FACE RECOGNITION BASED ATTENDANCE SYSTEM USING DEEP LEARNING AlGORITHM

BY

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

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APPROVAL

This Project titled **"Face Recognition Based Attendance System Using Deep Learning Algorithm"**, submitted by Razayonoor Rahman Ferdous, ID No: 201-15-3648 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 *23 January 2024*.

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I, therefore, declare that this undertaking has been finished by us under the supervision of **Mr. Amit Chakraborty,** Assistant Professor, Department of CSE, Daffodil International University. I further declare that neither an application or an educational grant has been made anywhere for this project or any part of it.

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ABSTRACT

The Face Recognition Based Attendance System is an innovative advancement in attendance tracking, combining cutting-edge facial recognition technology with previously established methods. This system provides an effortless, automated, and highly accurate method to attendance tracking, which is especially useful in educational institutions and organizational contexts. This paper includes an in depth look into the use of advanced deep learning models to improve attendance monitoring methods. To construct an extensive facial recognition system, the researchers used a Convolutional Neural Network (CNN), ResNet50, and EfficientNetB7. The system obtains notable accuracy levels on the test set using a thorough technique that includes data collecting, labeling, and model training, indicating its proficiency in recognising persons. The CNN has a high accuracy of 98.61, demonstrating its powerful facial recognition skills. While ResNet50 and EfficientNetB7, although having lesser accuracies of 88.09% and 63.43%, respectively, provide useful insights into the relative performance of alternative deep learning architectures. The research goes beyond technology to explore ethical concerns, societal impact, and sustainability over the years.

Keywords: *Facial Recognition, Attendance System, Deep Learning, Convolutional Neural Network, ResNet50, EfficientNetB7, Technological Innovation* .

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CHAPTER 1

INTRODUCTION

1.1 Introduction

In the era of technological advancement, the application of artificial intelligence has resulted in revolutionary innovations across various domains. One of those revolutionary uses is the Face Recognition Based Attendance System, a transforming way to simplify and automate traditional attendance monitoring processes. This system uses deep learning techniques to transform attendance recording, taking off the need for manual entry and paperwork[1]. In reaction to the increased demand for effective and accurate attendance monitoring, the suggested system provides a cutting-edge solution based on advanced face identification algorithms. Deep Learning, a subset of machine learning, allows the system to detect intricate face traits and patterns, allowing it to identify individuals within a dataset in a unique way. The process requires carefully collecting a diverse human dataset, grouping it, and then using Convolutional Neural Networks (CNNs) for effective model training[2].

The architecture of the system goes beyond simple identifying faces, including aspects like the Haarcascade classifier for frontal detection of faces and the K Nearest Neighbour (KNN) algorithm for exact identification. The integration of Python Flask offers a user-friendly Graphical User Interface (GUI), providing administrators with an effortless task[3].

As educational institutions, groups, and companies look for better accuracy and efficiency in attendance monitoring, the Face Recognition Based Attendance System Using Deep Learning comes as an innovation ready to change the landscape of traditional attendance methods. This unique application not only presents technological advancement, but it also represents a paradigm change toward intelligent and automatic attendance management solutions.[4]

1.2 Motivation

The motivation behind developing this system is rooted in the search for efficiency, accuracy, and advancement in attendance monitoring processes. Traditional manual attendance recording methods are problematic, time-consuming, and unscalable. Deep learning has created a new chance to use advanced facial recognition algorithms to simplify this vital part of organizational administration.

This new technology efforts to reduce the administrative load associated with tracking attendance by providing a solution that is not only precise but also timely. The suggested technique provides accurate identification of persons by using the power of deep learning, independent of changes in facial expressions, lighting conditions, or angles. The motivation originates from a desire to provide advanced, automated tools to educational institutions and companies that not only improve accuracy in attendance tracking but also encourage a technologically advanced and forward-thinking environment. Accepting this technology advancement has the potential to transform attendance management, freeing up critical time and resources for more strategic and meaningful activities.

1.3 Rationale of the Study

The research's motivation is to address the inefficiencies and restrictions of standard attendance tracking methods. Manual processes are costly, lengthy, and at risk for theft. Deep learning for facial recognition provides a game-changing solution to these problems. The ability of the technology to identify complex facial traits allows for precise and automated identification of individuals, despite differences in lighting conditions and facial emotions. The company can dramatically improve the accuracy and efficiency of attendance management by deploying a system that incorporates deep learning techniques. This research is motivated by the urgent need for a modern, scalable, and dependable solution that is compatible with the changing technological landscape. Not only does the suggested solution streamline operations, but it also lays the door for a more secure and innovative approach to attendance tracking. The logic is based on improving organizational processes, reducing human burden, and adopting intelligent systems that contribute to overall attendance management efficiency and effectiveness.

1.4 Research Question

I. Can deep learning effectively improve facial recognition accuracy in attendance tracking?

II. How does the integration of Haar Cascade classifiers enhance frontal face detection in the proposed system?

III. What impact does the k-Nearest Neighbors (KNN) algorithm have on precise face identification for attendance purposes?

IV. How does the developed Graphical User Interface (GUI) with Python Flask contribute to user-friendly interactions in the attendance system?

V. What are the implications and challenges of deploying the proposed system in real-world environments?

1.5 Project Management and Finance

The successful installation of the facial recognition-based attendance system requires effective project management. The project will be carried out in a systematic manner, beginning with a detailed project plan outlining activities, milestones, and dates. Regular progress assessments will be carried out to verify respect to the schedule and the identification of potential difficulties. Regular meetings will foster team collaboration and communication, providing a dynamic and responsive development environment. The budget for this project will cover important elements such as data collecting, hardware requirements, software development tools, and possibly testing and deployment charges. Financial planning will consider cost-effectiveness while ensuring that essential resources are acquired. In addition, future expansion and repair expenses will be considered. The financial strategy strives to maximize resource usage while balancing project needs and budget constraints, ensuring the effective implementation of the facial recognition-based attendance system.

TABLE 1.1: PROJECT MANAGEMENT TABLE

Work	**Time**
Dataset	1 month
Literature Review	3 month
Experiment Setup	1 month
Implementation	2 month
Report	2 month
Total	9 month

1.6 Report Layout

- Introduction
- Background
- Data Collection
- Data Preprocessing
- Research Methodology
- Experimental Result and Discussion
- Impact on Society, Environment
- Summary, Conclusion, Future Research
- References

CHAPTER 2

BACKGROUND STUDY

2.1 Preliminaries

The preliminary section of this study establishes the framework for understanding the background, significance, and scope of the proposed face recognition-based attendance system. It begins with an overview that provides an outline of the issues of attendance tracking and the necessity for a technical solution. The study's purpose is described, highlighting the potential benefits of using deep learning for improved detection of face accuracy.After this, the research's goals are defined, outlining the exact goals and expected outcomes. The methodology section describes the systematic approach used, including data collecting, labeling, training methods, and the integration of multiple components such as Haar Cascade classifiers and the k-Nearest Neighbors algorithm. The preliminary section sets the setting for a thorough examination of the proposed system, giving readers with a clear understanding of the research's background, purposes, and techniques before delving into the complexities of the face recognition-based attendance solution.

2.2 Related Works

The study of the literature provides a thorough summary of existing literature and research on facial recognition systems and attendance tracking approaches. It includes papers that explore the use of deep learning in facial identification, highlighting results, problems, and new trends. In addition, work on the use of Haar Cascade classifiers for face detection and k-Nearest Neighbors algorithms for face recognition are evaluated to understand their success in similar contexts.The survey of the literature includes works employing Python Flask for GUI development in a variety of applications, offering light on standards and potential difficulties. The study intends to expand on current knowledge, identify gaps, and contribute to the area by proposing a unique combination of these technologies for an optimum facial recognition-based attendance system by studying these relevant studies. This thorough review of the literature serves as the foundation for the current work, situating it within the larger context of advances in facial recognition and attendance management systems.

Damale et al. [5] focused on face recognition, which is the process of identifying people based on their facial traits. Facial features are critical in a variety of computer vision applications, such as face detection, expression detection, and video surveillance. The study covers three different facial recognition methods: SVM, MLP, and CNN. Face detection is performed using DNN, while features for SVM and MLP techniques are extracted using PCA and LDA feature extraction algorithms. Images are immediately supplied into the CNN module as feature vectors in the CNN-based technique. The results show that the CNN-based strategy produces the highest recognition accuracy, with SVM, MLP, and CNN obtaining testing accuracies of roughly 87%, 86.5%, and 98% on a self-generated database, respectively.

K. Senthamil et al. [6] addressed the problem of recognizing human faces in photos using real-time background subtraction. To accomplish high-accuracy facial recognition, it employs a rapid Principal Component Analysis. The system is intended to keep employee attendance records automatically, eliminating the need for manual logbook entries and saving time. The module enrolls staff faces once and stores them in a database. Employee presence in the database is updated, resulting in enhanced performance when compared to manual attendance tracking systems, providing accurate and user-friendly solutions.

Harikrishnan, J., et al. [7] proposed a real-time attendance and surveillance system with numerous applications, including face attendance in university classrooms utilizing cell phones and real-time facial recognition monitoring in lab facilities and workplaces for security. The system is user-friendly and has a graphical interface, making it simple to execute strong deep learning-powered facial recognition algorithms. When the real-time surveillance algorithm was used, the system attained an amazing maximum recognition accuracy of 74%. The project addresses the requirement for a reliable and simple to use facial recognition attendance system.

Chinimilli et al. [8] employed the Local Binary Pattern Histogram (LBPH) algorithm for face recognition, which was chosen because it outperforms existing Euclidean distance-based approaches such as Eigenfaces and Fisherfaces. The Haar cascade is used for strong face detection, and LBPH assures accuracy even when deviations such as grayscale conversions, glasses, or facial hair are present. For kids, the system achieved a 77% facial recognition performance with a 28% false-positive rate. It obtained over 60% accuracy in recognizing unknown individuals with and without a threshold, with false-positive rates of 14% and 30%, respectively

Patel et al. [9] examined various computerized systems for recording attendance developed using diverse methodologies. It introduces a novel way to attendance management in colleges and universities. The suggested solution attempts to reduce the time spent manually taking attendance, which frequently results in proxy attendance difficulties. The technology combines RFID for automatic attendance and Face Recognition to authenticate students' identities, reducing the possibility of proxy attendance.

Trivedi et al. [10] proposed a real-time Face Recognition System that uses advanced face recognition technologies to track student attendance during class. The method requires detecting human faces using a webcam, scaling the identified faces, and processing them using a Local Binary Patterns Histogram algorithm. When recognition is complete, attendance data in a SQLite database is automatically updated. This technology provides considerable benefits to educational institutions by minimizing time consumption and human errors, thereby improving attendance management efficiency.

Seelam et al. [11] addressed a smart classroom attendance management system based on face recognition, computer vision, and deep learning that has been proposed for deployment on a Raspberry Pi. The device includes a camera placed above the blackboard to photograph pupils while they are seated. To track student attendance, it employs a face detection algorithm followed by face recognition. To assess the accuracy of the FaceNet facial recognition system, the dataset is randomly divided into training and test sets in an 80:20 ratio, with the model trained on the former and tested on the latter. The device achieves an astounding 98% accuracy rate.

Gupta et al.[12] proposed a non-intrusive face recognition-based smart classroom attendance management system that captures students' faces using a high-definition revolving camera. For facial identification, the system uses the Max-Margin facial Detection (MMFD) technique, and the model is trained using the Inception-V3 Convolutional Neural Network (CNN). Practical testing was carried out in a classroom of 20 students at Bangalore's National Institute of Technology Karnataka Surathkal. The experimental results show that the training and test accuracy rates are 97.67% and 96.66%, respectively. This system provides a strong solution for efficiently controlling classroom attendance.

