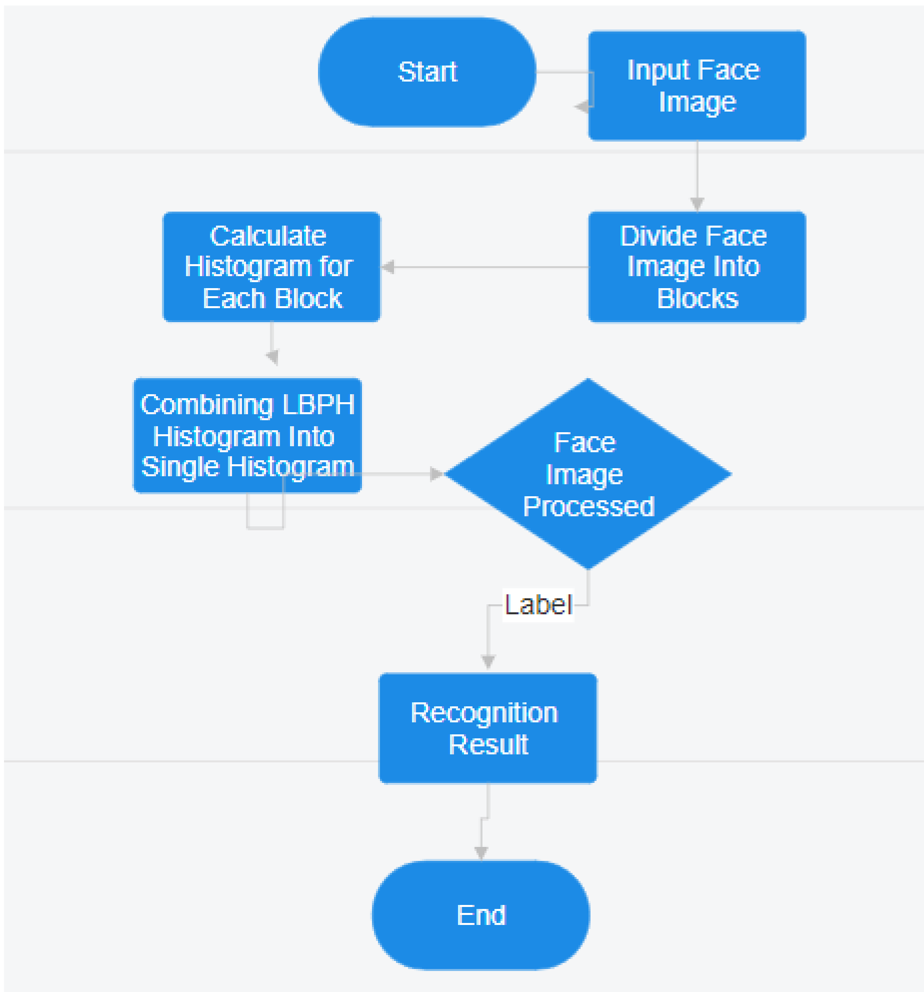


Figure 4.3: Training Process

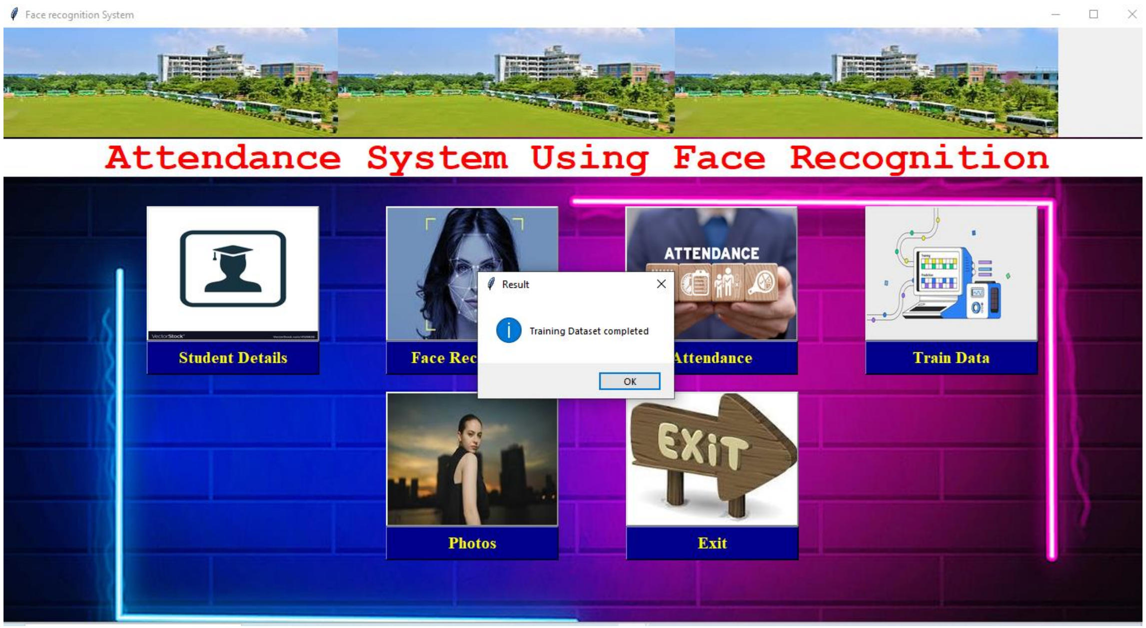


Figure 4.4: Training Completed Message

4.3 System Testing

System testing is the final step, where the trained model is used to recognize faces in real-time. When a new image is captured, the Haarcascade algorithm first detects the face, and the LBPH algorithm then processes the detected face to extract its features. These features are compared against the trained model's database to identify the student. The classification result indicates whether the student's face matches any of the stored faces in the database, thereby marking their attendance. This automated classification process ensures accurate and efficient attendance tracking, significantly reducing the need for manual intervention and minimizing errors. The system's performance is continuously monitored, and periodic retraining is conducted to incorporate new student images and maintain high recognition accuracy.