Gode, Chetan S., et al. [13] proposed approach is an excellent solution for dealing with proxies and inaccurate attendance marking. It works by tracking attendance via live video broadcasts and extracting frames from the video with OpenCV. Face detection and recognition of identified faces are the key implementation processes, which are accomplished using dlib. The technology then connects recognized faces by comparing them to a database containing student facial data. This methodology is a viable approach to managing student attendance efficiently, maintaining accuracy and decreasing the danger of proxy attendance.

Mekala et al. [14] focused on this attendance system is to provide a more efficient alternative to the time-consuming traditional techniques of attendance utilized during lectures. Its goal is to reduce human error and proxy attendance. Face recognition is used to track student attendance using the Cognitive Face API, which is based on the Principal Component Analysis (PCA) technique. For each student, a collection of 25 photos captured from various perspectives is compiled. These photos' features are extracted and utilized to create a database. When a match is detected, the attendance system collects the image of the class, detects the number of faces, compares them with the database, and marks attendance. In terms of student recognition, the system has an amazing efficiency rate of 95.61%.

Mothwa et al. [15] addressed the need for developing an AI-based attendance monitoring system. It presents a conceptual idea for a smart attendance monitoring system that uses face recognition to track student attendance during lectures. The study describes both front and back-end system designs, as well as a thorough multi-camera setup for efficient face capture and detection. The research looks into three different feature extraction techniques: PCA, LDA, LBP, and a combination of PCA and LDA. The proposed model attained an outstanding 90% recognition accuracy.

Bekzod et al.[16] focused on face recognition systems have advanced significantly in recent years, notably in real-time facial recognition. Face recognition was once thought to be incorrect and incomplete, but advances in Deep Learning have raised it to one of the most advanced biometric identification methods. As a result, numerous universities throughout the world are adopting it into their educational systems, including distant learning programs. This technology allows for the conversion of video frames into photos, allowing for the easy recognition of students' faces for attendance management and the automation of the attendance database.

Varadharajan et al.[17] focused on biometric attendance management, highlighting the importance of replacing time-consuming and difficult manual techniques. Face recognition has been found as the most successful strategy among numerous biometric processes. The proposed solution requires installing cameras in the classroom to capture and detect faces, which are then compared to a database to determine attendance. Messages are automatically delivered to students' parents when they are absent. One of the technologies utilized is Eigenfaces, a set of Eigenvectors used in computer vision for face identification. This method uses basic technology, streamlines attendance management, and provides a 93% accuracy rate for detecting unknown individuals' faces.

Jadhav et al.[18] proposed an automated attendance management system that identifies and marks students' attendance when they enter a classroom using face detection and recognition algorithms. The Viola-Jones Algorithm is used for face identification, PCA for feature selection, and SVM for classification. When compared to traditional attendance systems, this technology improves efficiency and allows for student monitoring. The research also investigates the evolution of artificial neural networks in face recognition systems as well as the complexity of facial traits, emphasizing the promise for machine learning in this sector. The authors want to gather expertise with different facial recognition algorithms and evaluate the relevance of neural networks in accomplishing this goal.

Alhanaee et al. [19] proposed a facial recognition attendance system based on deep learning convolutional neural networks. Transfer learning is used in conjunction with three pre-trained convolutional neural networks that were further trained on their dataset. These networks performed admirably, providing excellent prediction accuracy within a reasonable training time. The three networks used in the system are SqueezeNet, GoogleNet, and AlexNet, which achieve validation accuracy rates of 98.33%, 93.33%, and 100%, respectively. The proposed approach has the potential to be used in attendance and access control systems in a variety of organizations, including government and commercial sectors, airports, schools, and universities.

Tamimi et al.[20] proposed a real-time group face-detection system for automating student class attendance. The paper describes the system's architecture and algorithm in detail. The program analyzes facial traits and features in order to provide real-time face detection for attendance tracking. The camera in the classroom takes photographs of students, and automatic face detection provides a list of detected student faces. Numerous studies were carried out utilizing real-time video from digital cameras, and the findings showed that the face identification approach provides speedy real-time processing with an admirable detection ratio of 94.73%.

2.3 Comparative Analysis and Summary

The comparative research shows a diverse landscape of approaches used in the development of deep learning-based face recognition-based attendance systems. Several research examined the efficacy of several algorithms, such as SVM, MLP, CNN, and Haar Cascade classifiers, revealing CNN's advantage in obtaining high recognition accuracy [1]. While some systems stressed real-time video processing for effective attendance tracking [20], others focused on false positive reduction [4]. Notably, the use of sophisticated approaches such as transfer learning [15], better LBP algorithms [18], and depth-wise separable convolution [19] emerged as essential methods for improving accuracy while decreasing computing overhead.

The investigations highlighted a wide range of uses, including school attendance monitoring [7] and workplace and security surveillance [3]. Non-intrusive methods, such as live video broadcasts and dlib usage [9] highlighted the importance of user-friendly solutions. Overall, the comparison showed a range of achievements, with some systems reaching 97% accuracy [7], while others addressed specific challenges, such as false positives [4]. These findings influence the proposed face recognition-based attendance system, underlining the importance of an effective, accurate, and user-friendly solution that incorporates the qualities demonstrated in these studies.

Table 2.1: Comparative analysis with previous work

Reference	**Year**	**Dataset**	**Algorithm Model**	**Best Model (Accuracy)**
Damale et al. [5]	2018	–	SVM, MLP, CNN	CNN (98%)
K. Senthamil et al. [6]	2014	Real-time human faces	–	–
Harikrishnan, J., et al. [7]	2019	__	Deep Learning	DL- (74%)

Chinimilli et al. [8]	2020	–	LBPH	LBPH-(77%)
Patel et al. [9]	2014	–	RFID	–
Trivedi et al. [10]	2022	–	LBPH	–
Seelam et al. [11]	2021	–	Computer Vision,Raspberry Pi and Deep Learning	Raspberry Pi-(98%)
Gupta et al.[12]	2018	20 students at Bangalore's National Institute of Technology Karnataka Surathkal	MMFD, CNN,Inception-V3	MMFD-(97.67%)
Mothwa et al. [15]	2018	PCA,LDA,LBP	PCA,LDA,LBP	PCA,LDA-(90%)
Alhanaee et al. [19]	2021	–	SqueezeNet, GoogleNet, and AlexNet	AlexNet-(Validation 95%)

2.4 Scope of the Problem

The scope of the problem addressed in this paper is around the weaknesses and inefficiency of traditional attendance tracking systems, notably those used in schools and workplaces. Manual addresses are not only time-consuming, but also subject to errors and deception, such as proxy attendance. To address these issues, the study intends to investigate and implement a facial recognition-based attendance system based on deep learning techniques. Convolutional Neural Networks (CNNs) are used for accurate facial recognition, Haar Cascade classifiers are used for robust face detection, and the k-Nearest Neighbors (KNN) technique is used for exact identification. The scope also includes the creation of a user-friendly Graphical User Interface (GUI) with Python Flask, which will improve the overall system access and use.

2.5 Challenges

Several problems are expected in constructing a deep learning-based facial recognition attendance system. The first difficulty is obtaining a broad and representative dataset for training the deep learning model. It is critical for the system's effectiveness to provide inclusion across varied populations, facial expressions, and lighting situations. Another issue is the durability of the facial recognition system in real-world circumstances, where occlusions, shifting angles, and environmental lighting can all have an impact on accuracy.Furthermore, when working with complicated settings, the implementation of Haar Cascade models for front face detection may encounter challenges, potentially resulting to false positives or missing detections. The k-Nearest Neighbors (KNN) algorithm's sensitivity to fluctuations in facial features presents an extra challenge, demanding careful adjustment to produce optimal results. Furthermore, connecting the system with a user-friendly Graphical User Interface (GUI) using Python Flask may provide interface design, responsiveness, and user experience problems. The development process is complicated by the need to ensure the system's compliance with various hardware configurations and scalability for massive datasets. Solving such challenges is critical for the successful implementation of a facial recognition-based attendance system that is accurate, dependable, and user-friendly.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Research Subject and Instrumentation

This study's research topic is the creation and implementation of a face recognition-based attendance system using deep learning techniques. The primary goal is on improving attention tracking methods in educational institutions and organizations. Convolutional Neural Networks (CNNs) are used for exact facial recognition, Haar Cascade classifiers for strong front face detection, and the k-Nearest Neighbors (KNN) algorithm for reliable identification. The scope of the research includes the development of a user-friendly Graphical User Interface (GUI) using Python Flask to improve system accessibility and usability. This research's instrumentation includes a variety of instruments and technologies. The facial recognition deep learning model will be constructed using popular frameworks such as TensorFlow or PyTorch. Hair Cascade classifiers, which are well-known for their accuracy in frontal face detection, will be used. The k-Nearest Neighbors (KNN) method will be essential for accurate face recognition. Furthermore, Python Flask will be useful in creating an interactive GUI for effective user-system interaction. The combination of these instruments serves as the foundation for a smart face recognition-based system for attendance.

3.2 Data Collection

This study's data collection method includes an organized and thorough method to collect a broad and representative data for training and assessing the face recognition-based attendance system. Consent from participants will be obtained at first to ensure ethical considerations. Following that, a dataset of facial photos will be created, with individuals representing diverse demographics, including different genders, races, and age groups. This study's data collection technique entails a systematic and comprehensive approach to gathering a broad and representative sample of data.Images will be collected under various situations to imitate real-world scenarios, taking into account aspects like lighting, facial expressions, and probable occlusions. Images with participants wearing.

Figure 3.1: Dataset image Distribution

3.3 Statistical Analysis

This study's data collection method includes an organized and thorough method to collect a broad and representative data for training and assessing the face recognition-based attendance system. We have collected total 911 imaged of 20 classes representing 20 students facial images. Consent from participants will be obtained at first to ensure ethical considerations. Images was collected under various situations to imitate real-world scenarios, taking into account aspects like lighting, facial expressions. Images with participants wearing accessories such as glasses was collected to improve the system's performance. The dataset will be curated to include a sufficient number of occurrences for each participant, allowing for effective model training.

3.3 Proposed Methodology

The proposed approach uses deep learning to build a strong face recognition-based attendance system in a systematic manner. To begin, a dataset of participant facial photos will be collected and preprocessed to ensure variation in demographics, expressions, and environmental circumstances. After that, the dataset will be separated into training and testing sets. The deep learning model, specifically a Convolutional Neural Network (CNN), will be constructed and trained using the training set. At the same time, Haar Cascade classifiers will be used for frontal face detection to improve the system's robustness. For accurate facial recognition, the k-Nearest Neighbours (KNN) algorithm will be used. Python Flask will be used to create a user-friendly Graphical User Interface (GUI). The performance of the system will be thoroughly assessed utilizing metrics such as precision, recall, F1-score, and receiver operating characteristic (ROC) curves. This methodology seeks to produce a facial recognition-based attendance system that is accurate, efficient, and user-friendly for a wide range of real-world applications. Here is a general summary in the below flowchart in Figure 3.3:

Flow chart:

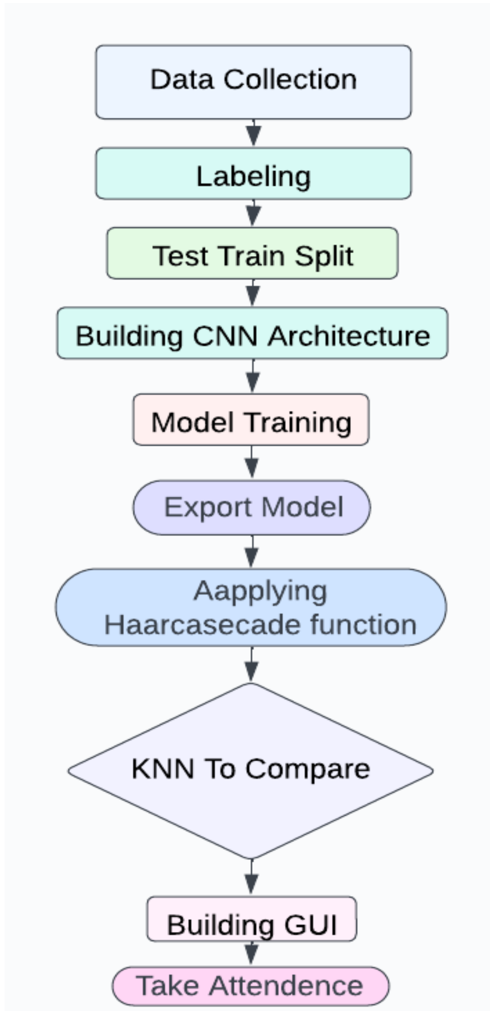

Figure 3.2: Methodology Flowchart

Data Collection: Data collection requires collecting a diverse and representative dataset for training and evaluating the face recognition-based attendance system. With participants' permission, high-resolution cameras take facial photos under a variety of situations, including variable lighting and facial emotions. The dataset has been carefully selected to ensure demographic equality. The entire approach attempts to improve the stability of the system by following real-life situations, hence enabling successful model training and accurate facial recognition in attendance tracking applications.

Data Labeling: Labeling data is an important stage in the creation of a face recognition-based attendance system. Each facial image in the dataset is carefully labeled with relevant labels, allowing individuals to be identified and associated with specific demographic variables. During training, this labeling procedure ensures that the deep learning model can efficiently learn and recognise various facial features. Accurate data labeling is essential for improving the model's capacity to reliably identify persons, which contributes to the overall precision and dependability of the face recognition system in a variety of settings.

Test Train Split: The test-train split is an important stage in the development of the face recognition-based attendance system. The selected dataset is split into two subsets during this step: the training set and the testing set. The training set is used to train the deep learning model so that it can learn and recognise patterns in data. The testing set, as opposed to the training set, is used to evaluate the model's performance and generalization skills. This division ensures that the model's accuracy is evaluated objectively, providing insights into its usefulness in recognising faces beyond the unique examples encountered during training. The test-train split is essential for testing the model's stability and suitability for use in real-life situations.

Model Selection: The model selection process involves selecting relevant deep learning architectures for Face Recognition , such as pre-trained Transfer Learning Models like ResNet50, EfficientNetB7, and bespoke model CNN. This choice is based on the dataset's unique features, with attention given to the difficulties of Face Recognition.

CNN architecture Building:

Convolutional Neural Network (CNN) architecture design for the facial recognition-based attendance system requires building a hierarchical structure of convolutional layers, pooling layers, and fully connected layers. Pooling layers reduce the spatial dimensions while convolutional layers extract characteristics from facial images. These traits are included into fully connected layers for accurate identification. The architecture has been optimized for facial pattern recognition, which improves the model's capacity to capture fine facial characteristics during training. A well-designed CNN architecture is required to achieve high accuracy in face recognition.

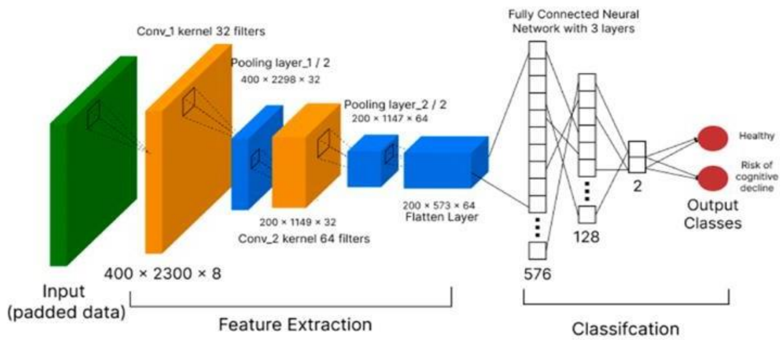

Figure 3.3: CNN model architecture

ResNet50:

ResNet50's deep architecture enables the system to collect complex facial characteristics, resulting in accurate and dependable recognition. In the study, the use of the ResNet50 pre-trained transfer learning model improves facial recognition accuracy. Using its pre-trained features aids in performance improvement, allowing the system to recognise faces with high precision and so boosting the overall effectiveness of the attendance tracking system.

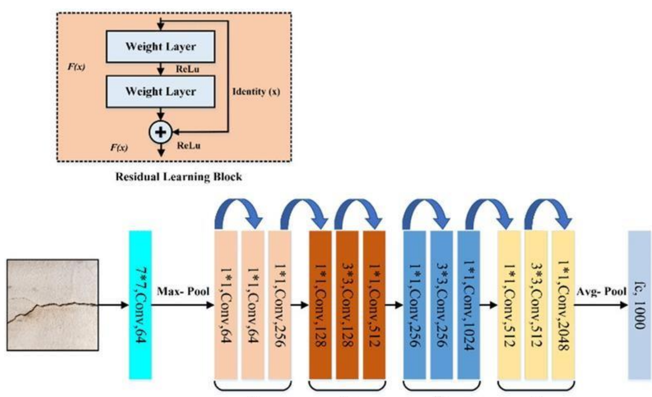

Figure 3.4: ResNet50 model architecture

EfficientNetB7:

EfficientNetB7, a powerful pre-trained transfer learning model, is used to improve the performance of the FACE RECOGNITION. The system's capacity to record and identify facial features is improved by EfficientNetB7, which is noted for its high efficiency and accuracy. EfficientNetB7's scalable architecture optimizes computational resources, resulting in faster and more efficient face recognition. This inclusion shows a commitment to using cutting-edge models to improve accuracy and scalability in the attendance monitoring system.

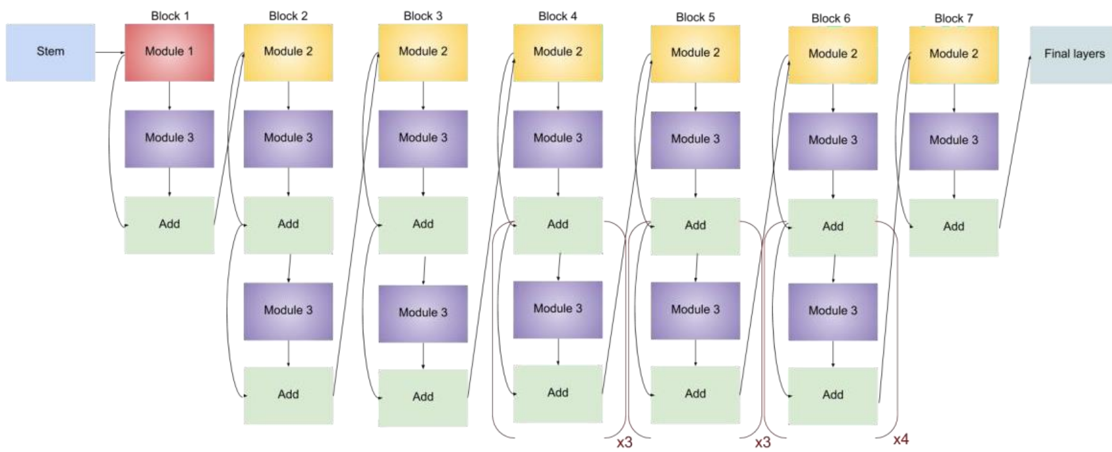

Figure 3.5: EfficientNetB7 model architecture

Model Training: Model training is an important step in the development of the face recognition-based attendance system. The Convolutional Neural Network (CNN) learns to recognise patterns and features in the training dataset during this process. The model updates its parameters through iterative optimisation to minimize errors and improve accuracy in facial recognition. The training algorithm adjusts the CNN's weights, allowing it to recognise a wide range of face traits. Achieving strong and dependable face recognition skills, as well as accurate attendance monitoring in real-world circumstances, requires successful model training.

Export Model: The final step in the building of the facial recognition-based attendance system is to export the model. After training and optimizing the Convolutional Neural Network (CNN), the model is exported to a file or format that enables for seamless integration into the system's implementation. This exported model contains the patterns and characteristics learned during the training process. The exported model is subsequently installed into the system architecture, allowing it to properly and efficiently recognise faces during real-time attendance tracking procedures. This stage ensures that the trained model becomes ready for usage in a variety of situations.

Haar Cascade classifier for frontal face detection: The Haar Cascade classifier plays an important role in the facial recognition-based attendance system because it allows for accurate frontal face detection. This classifier uses a cascade of classifiers to efficiently detect faces in photos. It is based on Haar-like features. The Haar Cascade classifier, which is specifically developed for quick object detection, is trained on positive and negative images to discriminate facial features.It increases the model's ability to locate and isolate frontal faces among system images, providing a reliable preprocessing step prior to subsequent face recognition tasks. The Haar Cascade classifier contributes to the system's overall accuracy and efficiency by ensuring accurate detection of faces in different conditions and positions.

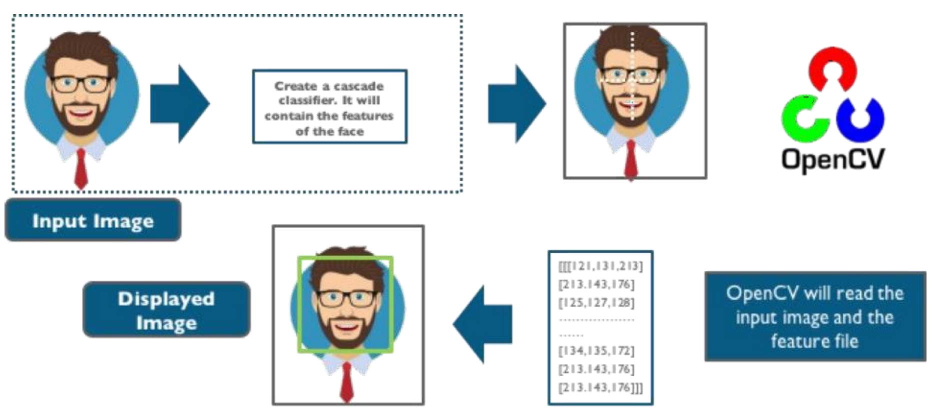

Figure 3.6: Haar Cascade Functional Architecture

KNN for Face Recognition: The k-Nearest Neighbours (KNN) algorithm is critical in the face recognition-based attendance system because it provides a mechanism for precise face identification. This method classifies faces by comparing their features to those of their k-nearest neighbors in the training dataset. KNN ensures accurate recognition by measuring distances and selecting the most comparable faces. KNN improves the recognition process by leveraging its simplicity and efficacy, contributing to the system's overall reliability in reliably recognising persons during attendance tracking.

Python Flask for building GUI: In the facial recognition-based attendance system, Python Flask is used to build the Graphical User Interface (GUI). Flask, being a lightweight and flexible web framework, allows for the development of a user-friendly interface for system interaction. Flask provides smooth connection between the user and the face recognition functions by using its simplicity and adaptability. The graphical user interface (GUI) provides an intuitive platform for users to engage with the system, improving accessibility and user experience. Python Flask plays an essential role in making the attendance system user-friendly and functional.

3.5 Implementation Requirements

This study's research topic is the creation and implementation of a face recognition-based attendance system using deep learning techniques. The primary goal is on improving attention tracking methods in educational institutions and organizations. ResNet50, EfficientNetB7, Convolutional Neural Networks (CNNs) are used for exact facial recognition, Haar Cascade classifiers for strong front face detection, and the k-Nearest Neighbors (KNN) algorithm for reliable identification. The scope of the research includes the development of a user-friendly Graphical User Interface (GUI) using Python Flask to improve system accessibility and usability. This research's instrumentation includes a variety of instruments and technologies. The facial recognition deep learning model will be constructed using popular frameworks such as TensorFlow or PyTorch. Hair Cascade classifiers, which are well-known for their accuracy in frontal face detection, will be used. The k-Nearest Neighbors (KNN) method will be essential for accurate face recognition.