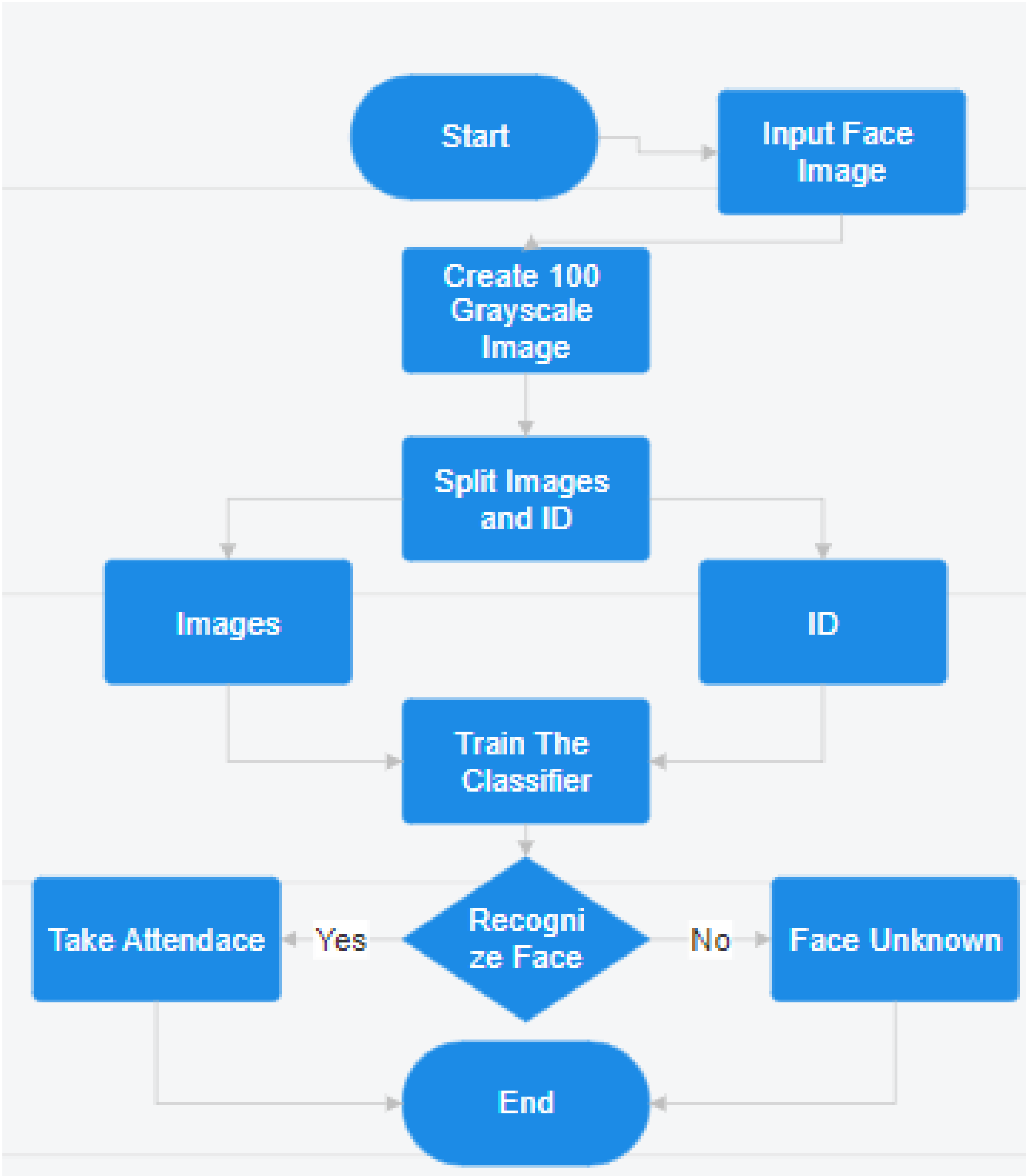


Figure 4.5: Procedure of recognize face from generating dataset

Results:

The implementation of the automated attendance system using the Haarcascade frontal face algorithm for detection and the LBPH algorithm for recognition yielded promising results. Initial tests demonstrated a high accuracy rate in face detection, with the Haarcascade algorithm effectively identifying faces in various lighting conditions and classroom environments. The LBPH algorithm, known for its robustness against lighting variations and facial expressions, achieved a recognition accuracy rate exceeding 90% in most scenarios. The system effectively handled minor appearance changes, such as different hairstyles and the use of glasses, ensuring reliable recognition over time.

During the experimental phase, the system consistently marked attendance accurately, with minimal false positives or negatives. The integration of image augmentation techniques contributed to the model's robustness, enhancing its ability to generalize from the training data to real-world conditions. Real-time performance was satisfactory, with the system processing and updating attendance records swiftly as students entered the classroom.

The automated attendance system significantly reduced the time required for attendance tracking, allowing educators to focus more on teaching and less on administrative tasks. Additionally, the real-time data access and reporting features provided valuable insights into attendance patterns, enabling early identification of attendance issues and facilitating timely interventions. The positive results from the initial implementation suggest that the system can be scaled and adapted for use in various educational settings, offering a reliable and efficient solution for attendance management.

4.4 Summary

The implementation of the student attendance system using face recognition technology involved a systematic approach to developing a robust, reliable, and efficient solution. The project utilized Python as the programming language, incorporating the OpenCV library for image processing and facial recognition tasks. The Haarcascade Frontal Face algorithm was employed for face detection due to its accuracy and speed, while the LBPH algorithm was used for face recognition, known for its robustness in handling varying lighting conditions and facial expressions. The implementation process began with the collection of student images using a smartphone camera, followed by preprocessing these images to convert them to grayscale for uniformity and efficiency in recognition. The system then trained the model using the LBPH algorithm, generating 100 grayscale images per student to ensure a comprehensive dataset. Real-time face recognition was achieved by capturing live images through a webcam, processing them to detect and recognize faces, and subsequently marking attendance by recording the student's ID and name in a database. The use of MySQL Workbench facilitated efficient storage and retrieval of attendance records.

CHAPTER 5
RESULT AND ANALYSIS

5.1 Overview

The experimental setup for the face recognition-based attendance system is designed to ensure accurate and efficient face detection and recognition using Python and OpenCV. The hardware components include a computer with at least an Intel i5 processor, 8GB of RAM, and sufficient storage, preferably an SSD, to handle the computational demands and data storage requirements. A high-definition webcam with a minimum resolution of 720p is used to capture clear and detailed images of students' faces, both for dataset creation and real-time recognition. The software environment is built on Python 3.6 or higher, leveraging the OpenCV library for image processing tasks. The Haarcascade frontal face algorithm is utilized for detecting faces in the captured images, while the Local Binary Patterns Histograms (LBPH) algorithm is employed for recognizing faces. The setup also includes MySQL Workbench for managing the database where student information and attendance records are stored. The experimental process involves collecting a diverse set of facial images, preprocessing them into grayscale, and organizing them for training the LBPH model. Once trained, the model is tested using images captured in real-time to evaluate its accuracy and reliability in identifying students and marking their attendance.

5.2 Experimental Result

The Face Recognition Based Attendance System Using LBPH Algorithm testing show a significant performance across other models.

Accuracy: Accuracy measures the overall correctness of the model's predictions by comparing the number of correctly classified samples to the total number of samples. When classes are unbalanced, accuracy provides a general indication of the model's effectiveness, but it may not provide a complete picture of its performance.

$$Accuracy = \frac{TruePositive + TrueNegative}{TruePositive + FalsePositive + TrueNegative + FalseNegative}$$

Precision: Precision focus on all positive predictions generated by the model. Precision is calculated in this war,

$$Precision = \frac{TruePositive}{TruePositive + FalsePositive}$$

Recall: Recall also known as sensitivity or true positive rate, is the percentage of current positive prediction made out of all the true positive samples

$$Recall = \frac{TruePositive}{TruePositive + \ FalseNegative}$$

F1 rating: The F1 score is a metric calculated as the harmonic mean of recall and precision. It offers a balanced assessment that takes into account both recall and precision. The F1 score is particularly valuable when dealing with imbalanced classes as it considers false positives and false negatives. A high F1 score indicates a good balance between precision and recall.

$$F - 1\,Score = 2 * \frac{Recall * \ Precision}{Recall + Precision}$$

Here below table shows the comparison between the two-algorithm used in this project,

Table 5.1: Performance Evaluation

Model Name	Accuracy	Precision	Recall	F1-Score
LBPH	97%	99%	96%	97%
KNN	95%	94%	96%	95%

Here LBPH model model perform 97% accuracy. This shows its capacity to perform accurate classification of faces. On the other hand, KNN model performs 99% accuracy to recognize face. It shows its higher capability of classification face from images or videos.