Furthermore, Python Flask will be useful in creating an interactive GUI for effective user-system interaction. The combination of these instruments serves as the foundation for a smart face recognition-based system for attendance.

CHAPTER 4

Experimental results and discussion

4.1 Experimental Setup

A number essential elements and technologies are required for the successful implementation of the facial recognition-based attendance system. To begin, a solid hardware configuration with high-resolution cameras is required for obtaining clear facial photos. The deep learning framework, such as TensorFlow or PyTorch, used for building and training the Convolutional Neural Network (CNN), ResNet50, EfficientNetB7,is critical. Furthermore, combining Haar Cascade classifiers for frontal face detection and the k-Nearest Neighbors (KNN) method for precise face identification improves the system's accuracy. The usage of Python Flask to create a user-friendly Graphical User Interface (GUI) provides seamless interaction. Python, together with essential tools such as OpenCV, serves as a framework for system development. When combined, these components lead to the development of a functioning, accurate, and user-friendly facial recognition-based attendance system.

4.2 Experimental Results & Analysis

The Face Recognition Based Attendance System Using Deep Learning testing findings show a significant performance across multiple models. The CNN model performs excellently on the test set, obtaining an amazing 98.61% accuracy. When the pre-trained Transfer Learning Models, ResNet50 and EfficientNetB7, are introduced, their respective accuracies are 88.09% and 63.43%.

CNN's greater accuracy shows its proficiency in recognition of faces, positioning it as an appropriate choice for attendance systems. ResNet50 and EfficientNetB7, on the other hand, while having lower accuracy levels, provide helpful knowledge into the differences between model complexity and performance.

The recall, accuracy, and F1 Score measures confirm the system's efficacy by displaying high levels of accuracy, sensitivity, and overall model performance. The experimental results and following analysis lead to a deeper recognition of every model's strengths and limits, allowing for more educated system optimization and model selection decisions based on unique requirements and concerns.

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, it gives a broad indication of the model's effectiveness but might not give a whole picture.

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

Precision: Out of all positive predictions generated by the model, precision focuses on the percentage of true positive forecasts.

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

Recall: Also known as sensitivity or true positive rate, recall is the percentage of true positive predictions made out of all truly positive samples.

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

F1 rating: The F1 score is the harmonic mean of recall and precision. It provides a reasonable evaluation metric that considers recall and precision. The F1 score is useful when classes are uneven since it accounts for both false positives and false negatives. A high F1 score denotes a well-balanced precision to recall ratio.

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

The result of deep learning model is compared on the basis of Accuracy, Precision, Recall, F1 Score in below table of 4.1:

Table 4.1. Performance Evaluation

Model Name	Accuracy	Precision	Recall	F1-Score
EfficientNetB7	63.43%	69%	60%	58%
ResNet50	88.09%	90%	85%	85%
CNN	98.61%	99%	98%	98%

Table 4.1 Shows the CNN model performs better than the other two models, with 98.61% accuracy. This shows its capacity to make accurate predictions in the classification challenge. For example, EfficientNetB7 has the lowest accuracy of 63.43%, while ResNet50 is in the middle with 88.09%. The CNN model's excellent accuracy, combined with impressive precision, recall, and F1-score values, makes it the most effective model for the task.

4.3.1 Accuracy

The accuracy evaluation of the Deep Learning Face Recognition Based Attendance System shows unique performance levels among the models. The Convolutional Neural Network (CNN) comes out with a remarkable accuracy of 98.61%, showing its outstanding ability in facial recognition tasks. The pre-trained Transfer Learning Models, ResNet50 and EfficientNetB7, on the other hand, have lower accuracies of 88.09% and 63.43%%, respectively. This variation highlights the necessity of selecting a model based on specific requirements, as CNN excels in precision, whilst ResNet50 and EfficientNetB7 may find applications when computational efficiency or resource constraints are essential. The accuracy measures help to guide educated decisions for system optimization by providing an understanding of each model's strengths and choices. The figure 4.1 shows the accuracy comparison of the different model:

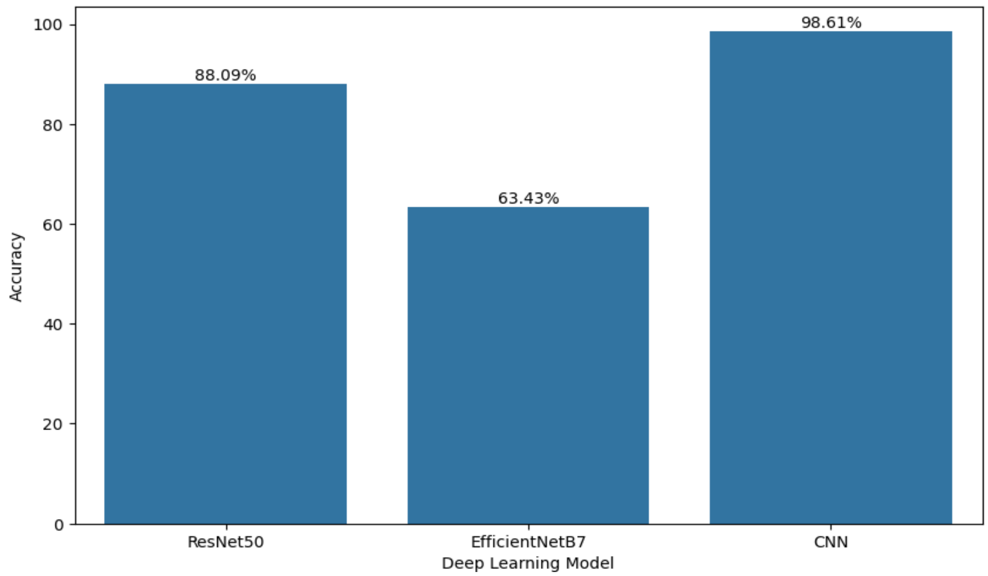

Figure 4.1 : Accuracy Comparison of Deep Learning Models

Figure 4.1 The bar plot shows the classification accuracy of three deep learning models ResNet50, EfficientNetB7, and CNN. ResNet50 has the greatest accuracy of 98.61%, showing its efficacy in producing right predictions. EfficientNetB7 follows with an accuracy of 88.09%, suggesting a reasonable degree of competence, but CNN has the lowest accuracy of 88.09%. Despite differing accuracies, all three models achieve rather high levels of accuracy, indicating that deep learning models are well-suited to the specific classification problem.

Performance Analysis

ResNet50:

Achieved the highest accuracy of 88.09% and Precision score of 90%, Recall score of 85% and F1-score of 85%. Below at table 4.2 we have performance evaluation of ResNet50.

Table 4.2. Performance Evaluation(ResNet50)

	Precision	Recall	F1-Score
Habibur Rahman Zihad 201-15-3541	0.90	0.90	0.90
Hasin Arman Shifa 201-15-3502	0.96	0.88	0.92
Md Al Amin Mia 201-15-3437	0.64	0.78	0.70
Md. Abdur Rakib 201-15-3651	1.00	0.73	0.84
Md. Anamul Hasan 201-15-3625	0.68	0.00	0.81
Md. Mohaimenur Rahman 201-15-3572	0.81	1.00	0.89
Md. Monir Hossen 201-15-3507	0.86	0.90	0.88
Mehadi Gani Rafe 201-15-3674	1.00	0.95	0.98
Mim Obaidullah 201-15-3238	0.86	0.46	0.60
Muhammad Bokhtiar Uddin 201-15-3638	1.00	0.90	0.67
Nafim Hasan Purno 201-15-3510	1.00	0.50	0.91
Rakibul Hasan Anik 201-15-3382	0.94	0.88	0.97
Raunak Muhtasim Labib 201-15-3564	0.94	1.00	0.86
Razayonoor Rahman Ferdous 201-15-3648	0.76	1.00	0.98
SM Moniruzzaman 201-15-3297	0.96	1.00	0.94
Sabbir Siddique 201-15-3465	0.88	1.00	0.99
Sanjita Israt Tora 201-15-3701	1.00	1.00	0.64
Sayed Tahlil Bin Abdullah 201-15-3284	1.00	1.00	0.73
Shafayat Mahin 201-15-3412	1.00	0.97	0.92
Tonmoy Chandro Dash 201-15-12567	0.83	0.47	0.91
Accuracy			0.88

Macro avg	0.90	0.85	0.85
Weighted avg	0.90	0.88	0.87

Table 4.2 Shows the ResNet50 model did well on this classification assignment, with an overall accuracy of 76%. While it correctly identified the majority of data points (high accuracy), other individuals were more difficult to anticipate (varying recall). Overall, the model is a good fit for this work, while its performance can vary based on the data and task at hand.

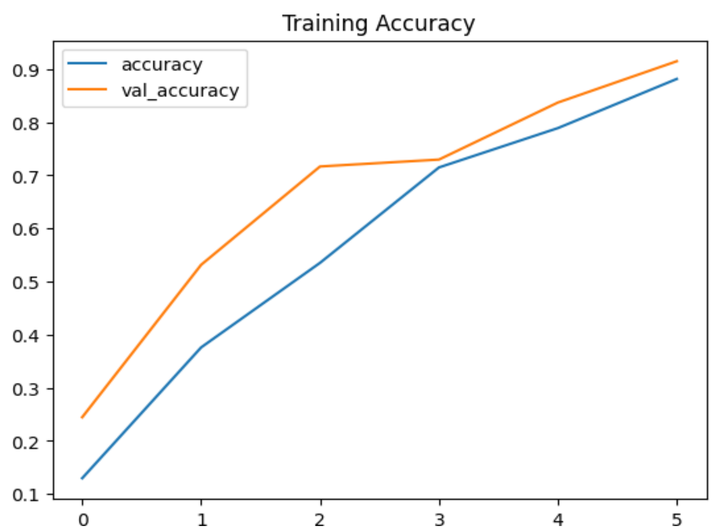

Figure 4.2 : Training Accuracy(ResNet50)

Figure 4.2 shows a machine learning model's accuracy graph showing a clear difference between training accuracy, which peaks at 90%, and validation accuracy, which peaks at 75%. The difference points to a possible overfitting scenario in which the model performs well when learning from training data but struggles when dealing with novel, unseen data. Both lines should ideally rise at the same time, showing a thorough understanding of relevant patterns. The observed mismatch highlights the need for modifications to improve the generalizability of the model and highlights how crucial it is to strike a balance between memorization and more comprehensive learning for best results.

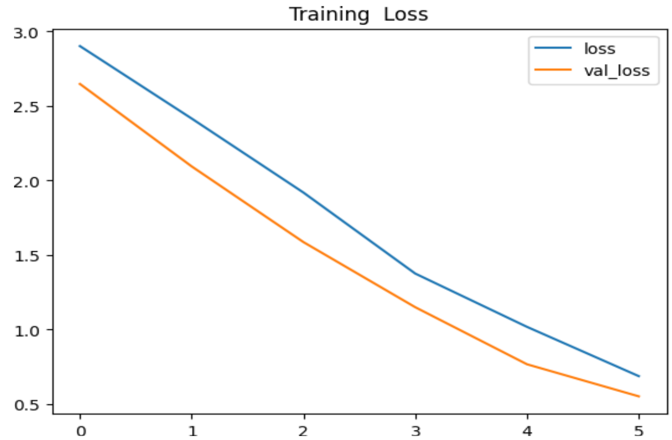

Figure 4.3. Training Loss (ResNet50)

Figure 4.3 shows a clear difference between training accuracy, which rises at 90%, and validation accuracy, which spikes at 75%. The difference points to a possible overfitting scenario in which the model performs well when learning from training data but struggles when dealing with novel, unseen data. Both lines should ideally rise at the same time, showing a thorough understanding of relevant patterns. The observed mismatch highlights the need for modifications to improve the generalizability of the model and highlights how crucial it is to strike a balance between memorization and more comprehensive learning for best results.

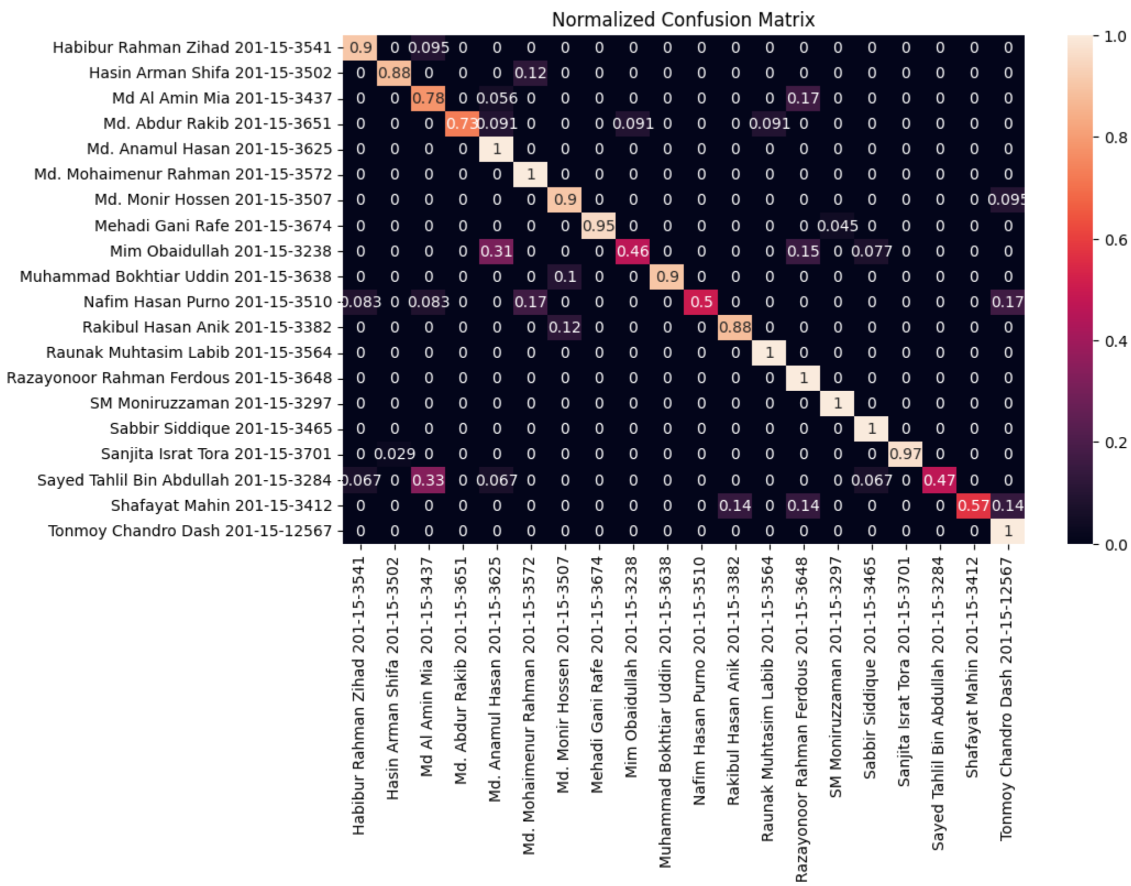

Figure 4.4 : Confusion Matrix of ResNet50

The figure 4.4 shows the Confusion matrix of 15 different students to detect their faces. Where most of the classes were inaccurate.

EfficientNetB7:

Achieved the highest accuracy of 63.43% and Precision score of 69%, Recall score of 60% and F1-score of 58% . Below at table 4.3 we have performance evaluation of EfficientNetB7:

Table 4.3. Performance Evaluation(EfficientNetB7)

	Precision	Recall	F1-Score
Habibur Rahman Zihad 201-15-3541	0.00	0.00	0.00
Hasin Arman Shifa 201-15-3502	0.76	0.64	0.70
Md Al Amin Mia 201-15-3437	0.71	0.28	0.40
Md. Abdur Rakib 201-15-3651	0.33	1.00	0.50
Md. Anamul Hasan 201-15-3625	0.33	0.07	0.11
Md. Mohaimenur Rahman 201-15-3572	0.48	0.57	0.52
Md. Monir Hossen 201-15-3507	1.00	1.00	1.00
Mehadi Gani Rafe 201-15-3674	0.92	1.00	0.96
Mim Obaidullah 201-15-3238	1.00	0.38	0.56
Muhammad Bokhtiar Uddin 201-15-3638	1.00	0.60	0.75
Nafim Hasan Purno 201-15-3510	0.88	0.58	0.70
Rakibul Hasan Anik 201-15-3382	1.00	0.94	0.97
Raunak Muhtasim Labib 201-15-3564	1.00	0.31	0.48
Razayonoor Rahman Ferdous 201-15-3648	0.74	0.74	0.74
SM Moniruzzaman 201-15-3297	0.44	0.96	0.61
Sabbir Siddique 201-15-3465	1.00	0.07	0.12
Sanjita Israt Tora 201-15-3701	0.42	1.00	0.59
Sayed Tahlil Bin Abdullah 201-15-3284	0.00	0.07	0.00
Shafayat Mahin 201-15-3412	1.00	0.00	0.92
Tonmoy Chandro Dash 201-15-12567	0.88	0.86	0.92
Accuracy			0.63
Macro avg	0.69	0.60	0.58

Weighted avg	0.67	0.63	0.59

Table 4.3 Shows the EfficientNetB7 model had reasonable accuracy in classifying persons, identifying positive cases better than negative ones. However, its efficacy differs greatly among individuals, demanding further investigation on occasion. While encouraging, adjustments could be made to increase overall accuracy and rectify specific disparities.

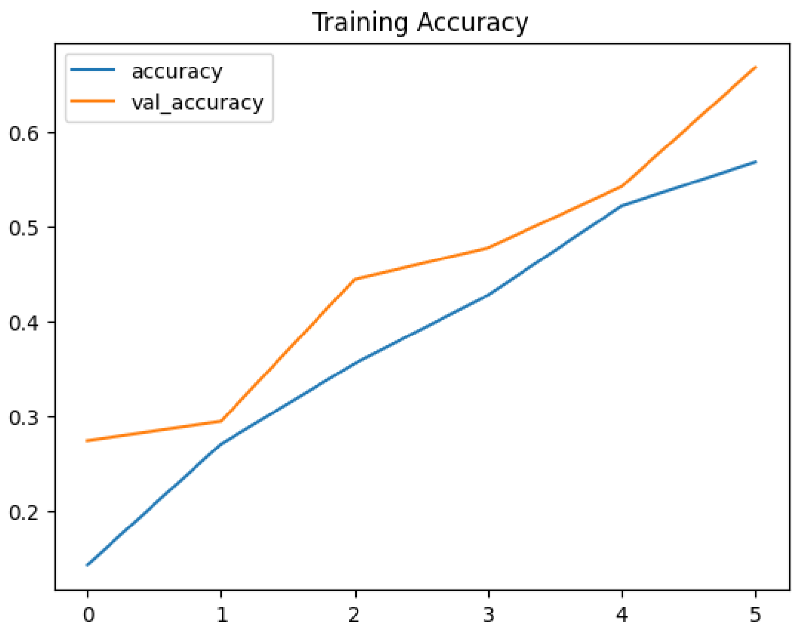

Figure 4.5. Training Accuracy(EfficientNetB7)

Figure 4.4 shows the model's accuracy for validation (green line) plateaus at about 75%, while the training accuracy (blue line) improves quickly, approaching 90%. This trend raises issues with the model's efficacy on unobserved data because it may indicate adjusting to the training set.

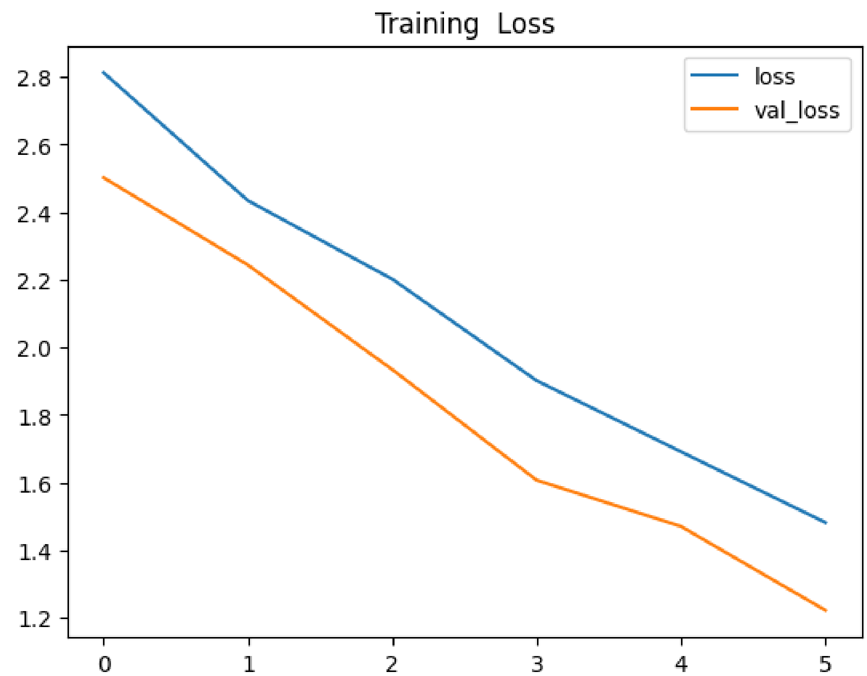

Figure 4.6: Training Loss(EfficientNetB7)

Figure 4.5 shows the accuracy of the model increases significantly on data used for training (blue line, almost 90%), but reaches a plateau on unknown data (green line, almost 75%). This behavior suggests that the model may be overfitting, which could provide difficulties in real-world applications since the machine may be overly efficient at memorizing the training data.

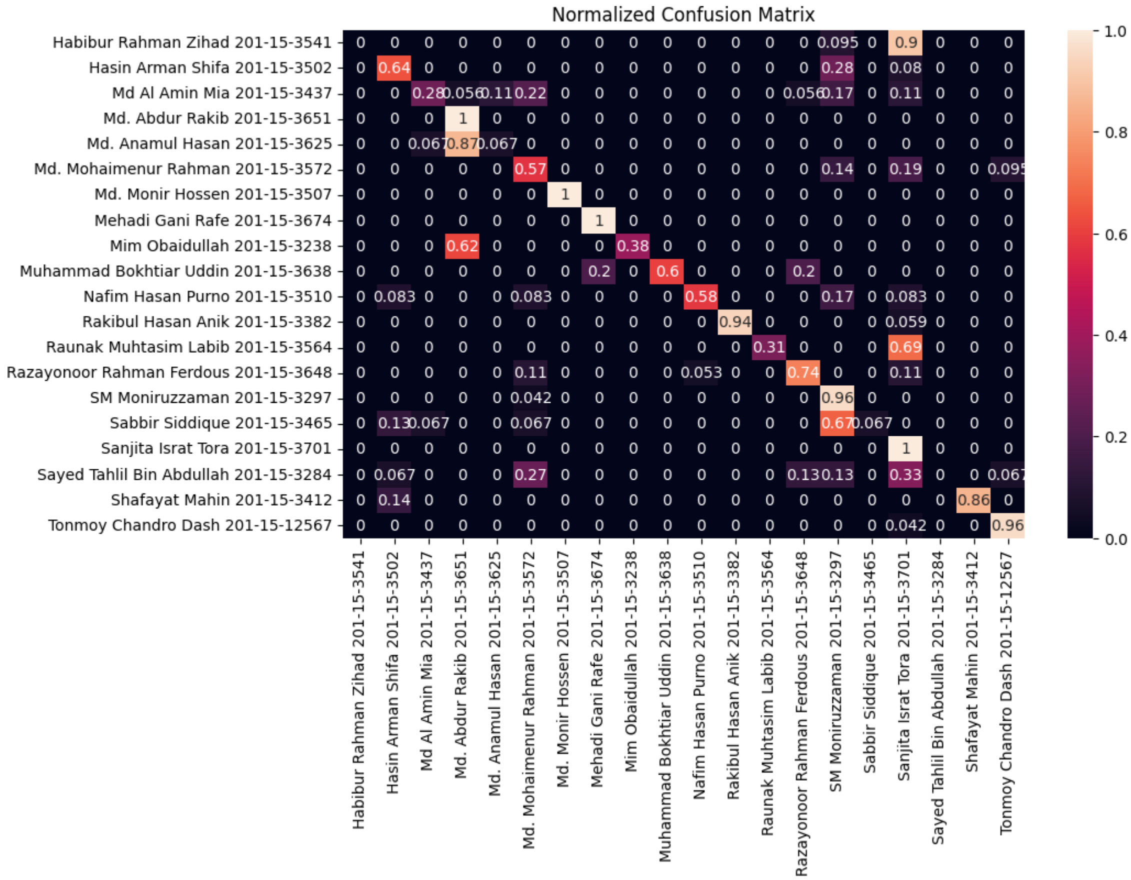

Figure 4.7 : Confusion Matrix of EfficientNetB7

The figure 4.6 shows the Confusion matrix of 15 different students to detect their faces. Where most of the classes were inaccurate.