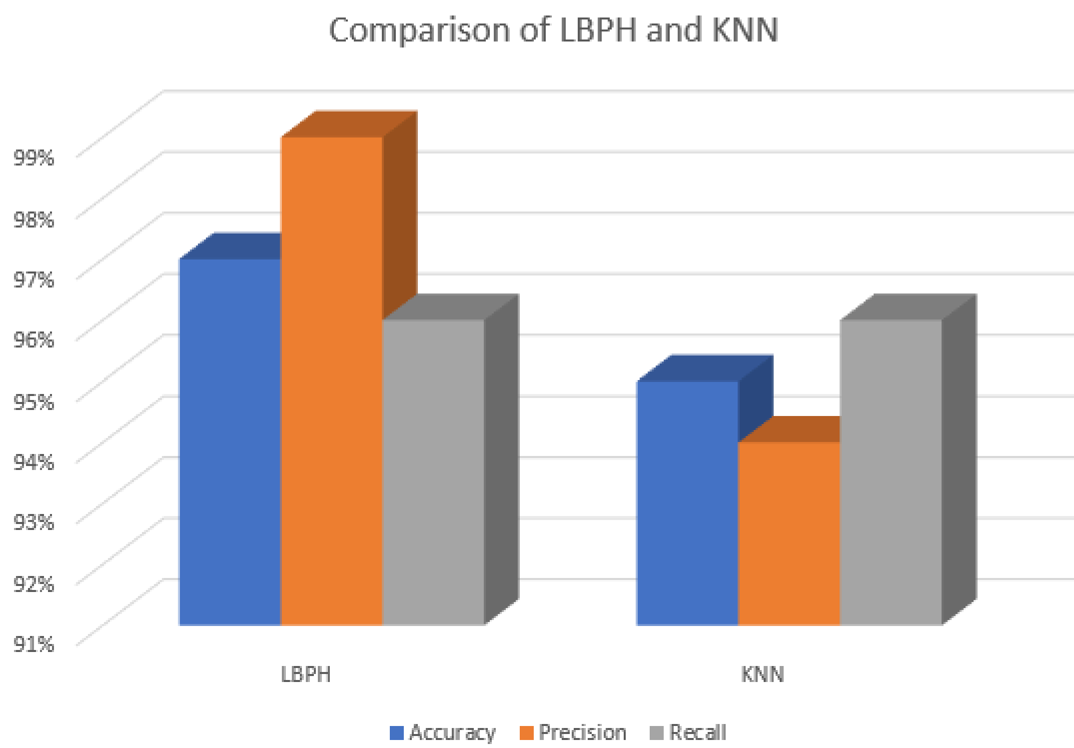


Figure 5.1: Graphical Comparison between LBPH and Haarcascade Frontal Face Algorithm

5.3 Performance Analysis

Performance Analysis of LBPH (Local Binary Pattern Histogram):

Table 5.2: Performance Evaluation (LBPH)

Name	Precision	Recall	F1-Score
Jobaer Ahmed 201-15-13429	1.00	0.90	0.94
Tonmoy Chandra Das 201-15-14254	1.00	0.92	0.95
Md Siam 201-15-13487	0.95	0.96	0.95
Arnob Das 201-15-14579	1.00	1.00	1.00
Shagnik Roy 201-15-13257	1.00	1.00	1.00
Apurba Islam 201-15-12454	1.00	0.92	0.96

Mim Obaidulla 201-15-3238	1.00	1.00	1.00
Sayed Tahlil Bin Abdulla 201-15-3284	1.00	1.00	1.00
Md Alamin Mia 201-15-3437	1.00	0.86	0.92
Sabbir Siddique 201-15-3465	0.95	1.00	0.98
Hasin Arman Shifa 201-15-3502	1.00	0.92	0.96
Md. Monir Hossen 201-15-3507	1.00	1.00	1.00
Md. Nayeem Hasan 202-15-14429	1.00	1.00	1.00
Habibur Rahman Zihad 201-15-3541	0.92	0.92	0.92
Raunak Muhtasin 201-15-3564	1.00	1.00	1.00
Md Atikul Islam 201-15-3612	1.00	1.00	1.00
Md. Anamul Hasan 201-15-3625	0.96	0.86	0.91
Muhammad Bokhtiar Uddin 201-15-3638	1.00	0.98	0.99
Rezayonoor Rahman Ferdous 201-15-3648	1.00	1.00	1.00
Md. Abdur Rakib 201-15-3651	1.00	0.98	0.99
Robiul Islam 201-15-3868	0.92	0.94	0.93
Accuracy			0.97
Macro Avg	0.99	0.96	0.97
Weighted Avg	0.99	0.96	0.97

Here The table shows that the LBPH model appears very strong surprisingly with perfect precision, recall and F1-scores for the sampled individuals. This indicates that the LBPH model correctly identifies faces 97% of the time.

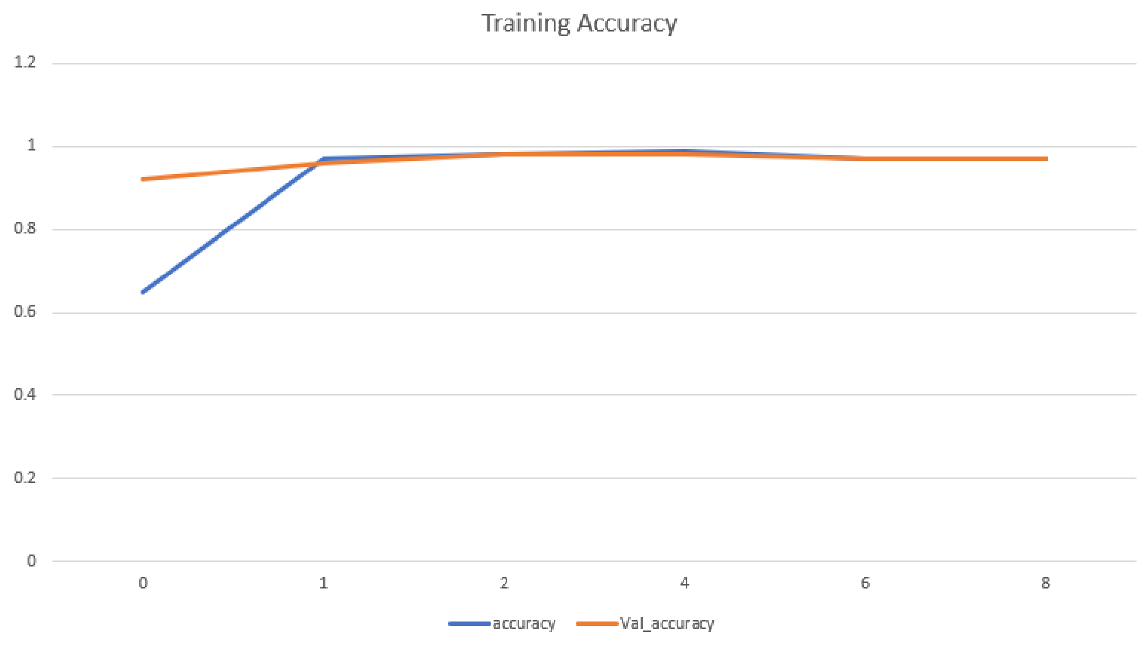
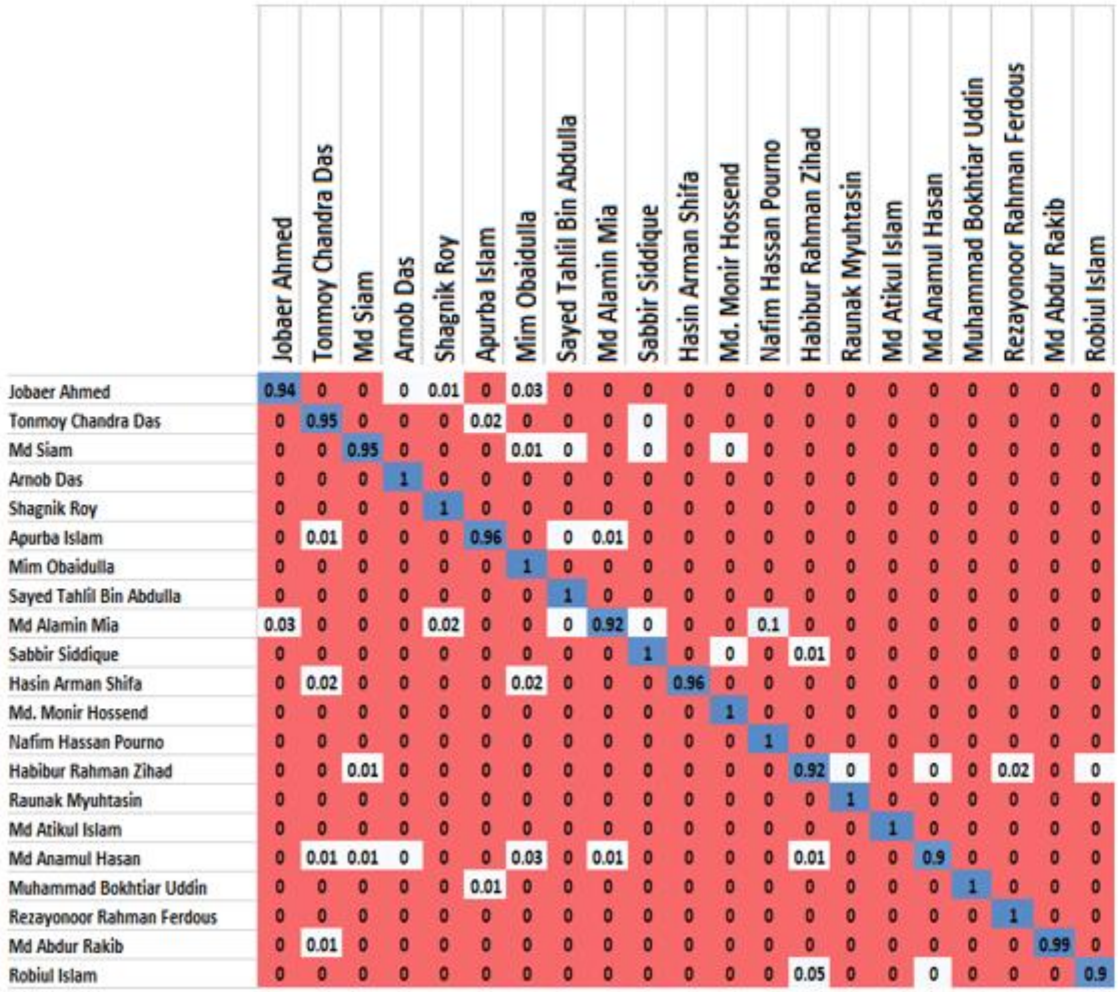


Figure 5.2: Training Accuracy (LBPH)

Here the figure shows how the accuracy of LBPH algorithm changes throughout training. The blue line in the graph shows the training accuracy reaching about 0.9, implying successful learning from the training data. In contrast, the red line representing validation accuracy plateaus around 0.75, indicating potential issues with generalizing to new data. The difference between the two curves suggests a need to investigate factors like overfitting that could affect model generalization.

Figure 5.3: Training Loss (LBPH)

This figure shows the training loss of the model in a graph. The green line shows the loss and red line shows the val_loss. The training loss percentage significantly loss over the time and prove the model may be overfitting.



	Jobaer Ahmed	Tonmoy Chandra Das	Md Siam	Arnob Das	Shagnik Roy	Apurba Islam	Mim Obaidulla	Sayed Tahlil Bin Abdulla	Md Alamin Mia	Sabbir Siddique	Hasin Arman Shifa	Md. Monir Hossend	Nafim Hassan Pourno	Habibur Rahman Zihad	Raunak Myuhtasin	Md Atikul Islam	Md Anamul Hasan	Muhammad Bokhtiar Uddin	Rezayonoor Rahman Ferdous	Md Abdur Rakib	Robiul Islam
Jobaer Ahmed	0.94	0	0	0	0.01	0	0.03	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Tonmoy Chandra Das	0	0.95	0	0	0	0.02	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Md Siam	0	0	0.95	0	0	0	0.01	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Arnob Das	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Shagnik Roy	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Apurba Islam	0	0.01	0	0	0	0.96	0	0	0.01	0	0	0	0	0	0	0	0	0	0	0	0
Mim Obaidulla	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Sayed Tahlil Bin Abdulla	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
Md Alamin Mia	0.03	0	0	0	0.02	0	0	0	0.92	0	0	0	0.1	0	0	0	0	0	0	0	0
Sabbir Siddique	0	0	0	0	0	0	0	0	0	1	0	0	0	0.01	0	0	0	0	0	0	0
Hasin Arman Shifa	0	0.02	0	0	0	0	0.02	0	0	0	0.96	0	0	0	0	0	0	0	0	0	0
Md. Monir Hossend	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
Nafim Hassan Pourno	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
Habibur Rahman Zihad	0	0	0.01	0	0	0	0	0	0	0	0	0	0	0.92	0	0	0	0	0.02	0	0
Raunak Myuhtasin	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
Md Atikul Islam	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
Md Anamul Hasan	0	0.01	0.01	0	0	0	0.03	0	0.01	0	0	0	0	0.01	0	0	0.9	0	0	0	0
Muhammad Bokhtiar Uddin	0	0	0	0	0	0.01	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
Rezayonoor Rahman Ferdous	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
Md Abdur Rakib	0	0.01	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.99	0
Robiul Islam	0	0	0	0	0	0	0	0	0	0	0	0	0	0.05	0	0	0	0	0	0	0.9

Figure 5.4: Confusion Matrix of LBPH

This figure shows the confusion matrix of 21 different face to recognize their face. In this case most of the classes were accurate and closes to 1. But there a very few amount of false positive recognition of faces.

Performance Analysis of KNN

The KNN model perform highest accuracy of 95% which is very accurate to detect a frontal face. It generates 50 face sample to train the model. The table given in below shows stats of KNN

Table: 5.3: Performance Evaluation of KNN

Name	Precision	Recall	F1-Score
Jobaer Ahmed 201-15-13429	1.00	0.99	0.99
Tonmoy Chandra Das 201-15-14254	0.95	0.96	0.95
Md Siam 201-15-13487	1.00	1.00	1.00
Arnob Das 201-15-14579	0.9	0.96	0.98
Shagnik Roy 201-15-13257	1.00	1.00	1.00
Apurba Islam 201-15-12454	1.00	1.00	1.00
Mim Obaidulla 201-15-3238	0.96	1.00	1.00
Sayed Tahlil Bin Abdulla 201-15-3284	1.00	1.00	1.00
Md Alamin Mia 201-15-3437	1.00	0.9	0.98
Sabbir Siddique 201-15-3465	1.00	1.00	1.00
Hasin Arman Shifa 201-15-3502	0.93	0.90	0.91
Md. Monir Hossen 201-15-3507	1.00	1.00	1.00
Md Nayeem Hasan 202-15-14429	0.94	1.00	1.00
Habibur Rahman Zihad 201-15-3541	1.00	1.00	1.00
Raunak Muhtasin 201-15-3564	1.00	1.00	1.00
Md Atikul Islam 201-15-3612	1.00	0.95	0.97
Md. Anamul Hasan 201-15-3625	1.00	1.00	1.00

Muhammad Bokhtiar Uddin 201-15-3638	1.00	1.00	1.00
Rezayonoor Rahman Ferdous 201-15-3648	0.9	1.00	1.00
Md. Abdur Rakib 201-15-3651	1.00	0.98	0.99
Robiul Islam 201-15-3868	1.00	1.00	1.00
Accuracy			0.99
Macro Avg	0.94	0.96	0.95
Weighted Avg	0.94	0.96	0.95

Table shows the model achieve an accuracy of 99%. This indicates the model performing quite good in classification of face from image. It performs nearly perfect scores across all metrics. It demonstrates very high training accuracy and minimal training loss.