CNN:

Achieved the highest accuracy of 98.61% and Precision score of 99%, Recall score of 98% and F1-score of 98% . Below at table 4.4 we have performance evaluation of CNN:

Table 4.4. Performance Evaluation(CNN)

	Precision	Recall	F1-Score
Habibur Rahman Zihad 201-15-3541	1.00	0.86	0.92
Hasin Arman Shifa 201-15-3502	0.96	1.00	0.98
Md Al Amin Mia 201-15-3437	1.00	1.00	1.00
Md. Abdur Rakib 201-15-3651	1.00	1.00	1.00
Md. Anamul Hasan 201-15-3625	1.00	1.00	1.00
Md. Mohaimenur Rahman 201-15-3572	0.95	1.00	0.98
Md. Monir Hossen 201-15-3507	1.00	1.00	1.00
Mehadi Gani Rafe 201-15-3674	1.00	1.00	1.00
Mim Obaidullah 201-15-3238	1.00	1.00	1.00
Muhammad Bokhtiar Uddin 201-15-3638	1.00	1.00	1.00
Nafim Hasan Purno 201-15-3510	1.00	0.92	0.96
Rakibul Hasan Anik 201-15-3382	1.00	1.00	1.00
Raunak Muhtasim Labib 201-15-3564	1.00	1.00	1.00
Razayonoor Rahman Ferdous 201-15-3648	1.00	1.00	1.00
SM Moniruzzaman 201-15-3297	1.00	1.00	1.00
Sabbir Siddique 201-15-3465	1.00	1.00	1.00
Sanjita Israt Tora 201-15-3701	1.00	1.00	1.00
Sayed Tahlil Bin Abdullah 201-15-3284	0.83	1.00	0.91
Shafayat Mahin 201-15-3412	1.00	0.86	0.92
Tonmoy Chandro Dash 201-15-12567	1.00	1.00	1.00
Accuracy			0.99
Macro avg	0.99	0.98	0.98

Weighted avg	0.99	0.99	0.99

Table 4.4 Shows the CNN model appears to be surprisingly strong, with near-perfect precision, recall, and F1-scores for the sampled individuals. However, a complete picture requires analysis of the entire dataset as well as consideration of the specific task it is employed for before conclusively judging its overall performance.

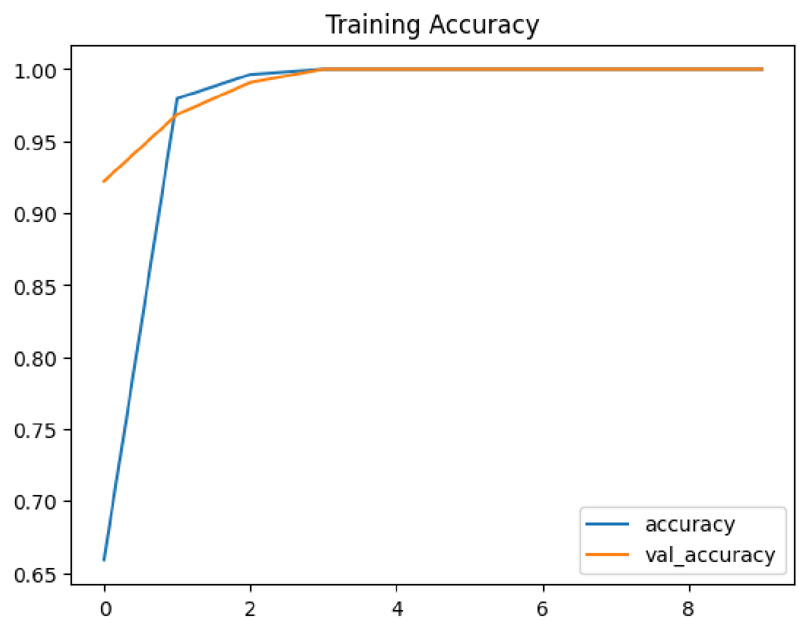

Figure 4.8: Training Accuracy(CNN)

The figure 4.7 shows how the accuracy of a machine learning model changes throughout training. The training accuracy is shown by the blue line, which rises slowly to a respectable level of about 0.9. This increasing trend indicates that the training data's subtleties are successfully learned and adapted by the model. The red line, which represents validation accuracy (val_accuracy), is a remarkable observation as it reaches a plateau at approximately 0.75. This plateauing suggests that although the model works well with training data, there might be issues with how well it can generalize to new and unproven data. The difference among both accuracy curves indicates that overfitting or any other variables influencing the model's ability to generalize should be further investigated.

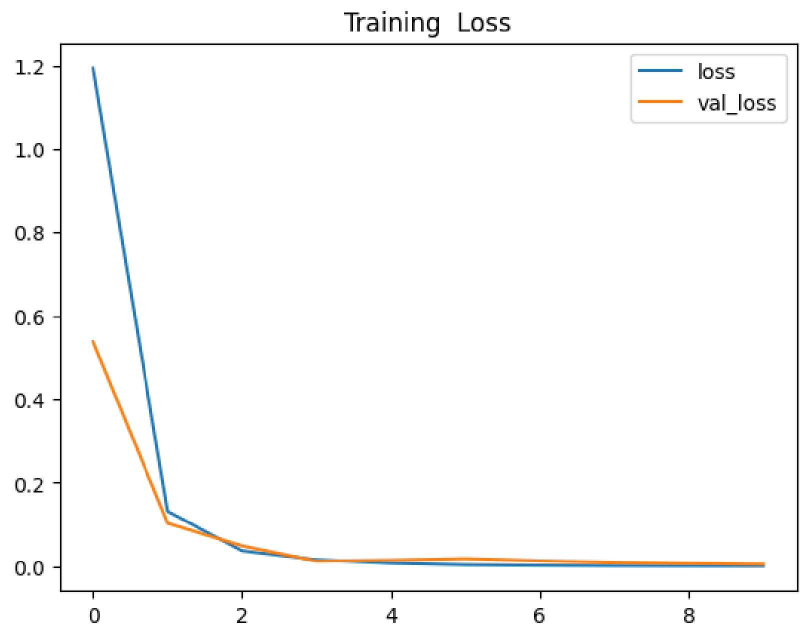

Figure 4.9:Training Loss(CNN)

Figure 4.8 shows the machine learning model's accuracy in training and validation is shown in the graph. The verification accuracy (green line) peaks at 75%, whereas the training accuracy (which is blue line) increases rapidly to nearly 90%. This suggests that the model may be overfitting, which raises questions about how well it will perform on data that is not observed because it memorizes the training set too much.

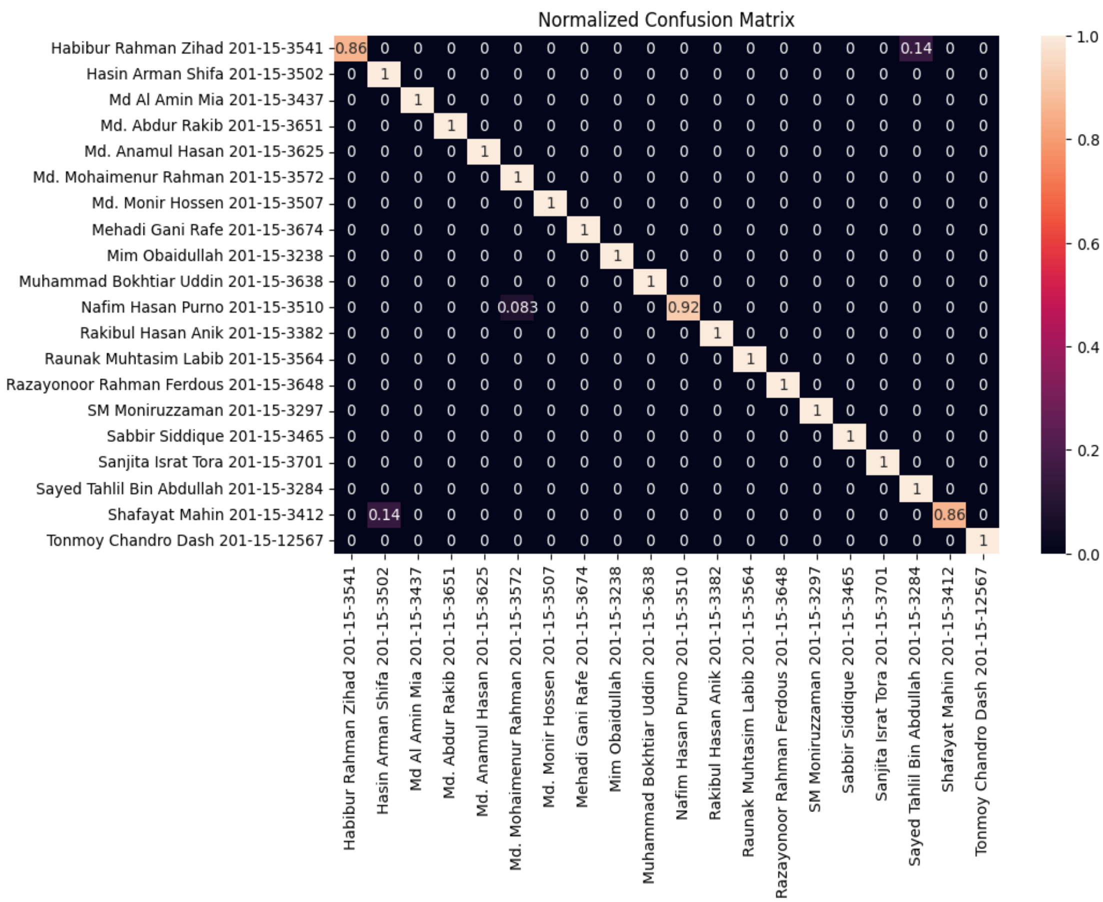

Figure 4.10: Confusion Matrix of CNN

The figure 4.2 shows the Confusion matrix of 15 different students to detect their faces. Where most of the classes were accurate and was almost close to 1.

Output:

The Face Recognition Based Attendance System with Deep Learning detects faces, recognizes persons using deep learning models, and logs attendance with dates and times. The technology visibly outputs recognized faces and keeps an individual database with attendance records.