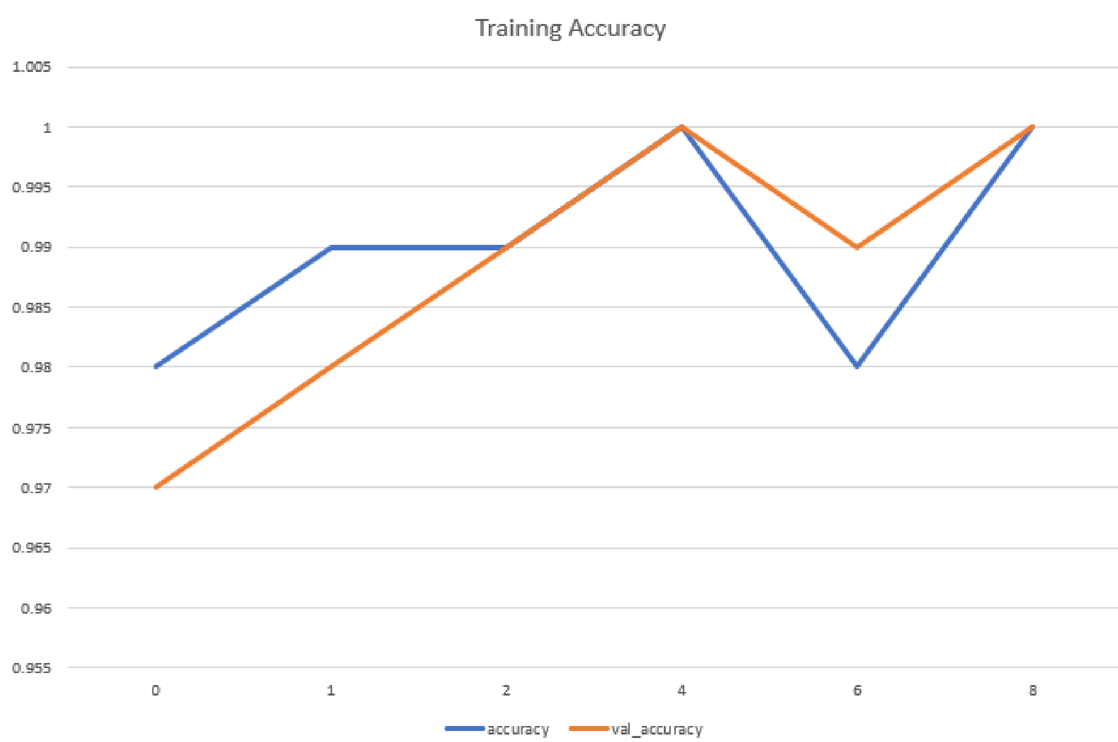


Figure 5.5: Training Accuracy (KNN)

The figure show training accuracy is going higher from 0.97 to 0.99. It is indicating maximum training accuracy for generating datasets

Figure 5.6: Training Loss (KNN)

The figure showing training loss of KNN. It is getting low from 0.4 to 0.05. It ensures there is no overfitting issue in training the model.

	Jobaer Ahmed	Tonmoy Chandra Das	Md Siam	Arnob Das	Shagnik Roy	Apurba Islam	Mim Obaidulla	Sayed Tahlil Bin Abdulla	Md Alamin Mia	Sabbir Siddique	Hasin Arman Shifa	Md. Monir Hossen	Md Nayeem Hassan	Habibur Rahman Zihad	Raunak Myuhtasin	Md Atikul Islam	Md Anamul Hasan	Muhammad Bokhtiar Uddin	Rezayonoor Rahman Ferdous	Md Abdur Rakib	Robiul Islam
Jobaer Ahmed	0.99	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Tonmoy Chandra Das	0	0.95	0	0	0	0.1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Md Siam	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Arnob Das	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Shagnik Roy	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Apurba Islam	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Mim Obaidulla	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Sayed Tahlil Bin Abdulla	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
Md Alamin Mia	0.02	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
Sabbir Siddique	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
Hasin Arman Shifa	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
Md. Monir Hossen	0	0	0	0	0	0	0	0	0	0	0.1	0.9	0	0	0	0	0	0	0	0	0
Md Nayeem Hassan	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
Habibur Rahman Zihad	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
Raunak Myuhtasin	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
Md Atikul Islam	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
Md Anamul Hasan	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
Muhammad Bokhtiar Uddin	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
Rezayonoor Rahman Ferdous	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
Md Abdur Rakib	0	0.01	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
Robiul Islam	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1

Figure 5.7: Confusion Matrix of KNN model

This figure shows the Confusion matrix of 21 different student to detect their faces. In this case most of the classes are accurate and near to 1.

5.4 Summary

In this project, we developed a facial recognition system for student attendance using the Haarcascade frontal face detection algorithm and the Local Binary Patterns Histograms (LBPH) recognition algorithm. The primary objective was to automate the attendance process by accurately detecting and recognizing student faces in real-time. Our approach utilized Python as the programming language, alongside essential libraries such as OpenCV for computer vision tasks and MySQL Workbench for database management.

The dataset generation process involved capturing 100 grayscale images of each student using a smartphone camera. These images were then processed and stored as training data. The Haarcascade frontal face algorithm was employed to detect faces, converting the RGB images to grayscale to simplify the recognition process. The LBPH algorithm was then used to recognize the detected faces. The model was trained using the entire dataset, and its performance was evaluated using external images not included in the training set. The resulting performance metrics indicated a high level of accuracy and efficiency in both face detection and recognition tasks.

Our experimental results, as illustrated by the confusion matrix and performance metrics, demonstrated that the KNN algorithm achieved an accuracy of 95%, with a precision, recall, and F1-score of 94%, 96%, and 95%, respectively. In contrast, the LBPH algorithm yielded an accuracy of 97%, with precision, recall, and F1-scores of 99%, 96%, and 97%, respectively. These results highlight the robustness and reliability of our approach, although the slightly lower performance of the LBPH algorithm suggests potential areas for further optimization.

The discussion also delves into the challenges encountered during the project. One significant challenge was ensuring the system's robustness to variations in lighting conditions, facial expressions, and occlusions. While the Haarcascade algorithm exhibited high performance under controlled conditions, its accuracy decreased slightly in less ideal environments. The LBPH algorithm, though slightly less accurate overall, demonstrated better resilience to such variations. This suggests that a hybrid approach, combining the strengths of both algorithms, could potentially yield even better results.

CHAPTER 6

Impact on society,

Environment and Sustainability

6.1 Impact on Life

The implementation of a face recognition-based attendance system has significant implications for various facets of society, encompassing education, technology, security, and privacy. This advanced system, developed using Python and leveraging algorithms like Haarcascade for face detection and LBPH for face recognition, introduces several transformative benefits and raises important ethical considerations.