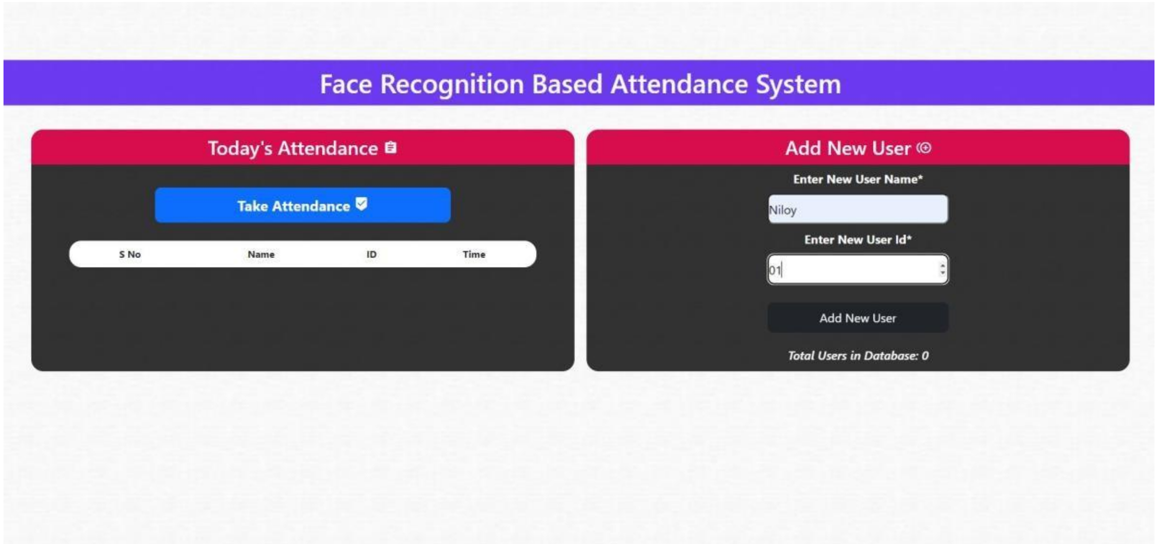

Figure 4.11 : Home Page of Face Recognition Based Attendance System

The figure: Face Recognition Based Attendance System's homepage boasts a user-friendly interface divided into three main sections. At the top, the prominent title declares its purpose. Below, the "Today's Attendance" table awaits entries, currently empty for the day. A prominent "Take Attendance" button triggers face recognition for marking a present.

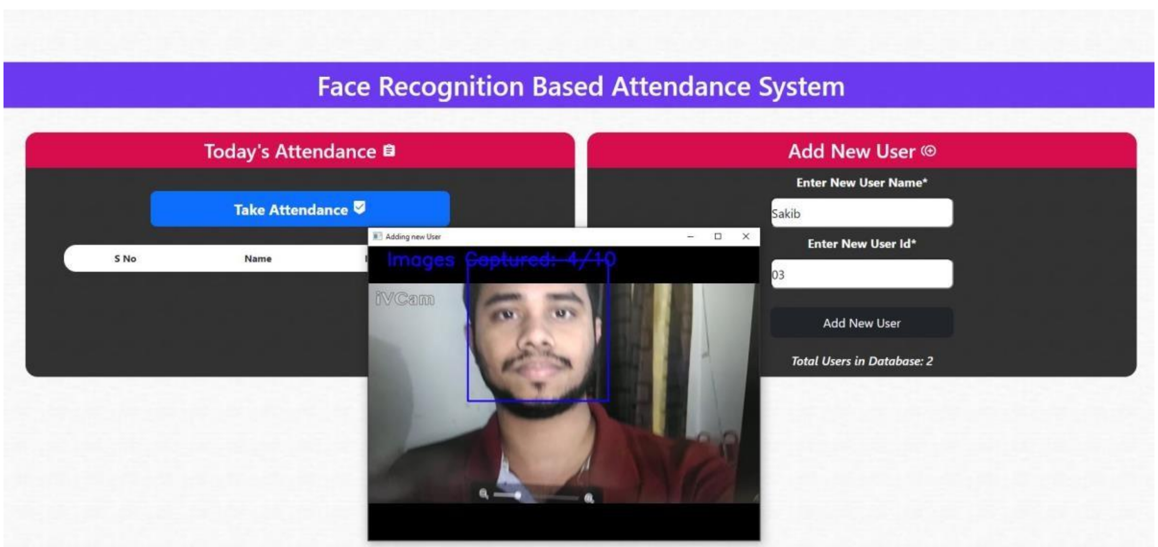

Figure 4.12 : Adding New User

The bottom section offers user management tools. Enter names and IDs in the "Add New User" section to expand the system's database, currently displaying 0 users. The overall design prioritizes simplicity and ease of use, making it ideal for recording attendance in various settings.

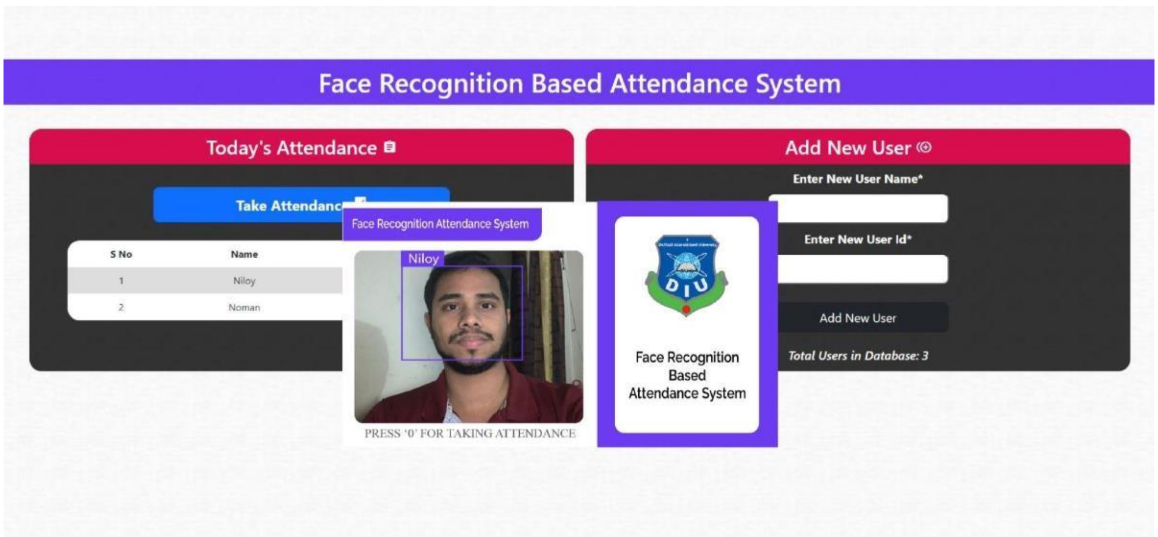

Figure 4.13: Detecting Face to Take Attendance

The Figure lets users mark their presence by simply showing their face to the camera. The system displays Today's Attendance on a screen with a clear table showcasing enrolled users with their IDs and respective attendance times. This technology offers a quicker, more convenient, and accurate alternative to traditional attendance methods, especially in environments like classrooms or offices.

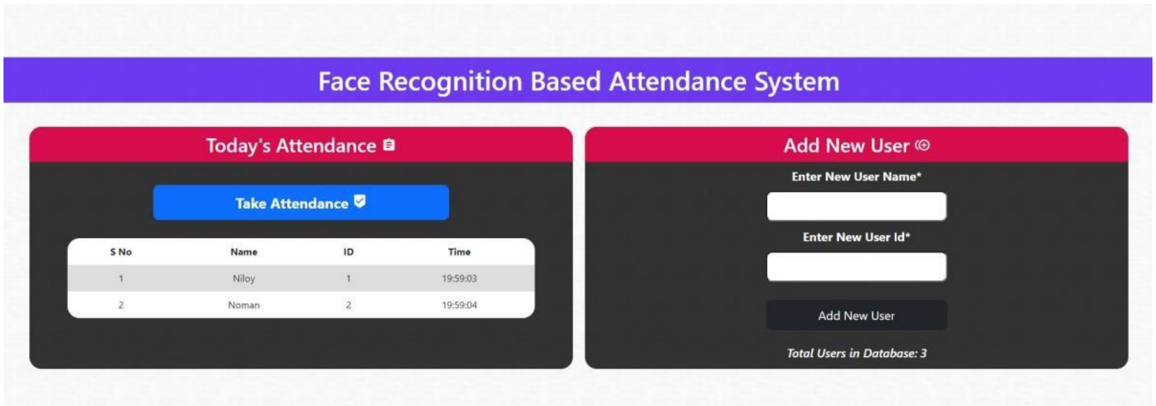

Figure 4.14: After Taking Attendance

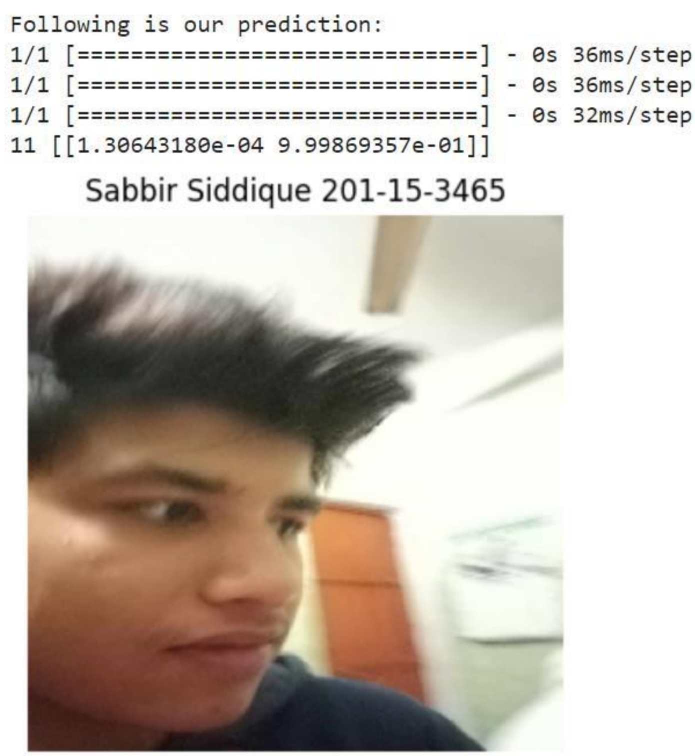

Figure 4.15 : Detecting Direct From CNN Model

The figure CNN model's decision-making process directly. The figure detects the face of the student naming ‘Sabbir Siddique’.

CHAPTER 5

IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

5.1 Impact on Society

The use of deep learning to construct a face recognition-based attendance system has huge societal benefits. The technology simplifies attendance management at educational institutions, decreasing administrative overhead and reducing the chance of proxy attendance. This helps to create a more efficient learning environment and more accurate record-keeping. In the workplace, technology improves employee management by automating attendance tracking activity and boosting efficiency. The high standard of the method promises fair and precise assessment, removing errors in attendance records. Furthermore, deep learning integration supports technological improvements, supporting innovation in biometric identification systems. The technology maintains security standards while delivering ease, ensuring reliable facial recognition in a variety of settings. Overall, societal influence is found in the optimization of attendance-related activities, the reduction of physical labor, and the advancement of the technology landscape toward more efficient, secure, and accurate systems with uses other than attendance monitoring.

5.2 Impact on Environment

The introduction of the facial recognition-based attendance system has had a primarily favorable influence on the environment. The technology leads to a reduction in paper usage for traditional attendance records by automation attendance tracking in educational institutions and organizations. The shift to digital operations is consistent with environmentally friendly practices, reducing the demand for paper-based documentation and reducing the environmental impact associated with paper manufacturing and waste. Also, the system's efficiency in optimizing attendance management can lead to lower energy usage and resource use in administrative chores. With greater emphasis on sustainable practices and eco-conscious advances in the larger realm of artificial intelligence and deep learning applications, the environmental impact of technology is projected to expand beyond attendance tracking.