Firstly, the educational sector stands to gain substantially from this technology. Traditional methods of attendance tracking are often manual, time-consuming, and prone to errors. By automating this process, educational institutions can save valuable time and resources. Teachers can focus more on instructional activities rather than administrative tasks, thus enhancing the overall quality of education. Moreover, accurate attendance records can help in identifying patterns related to student attendance, enabling early intervention in cases of chronic absenteeism. This can lead to improved academic performance and better student retention rates. In addition, the integration of such technology can foster a more disciplined and punctual student body, as the system reduces opportunities for proxy attendance and other forms of attendance fraud.

In terms of technological advancement, this project exemplifies the practical application of machine learning and computer vision in solving real-world problems. It highlights the potential of artificial intelligence to automate and enhance routine processes. The project also serves as an educational tool in itself, providing a learning opportunity for students and developers interested in AI and machine learning. By engaging with this technology, students can develop valuable skills that are highly sought after in the modern job market. This can have a broader economic impact by contributing to a more skilled workforce that is proficient in cutting-edge technologies.

However, the deployment of face recognition technology also brings to the forefront critical discussions about privacy and ethical use of personal data. Collecting and storing biometric data, such as facial images, necessitates stringent measures to protect individuals' privacy and prevent misuse. There is a risk that such data could be exploited for unauthorized surveillance or other intrusive activities if not adequately safeguarded. Therefore, it is imperative to implement robust data protection protocols and ensure that the use of this technology complies with relevant privacy laws and regulations. Transparency about how the data will be used and obtaining explicit consent from all individuals involved are essential steps in maintaining trust and upholding ethical standards.

Furthermore, there are societal concerns related to the potential biases in face recognition systems. Studies have shown that these systems can sometimes exhibit higher error rates for certain demographic groups, such as individuals with darker skin tones. This can lead to unfair treatment and reinforce existing inequalities if not addressed properly. It is crucial to use diverse and representative datasets to train the recognition models and to continuously monitor and improve the system's accuracy across different populations. Addressing these biases not only improves the system's reliability but also promotes fairness and inclusivity.

The security of the data collected by the system is another significant aspect. Ensuring that the data is securely stored and transmitted is vital to prevent data breaches and unauthorized access. This involves using encryption, secure access controls, and regular security audits. Schools and institutions implementing this technology must be diligent in maintaining these security practices to protect the sensitive information of their students.

From a broader perspective, the successful implementation of this technology can inspire confidence in the use of AI and machine learning in other sectors. It demonstrates how these technologies can be harnessed to improve efficiency, accuracy, and convenience in various applications. This can drive further innovation and adoption of AI-powered solutions in fields such as healthcare, transportation, and public administration, potentially leading to widespread societal benefits.

Moreover, the face recognition-based attendance system can serve as a catalyst for discussions about the ethical use of technology. It can prompt educational institutions to develop and adopt policies that balance technological advancements with the protection of individual rights. By setting a positive example, this project can influence how future technologies are developed and deployed, ensuring they contribute positively to society.

6.2 Impact on Society & Environment

The environmental impact of implementing a face recognition-based attendance system primarily revolves around the energy consumption and electronic waste associated with the hardware and software components. The use of computers, high-definition webcams, and servers for data storage and processing requires a significant amount of energy, contributing to the carbon footprint. Additionally, the production and eventual disposal of electronic devices add to electronic waste, which poses environmental hazards if not managed properly. However, by streamlining administrative processes and reducing the need for paper-based attendance records, this technology can also contribute to environmental sustainability. Efficient energy use practices, such as utilizing energy-efficient hardware and cloud-based services with lower carbon footprints, can mitigate some of these negative impacts. Furthermore, institutions can implement recycling programs for electronic devices to reduce waste.

6.3 Ethical Aspects

The deployment of a face recognition-based attendance system raises several ethical issues that must be carefully addressed to protect the rights and privacy of individuals. One of the primary concerns is the collection and storage of biometric data, which can be highly sensitive. Ensuring informed consent, transparency in data usage, and robust data protection measures are essential to uphold privacy rights. There is also the risk of algorithmic bias, where the system may perform differently across various demographic groups, leading to potential discrimination. It is crucial to use diverse and representative datasets and to continuously test and improve the system's accuracy and fairness. Moreover, the potential for misuse of facial recognition technology for unauthorized surveillance necessitates strict access controls and clear policies on data use to prevent ethical breaches.

6.4 Sustainability Plan

The deployment of a face recognition-based attendance system raises several ethical issues that must be carefully addressed to protect the rights and privacy of individuals. One of the primary concerns is the collection and storage of biometric data, which can be highly sensitive. Ensuring informed consent, transparency in data usage, and robust data protection measures are essential to uphold privacy rights. There is also the risk of algorithmic bias, where the system may perform differently across various demographic groups, leading to potential discrimination. It is crucial to use diverse and representative datasets and to continuously test and improve the system's accuracy and fairness. Moreover, the potential for misuse of facial recognition technology for unauthorized surveillance necessitates strict access controls and clear policies on data use to prevent ethical breaches.

6.5 Summary

The student attendance system using face recognition technology positively impacts society by enhancing the efficiency and accuracy of educational administration. It reduces manual errors and saves time for teachers, fostering a more focused learning environment. Environmentally, the system minimizes the need for paper-based attendance records, promoting sustainability. Additionally, it supports long-term sustainability in educational institutions by integrating advanced technology, reducing administrative workload, and improving data management. This project underscores the potential for technological solutions to create more efficient, eco-friendly, and sustainable educational practices.

Chapter 7
Conclusion and Future Work

7.1 Conclusions

The face recognition-based attendance system developed in this study represents a significant advancement in the automation of administrative tasks within educational institutions. By utilizing Python and OpenCV, the project harnessed the power of the Haarcascade frontal face algorithm for detecting faces and the LBPH algorithm for recognizing them. This combination proved effective in creating an automated attendance system that is both accurate and efficient, reducing the manual errors and administrative burdens associated with traditional methods.

One of the key achievements of this project was the successful implementation of a comprehensive data collection and preprocessing strategy. By capturing multiple grayscale images of each student, the system was able to train a robust model capable of recognizing faces under various conditions. This approach not only enhanced the accuracy of the recognition process but also ensured that the system could handle real-world variations in lighting, facial expressions, and angles.

The project's experimental setup, involving high-definition webcams and powerful computer systems, enabled real-time face detection and recognition. The use of Haarcascade for face detection ensured that faces were accurately identified in the captured images, while the LBPH algorithm provided reliable recognition of these faces. The seamless integration of these components resulted in an efficient and user-friendly system that could mark attendance automatically and provide instant feedback.

Comprehensive testing and validation were conducted to assess the system's performance. The results demonstrated a high level of accuracy in both face detection and recognition, confirming the system's effectiveness in real-world scenarios. The detailed documentation provided ensured that the system could be easily set up, operated, and maintained by users and developers, enhancing its reproducibility and long-term viability.

The ethical aspects of this project were carefully considered, with stringent data protection measures implemented to safeguard the biometric data collected. Ensuring user consent and transparency regarding data usage were essential steps in building trust and complying with privacy regulations. The project highlighted the importance of addressing ethical issues in the deployment of AI technologies, setting a positive example for future developments.

In summary, the face recognition-based attendance system developed in this study achieved its objectives of automating and improving attendance tracking in educational institutions. The successful integration of advanced algorithms and robust data protection measures resulted in a reliable and efficient solution. This project demonstrated the potential of AI and machine learning technologies in transforming educational processes and provided valuable insights into the practical application of these technologies.

7.2 Further Suggested Work

The development of a face recognition-based attendance system has laid the foundation for further research and enhancements in this field. One of the primary areas for future study is the improvement of the recognition algorithms to increase accuracy and fairness. This can be achieved by incorporating more diverse and extensive datasets during the training phase, ensuring that the system performs well across different demographic groups and under various conditions. Addressing algorithmic bias is crucial for creating a fair and equitable system.

Future research could also explore the integration of additional biometric markers or multimodal recognition methods to enhance the system's robustness. For example, combining face recognition with other biometric data such as voice recognition or fingerprint scanning could provide a more secure and reliable solution. This multimodal approach can improve accuracy and reduce the chances of false positives and negatives, making the system more effective in diverse environments.

The potential applications of this technology extend beyond educational institutions. Further studies could investigate its use in other sectors, such as corporate environments, healthcare facilities, and public transportation systems. Exploring these applications can provide insights into the versatility and scalability of face recognition technologies, paving the way for broader adoption and innovation.

Another area for future research is the long-term impact of face recognition-based attendance systems on student behavior and academic performance. By collecting and analyzing data over extended periods, researchers can assess how the use of such systems influences attendance patterns, punctuality, and overall student engagement. Understanding these impacts can help in refining the system and maximizing its benefits.

Additionally, future studies could focus on enhancing the user interface and experience of the system. Developing more intuitive and accessible interfaces can improve user adoption and satisfaction. This includes creating mobile applications or web-based platforms that allow users to interact with the system seamlessly.

Finally, further research should continue to address the ethical and privacy concerns associated with biometric data collection and usage. Developing advanced data protection measures, such as enhanced encryption techniques and secure data storage solutions, is essential for maintaining user trust and compliance with regulations. Ongoing efforts to ensure transparency and informed consent will be crucial in promoting the ethical use of face recognition technologies.

In conclusion, the face recognition-based attendance system developed in this study provides a solid foundation for further research and development. By exploring improvements in recognition algorithms, integrating additional biometric markers, expanding applications, and addressing ethical concerns, future studies can enhance the system's effectiveness and impact. This project has demonstrated the potential of AI technologies in transforming attendance tracking and offers valuable insights for future advancements in this field.

REFERENCES

[1] Lukas, S., Mitra, A.R., Desanti, R.I. and Krisnadi, D., 2016, October. Student attendance system in classroom using face recognition technique. In 2016 International Conference on Information and Communication Technology Convergence (ICTC) (pp. 1032-1035). IEEE.

[2] Kar, N., Debbarma, M.K., Saha, A. and Pal, D.R., 2012. Study of implementing automated attendance system using face recognition technique. International Journal of computer and communication engineering, 1(2), pp.100-103.

[3] Patil, A. and Shukla, M., 2014. Implementation of classroom attendance system based on face recognition in class. International Journal of Advances in Engineering & Technology, 7(3), p.974.

[4] Jha, A., 2007. Class room attendance system using facial recognition system. The International journal of Mathematics, science, technology and Management, 2(3), pp.4-7.

[5] Jadhav, A., Jadhav, A., Ladhe, T. and Yeolekar, K., 2017. Automated attendance system using face recognition. International Research Journal of Engineering and Technology (IRJET), 4(1), pp.1467-1471.

[6] Winarno, E., Al Amin, I.H., Februariyanti, H., Adi, P.W., Hadikurniawati, W. and Anwar, M.T., 2019, December. Attendance system based on face recognition system using cnn-pca method and real-time camera. In 2019 International Seminar on Research of Information Technology and Intelligent Systems (ISRITI) (pp. 301-304). IEEE.

[7] Chakraborty, P., Muzammel, C.S., Khatun, M., Islam, S.F. and Rahman, S., 2020. Automatic student attendance system using face recognition. International Journal of Engineering and Advanced Technology (IJEAT), 9, pp.93-99.

[8] E Arsenovic, M., Sladojevic, S., Anderla, A. and Stefanovic, D., 2017, September. FaceTime—Deep learning based face recognition attendance system. In 2017 IEEE 15th International symposium on intelligent systems and informatics (SISY) (pp. 000053-000058). IEEE.

[9] Surve, M., Joshi, P., Jamadar, S. and Vharkate, M., 2020. Automatic attendance system using face recognition technique. International Journal of Recent Technology and Engineering (IJRTE), 9(1), pp.2134-2138.

[10] Vishe, A., Shirsath, A., Gujar, S. and Thakur, N., Student attendance system using face recognition. Engpaper Journal.

[11] Pauzan, M. (2024). Smart and Portable Attendance System Based on Face Recognition that Implements the Local Binary Pattern (LBP) Algorithm. Gema Wiralodra, 15(1), 436-443.

[12] Elias, S. J., Hatim, S. M., Hassan, N. A., Abd Latif, L. M., Ahmad, R. B., Darus, M. Y., & Shahuddin, A. Z. (2019). Face recognition attendance system using Local Binary Pattern (LBP). Bulletin of Electrical Engineering and Informatics, 8(1), 239-245.

[13] SudhaNarang, K. J., & MeghaSaxena, A. (2018). Comparison of face recognition algorithms using Opencv for attendance system. International Journal of Scientific and Research Publications, 8(2), 2250-315.

[14] Khan, S., Akram, A., & Usman, N. (2020). Real time automatic attendance system for face recognition using face API and OpenCV. Wireless Personal Communications, 113(1), 469-480.

[15] Trivedi, A., Tripathi, C. M., Perwej, Y., Srivastava, A. K., & Kulshrestha, N. (2022). Face recognition based automated attendance management system. Int. J. Sci. Res. Sci. Technol, 9, 261-268.

[16] Bah, S. M., & Ming, F. (2020). An improved face recognition algorithm and its application in attendance management system. Array, 5, 100014.

[17] Alhanaee, K., Alhammadi, M., Almenhali, N., & Shatnawi, M. (2021). Face recognition smart attendance system using deep transfer learning. Procedia

[18] Prangchumpol, D. (2019, October). Face recognition for attendance management system using multiple sensors. In Journal of Physics: Conference Series (Vol. 1335, No. 1, p. 012011). IOP Publishing.

[19] Nithya, D. (2015). Automated class attendance system based on face recognition using PCA algorithm. International Journal of Engineering Research & Technology (IJERT).

[20] Anshari, A., Hirtranusi, S. A., Sensuse, D. I., & Suryono, R. R. (2021, July). Face recognition for identification and verification in attendance system: A systematic review. In 2021 IEEE International Conference on Communication, Networks and Satellite (COMNETSAT) (pp. 316-323). IEEE.
[21] Bussa, S., Mani, A., Bharuka, S., & Kaushik, S. (2020). Smart attendance system using OPENCV based on facial recognition. Int. J. Eng. Res. Technol, 9(3), 54-59.
[22] Yusof, Y. W. M., Nasir, M. M., Othman, K. A., Suliman, S. I., Shahbudin, S., & Mohamad, R. (2018). Real-time internet based attendance using face recognition system. International Journal of Engineering & Technology, 7(3.15), 174-178.
[23] Suresh, V., Dumpa, S. C., Vankayala, C. D., Aduri, H., & Rapa, J. (2019). Facial recognition attendance system using python and OpenCv. Quest Journals Journal of Software Engineering and Simulation, 5(2), 2321-3809.
[24] Chowdhury, S., Nath, S., Dey, A., & Das, A. (2020, December). Development of an automatic class attendance system using cnn-based face recognition. In 2020 Emerging Technology in Computing, Communication and Electronics (ETCCE) (pp. 1-5). IEEE.
[25] Godswill, O., Osas, O., Anderson, O., Oseikhuemen, I., & Etse, O. (2018). Automated student attendance management system using face recognition. International Journal of Educational Research and Information Science, 5(4), 31-37.