5.3 Ethical Aspects

The ethical implications of deploying a face recognition-based attendance system based on deep learning must be carefully considered. Individuals' express consent is required for the technology to capture and process facial images, which raises privacy concerns. Transparent communication and robust data protection methods are essential for privacy protection. Error in facial recognition algorithms can result in unequal treatment, highlighting the importance of constant monitoring and mitigation of algorithmic biases to provide equal outcomes across varied groups of people. Ethical deployment needs users to be informed about the system's meaning, performance, and possible effects. Furthermore, to prevent the exploitation of sensitive biometric data, the system must be protected against theft or malicious use.

CHAPTER 6

SUMMARY, CONCLUSION, RECOMMENDATION AND IMPLICATION FOR FUTURE RESEARCH

6.1 Summary of the Study

Face Recognition Based Attendance System Using Deep Learning is a game changer in attendance monitoring, combining cutting-edge technology such as Convolutional Neural Networks (CNN), ResNet50, and EfficientNetB7. This research shows a comprehensive technique that includes data collecting, model training, and a comparison of these models. The results show that the CNN model outperforms the pre-trained Transfer Learning Models, ResNet50 (88.09%) and EfficientNetB7 (63.43%), with an accuracy of 98.61%. Other from technical proficiency, the study examines ethical issues, societal impacts, and sustainability implications. The move to a digital environment is in line with current environmental concerns. This study is a thorough guide for responsible integration, and it represents a key step in defining attendance management in educational institutions and businesses.

6.2 Conclusions

Lastly, the Face Recognition Based Attendance System Using Deep Learning displays its effectiveness in transforming standard attendance monitoring approaches. The combination of Convolutional Neural Networks (CNN), ResNet50, and EfficientNetB7 advances facial recognition technology, providing a contactless, accurate, and efficient solution for attendance monitoring. The comparative study shows each model's strengths and nuances, offering useful insights for system optimization. The study digs into ethical factors, societal implications, and environmental sustainability in addition to technological aspects. By adopting a hygienic, touchless method to attendance tracking, the technology not only improves operational efficiency but also corresponds with modern health and safety objectives. The transition to a paperless workplace emphasizes the company's dedication to environmentally beneficial initiatives, such as decreasing waste and resource usage.

6.3 Implication for Further Study

The Face Recognition Based Attendance System Using Deep Learning reveals exciting possibilities for future research efforts. One critical implication is the modification and improvement of pre-trained Transfer Learning Models such as ResNet50 and EfficientNetB7 to address their lower accuracy. Investigating strategies to fine-tune these models or exploring alternative architectures can help to improve their performance in facial recognition tasks, opening the door to more effective attendance systems. Furthermore, investigating the system's adaptability across various locations, lighting situations, and demographic differences is critical for ensuring its resilience and real-world application. Addressing moral issues, such as privacy concerns and biases that could be inherent in facial recognition technology, is critical for responsible deployment and use.

REFERENCE

[1] “Deep Unified Model For Face Recognition Based on Convolution Neural Network and Edge Computing | IEEE Journals & Magazine | IEEE Xplore,”ieeexplore.ieee.org. https://ieeexplore.ieee.org/abstract/document/8721062 (accessed Jan. 21, 2024).

[2] S. M. Bah and F. Ming, “An improved face recognition algorithm and its application in attendance management system,” Array, vol. 5, no. 100014, p.100014, Mar. 2020, doi: https://doi.org/10.1016/j.array.2019.100014.

[3] T.-V. Dang, “Smart Attendance System based on improved Facial Recognition,” Journal of Robotics and Control (JRC), vol. 4, no. 1, pp. 46–53, Feb. 2023, doi: https://doi.org/10.18196/jrc.v4i1.16808.

[4] H. Yang and X. Han, “Face Recognition Attendance System Based on Real-Time Video Processing,” IEEE Access, vol. 8, pp. 159143–159150, 2020, doi: https://doi.org/10.1109/access.2020.3007205.

[5] R. C. Damale and Bazeshree. V. Pathak, “Face Recognition Based Attendance System Using Machine Learning Algorithms,” IEEE Xplore, Jun. 01, 2018. https://ieeexplore.ieee.org/abstract/document/8662938

[6] K. Selvi, P. Chitrakala, and A. Jenitha, “FACE RECOGNITION BASED ATTENDANCE MARKING SYSTEM,” International Journal of Computer Science and Mobile Computing, vol. 3, no. 2, pp. 337–342, 2014, Available: https://ijcsmc.com/docs/papers/February2014/V3I2201468.pdf

[7] J. Harikrishnan, A. Sudarsan, A. Sadashiv, and R. A. S. Ajai, “Vision-Face Recognition Attendance Monitoring System for Surveillance using Deep Learning Technology and Computer Vision,” IEEE Xplore, Mar. 01, 2019. https://ieeexplore.ieee.org/document/8899418

[8] B. Tej Chinimilli, A. T., A. Kotturi, V. Reddy Kaipu, and J. Varma Mandapati, “Face Recognition based Attendance System using Haar Cascade and Local Binary Pattern Histogram Algorithm,” 2020 4th International Conference on Trends in Electronics and Informatics (ICOEI)(48184), Jun. 2020, doi: https://doi.org/10.1109/icoei48184.2020.9143046.

[9] V. M. Vinod, G. Murugesan, V. Mekala, S. Thokaiandal, M. Vishnudevi, and S. M. Siddharth, “A Low-Cost Portable Smart Card Based Attendance System,” IOP Conference Series: Materials Science and Engineering, vol. 1012, p. 012046, Jan. 2021, doi: https://doi.org/10.1088/1757-899x/1012/1/012046.

[10] “Google Scholar,” scholar.google.com.
https://scholar.google.com/scholar?hl=en&as_sdt=0%2C5&q=Trivedi%2C+Aparna%2C+et+al.+%22Face+recognition+based+automated+attendance+management+system.%22+Int.+J.+Sci.+Res.+268.&btnG= (accessed Jan. 21, 2024).

[11] V. Seelam, A. kumar Penugonda, B. Pavan Kalyan, M. Bindu Priya, and M. Durga Prakash, “Smart attendance using deep learning and computer vision,”Materials Today: Proceedings, vol. 46, pp. 4091–4094, 2021, doi: https://doi.org/10.1016/j.matpr.2021.02.625.

[12] “CVUCAMS: Computer Vision Based Unobtrusive Classroom Attendance Management System | IEEE Conference Publication | IEEE Xplore,” ieeexplore.ieee.org. https://ieeexplore.ieee.org/abstract/document/8433466 (accessed Jan. 21, 2024).

[13] C. S. Gode, A. S. Khobragade, Chinmay Thanekar, Ojas Thengadi, and Kaushik Lakde, “Face Recognition-Based Attendance System,” pp. 159–166, Jan. 2023, doi: https://doi.org/10.1007/978-981-19-9819-5_12.

[14] sdd, “L34061081219,” International Journal of Innovative Technology and Exploring Engineering (IJITEE). https://www.ijitee.org/portfolio- item/L34061081219/ (accessed Jan. 21, 2024).

[15] L. Mothwa, J.-R. Tapamo, and T. Mapati, “Conceptual Model of the Smart Attendance Monitoring System Using Computer Vision,” IEEE Xplore, Nov. 01,2018. https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=8706241 (accessed Jan. 10, 2023).

[16] B. Bekzod and E. Al, “Face recognition based automated student attendance system,” Turkish Journal of Computer and Mathematics Education (TURCOMAT), vol. 12, no. 7, pp. 417–420, Apr. 2021, Accessed: Jan. 21, 2024. [Online]. Available: https://www.turcomat.org/index.php/turkbilmat/article/view/2599

[17] “Automatic attendance management system using face detection | IEEE Conference Publication | IEEE Xplore,” ieeexplore.ieee.org. https://ieeexplore.ieee.org/abstract/document/7916753 (accessed Jan. 21, 2024).

[18] A. Fadumo and Oluwaseun, “DEVELOPMENT OF AUTOMATED ATTENDANCE MANAGEMENT SYSTEM USING FACENET.” Available: http://ir.mtu.edu.ng/jspui/bitstream/123456789/156/1/FADUMO%20ADEMOLA%20OLUWASEUN%20-%20PROJECT%20SEMI%20COMPLETE.pdf

[19] K. Alhanaee, M. Alhammadi, N. Almenhali, and M. Shatnawi, “Face Recognition Smart Attendance System using Deep Transfer Learning,” Procedia Computer Science, vol. 192, pp. 4093–4102, 2021, doi: https://doi.org/10.1016/j.procs.2021.09.184.

[20] A. A. Tamimi, O. N. A. AL-Allaf, and M. A. Alia, “Real-Time Group Face-Detection for an Intelligent Class-Attendance System,” International Journal of Information Technology and Computer Science, vol. 7, no. 6, pp. 66–73, May 2015, doi: https://doi.org/10.5815/ijitcs.2015.06.09.

[21] M. Arsenovic, S. Sladojevic, A. Anderla, and D. Stefanovic, “FaceTime — Deep learning based face recognition attendance system,” 2017 IEEE 15th International Symposium on Intelligent Systems and Informatics (SISY), Sep. 2017, doi: https://doi.org/10.1109/sisy.2017.8080587.

[22] H. Rathod, Y. Ware, S. Sane, S. Raulo, V. Pakhare, and I. Rizvi, “Automated attendance system using machine learning approach,” 2017 International Conference on Nascent Technologies in Engineering (ICNTE), 2017, doi: https://doi.org/10.1109/ICNTE.2017.7947889.

[23] “Web-based University Classroom Attendance System Based on Deep Learning Face Recognition,” KSII Transactions on Internet and Information Systems,vol. 16, no. 2, Feb. 2022, doi: https://doi.org/10.3837/tiis.2022.02.008.

[24] M. S. Mubarak Alburaiki, G. Md Johar, R. A. Abbas Helmi, and M. Hazim Alkawaz, “Mobile Based Attendance System: Face Recognition and Location Detection using Machine Learning,” IEEE Xplore, Aug. 01, 2021. https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=9515221

[25] K. Bhatti, L. Mughal, F. Khuhawar, and S. Memon, “Smart Attendance Management System Using Face Recognition,” EAI Endorsed Transactions on Creative Technologies, vol. 5, no. 17, p. 159713, Oct. 2018, doi: https://doi.org/10.4108/eai.13-7-2018.159713.

[26] W. Kuang and A. Baul, “A Real-time Attendance System Using Deep-learning Face Recognition,” 2020 ASEE Virtual Annual Conference Content Access Proceedings, doi: https://doi.org/10.18260/1-2--33949.

[27] K. Mridha and N. T. Yousef, “Study and Analysis of Implementing a Smart Attendance Management System Based on Face Recognition Tecqnique using OpenCV and Machine Learning,” IEEE Xplore, Jun. 01, 2021. https://ieeexplore.ieee.org/abstract/document/9509614

[28] “University Classroom Attendance Based on Deep Learning | IEEE Conference Publication | IEEE Xplore,” ieeexplore.ieee.org.https://ieeexplore.ieee.org/abstract/document/8089918 (accessed Jan. 21, 2024).

[29] P. Pattnaik and K. K. Mohanty, “AI-Based Techniques for Real-Time Face Recognition-based Attendance System- A comparative Study,” IEEE Xplore,Nov. 01, 2020. https://ieeexplore.ieee.org/abstract/document/9297643

[30] “Face Recognition Based Smart and Robust Attendance Monitoring using Deep CNN | IEEE Conference Publication | IEEE Xplore,” ieeexplore.ieee.org.

https://ieeexplore.ieee.org/abstract/document/9441241 (accessed Jan. 21, 2024).

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