Appendix A

Course Outcomes, Complex Engineering Problems (EP) and Complex Engineering Activities (EA) Addressing

Title:
Attendance System Based on Face Recognition Using LBPH method

Student ID: 201-15-14254

CO Description for FYDP

CO	CO Descriptions	PO
	Phase -I	
CO1	Integrate recently gained and previously acquired knowledge to identify a **pneumonia detection** problem for the Final Year Design Project (FYDP)	**PO1**
CO2	Analyze different aspects of the goals in designing a solution for this FYDP	**PO2**
CO3	Explore diverse problem domains through a literature review, delineate the issues, and establish these goals for the FYDP	**PO4**
CO4	Perform economic evaluation and cost estimation and employ suitable project management procedures throughout the development life cycle of the FYDP	**PO11**
	Phase -II	
CO5	Design and develop technical solutions and system components or processes that meet specified requirements, ensuring compliance with public health and safety standards, as well as considering cultural, socioeconomic, and environmental factors in this FYDP	**PO3**
CO6	Choose and apply appropriate methodologies, resources, and contemporary engineering and IT technologies to address complex engineering processes, encompassing prediction and modeling, while adhering to relevant constraints in this FYDP	**PO5**
CO7	Analyze societal, health, safety, legal, and cultural considerations, along with associated responsibilities, in the context of professional engineering practice and the resolution of this problem, employing logical reasoning guided by contextual understanding.	**PO6**
CO8	Comprehend and evaluate the enduring sustainability and impact of professional engineering endeavors in addressing intricate engineering challenges within social and environmental frameworks.	**PO7**
CO9	Implement ethical principles and adhere to professional standards and norms in this FYDP	**PO8**
CO10	Capable of operating proficiently both individually and as a team member or leader across diverse teams and interdisciplinary settings in this FYDP.	**PO9**

CO11	Proficiently communicate with the engineering community and broader society regarding complex engineering endeavors, including the ability to comprehend and generate comprehensive reports and design documentation, as well as provide and receive clear instructions throughout this FYDP.	**PO10**
CO12	Acknowledge the importance of self-directed and life-long learning within the evolving landscape of technology, and possess the readiness and capability to engage in lifelong learning endeavors.	**PO12**

Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP), and Attainment of Complex Engineering Activities (EA)

Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP):

SN	EP Definition	Attainment	CO	Justification (with Knowledge Profile)	References
1.	**EP1: Depth of Knowledge required**	Yes	CO1, CO2, CO3, CO5, CO6, CO7 and CO8	This project demonstrates **fundamental engineering (K3)** principles by employing LBPH Algorithm, Haarcascade face detection and grayscale conversion for image processing and classification tasks. The project demonstrates **specialist knowledge (K4)** by conducting transfer learning with advanced Haarcascade algorithm, LBPH architecture and image grayscale conversion to process image and recognize face	**Page no:** [23-32]
				The project applies **engineering practice & design (K5)** by the figure of process of experiments. The project addresses **engineering practice & technology (K6)** by employing LBPH model.	**Page no:** [38-49]
				This project ensures to **K8 (Research Literature)** by synthesizing insights from recent studies, to Automated attendance using Face recognition showcasing a comprehensive understanding of current methodologies.	**Page no:** [8-13]

2.	**EP2: Range of Conflicting Requirements**	Yes	CO2, and CO7	This project addresses **EP-2** by recognizing face including limitations of traditional methods and the complexities of integrating transfer learning and LBPH. Through comparative analysis, it confronts challenges in understanding spatial distributions, offering insights for refining diagnostic methodologies.	**Page no:** [23-32]
3.	**EP3: Depth of analysis required**	Yes	CO2, and CO6	This project addresses **EP-3** by meticulously comparing experimental outcomes, highlighting accuracy of Haarcascade and LBPH as the chosen significant solution for enhancing face detection and recognition	**Page no:** **[38-49]** **Section:** [4.2]
4.	**EP4: Familiarity of Issues**	Yes	CO3	To give the system smoothness and more accuracy We conducted an in -depth analysis to datasets to carefully choose a specific algorithm to find better result	**Page no:** [17-23] **Section:** [2.2, 2.4]
5.	**EP5: Extends of application codes**	Yes	CO5	To analyses the requirement and a good quality of software assurance we are capable to extends applications codes.	**Page no:** **[59-60]**
6.	**EP6: Extends of stakeholders involved and conflicting requirements**	Yes	CO8	For the requirement of project, we have met several types of people to collect a survey on their impressions in this project and collecting data set.	**Page no:** **[17-23]**

7.	**EP7: Interdependence**	Yes	CO5	This project comprises several subsystems that depend on each other. These include tasks such as collecting data, processing it, training machine learning models, conducting predictive analysis, and developing a front -end application.	**Page no:** [23-32]

Addressing CO11 with Complex Engineering Activities (EA) [Some or all of the following]:

SN	EA Definition	Attainment	CO	Justification	References
1.	**EA1: Range of resources**	Yes	CO11	This project utilizes diverse resources such as smartphone camera, GPUs, deep learning frameworks, datasets, and ethical considerations to ensure systematic research and contribute to advancements in attendance system through face recognition	**Page no:** [33-37]
2.	**EA2: Level of interaction**	Yes		This project uses Python Tkinter library to build graphical user interface to interact with human	Page no: [34]
3.	**EA3: Innovation**	No		N/A	N/A
4.	**EA4: Consequences for society and the environment**	Yes		This project contributes to institution by improving attendance system through automated attendance	**Page no:** [59-60]
5.	**EA-5: Familiarity**	Yes		This project expands upon existing research by examining a combination between Haarcascade and LBPH method that demonstrated through Automated and time saving approach of attendance.	**Page no:** [8-11]

Addressing CO (4, 9, 10, and 12):

SN	COs	Attainment	Justification	References
1	CO4	Yes	This project aligns with CO4 by combining efficient project management and careful financial control, incorporating detailed planning, allocating resources effectively, and accurately estimating budgets to make the most of resources at every stage of the research process.	**Page no:** [1-7]
2	CO9	Yes	The project shows a commitment to ethical guidelines by giving importance to protecting Student privacy, obtaining consent based on full information, and openly documenting the research process. This ensures that knowledge is shared responsibly and contributes to Educational Institution well-being through the ethical use of face detection technologies that covers CO9.	**Page no:** [54]
3	CO10	No	N/A	N/A
4	CO12	Yes	The project's dedication to continuous learning **(CO12)** and adaptation within the dynamic technological landscape is reflected in its comprehensive data collection, rigorous statistical analysis, meticulous methodology development, and thorough experimental results and analysis, showcasing a commitment to staying updated and refining techniques to address modern challenges.	**Page no:** [35-48]

ATTENDANCE SYSTEM BASED ON FACE RECOGNITION USING LBPH METHOD

ORIGINALITY REPORT

22%	15%	4%	14%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	Submitted to Daffodil International University Student Paper	8%
2	dspace.daffodilvarsity.edu.bd:8080 Internet Source	5%
3	fastercapital.com Internet Source	1%
4	www.ijraset.com Internet Source	1%
5	isteonline.in Internet Source	<1%
6	Submitted to University of West London Student Paper	<1%
7	"Accelerating Discoveries in Data Science and Artificial Intelligence I", Springer Science and Business Media LLC, 2024 Publication	<1%
8	www.ijnrd.org Internet Source	<1%
	docplayer.net	