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Class Attendance System Using Facial Recognition

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ABSTRACT

This study aimed to develop an automated attendance system using facial recognition technology to address the challenges of traditional methods like roll calls and swipe cards. The system would capture and verify student identities through facial recognition, making it more hygienic and user-friendly. The project aligned with Sustainable Development Goals (SDGs) such as Quality Education, Industry Innovation, and Responsible Consumption and Production. It enhances Quality Education by promoting accurate and efficient attendance tracking, reducing administrative workload, and allowing educators to focus more on teaching. By integrating advanced technology into daily educational practices, it aligns with Industry Innovation, showcasing practical applications of biometric systems. Additionally, it contributes to responsible resource use by minimizing the need for paper-based records, thus aligning with sustainable practices. The system involved creating a database to store student facial features, extracting facial features for identity verification, and generating attendance records. Performance was evaluated through testing, focusing on factors like threshold values (where a value of 0.5 provided optimal performance), lighting conditions, and camera quality. The results showed high accuracy in student identification and attendance recording, and the system allowed for data exportation to CSV files and a user-friendly interface. However, the system's performance was affected by environmental conditions, indicating areas for further optimization. The implementation of this facial recognition attendance system has significant implications for educational institutions, enhancing efficiency, security, and promoting an inclusive administrative process.

1. INTRODUCTION

In educational institutions, student attendance is a critical factor influencing academic performance. Research indicates that regular class attendance is significantly correlated with academic achievement. According to studies [1], there is a 0.52% improvement in student performance for each additional class attended. Another study [2] which was conducted on 331 undergraduate medical students showed that there was a positive statistically significant correlation between students' attendance and academic performance ($r = 0.360$, $P < 0.01$). However, despite its importance, many students do not fully appreciate the value of attending lectures regularly, with less than half recognizing its significance. This discrepancy underscores the need for effective attendance monitoring systems to mitigate excessive absenteeism and ensure students' academic success.

Traditional attendance management methods, such as manual roll calls and the use of swipe cards, present several challenges. These methods are time-consuming, prone to human error, and can be easily manipulated, leading to inaccurate attendance records [3]. Additionally, methods requiring physical contact, such as fingerprint recognition systems, raise hygiene concerns and entail high maintenance costs [4]. These drawbacks highlight the necessity for more efficient and reliable attendance management solutions.

Biometric systems, which identify individuals based on physiological or behavioral characteristics, offer a promising alternative. Facial recognition as a biometric system is one of such that stands out due to its non-contact nature and growing accessibility. This technology aligns with several Sustainable Development Goals (SDGs), including Quality Education (SDG 4), Industry Innovation (SDG 9), and Responsible Consumption and Production (SDG 12), by enhancing administrative efficiency and promoting a more inclusive educational environment.

Different biometric methods offer varying degrees of accuracy, reliability, and user convenience. One of the oldest and very common biometric system is the Fingerprint recognition. It involves capturing the unique patterns of ridges and valleys on a finger [5]. This method is known for its high accuracy and reliability which reduces the occurrence of impersonation to the barest minimum [6]. However, it requires physical contact [7], which can lead to hygiene issues and sensor wear over time.

Palmprint recognition is similar to fingerprint recognition but uses the palm's unique patterns. For the acquisition of palmprints, there is the contact-based — where the hand of the user is pressed on a flat surface and a photo is taken with a digital camera — and the contactless approach which involves the use of sensors — digital camera, scanner, video camera and Color Charge Couple based (CCD-based) [8] — to acquire a photo. While it can capture more data points than fingerprints, the equipment required is usually more expensive and larger, making it less practical for some applications.

Iris recognition involves capturing the unique patterns in the colored ring of the eye (iris) which is encircled by the sclera [9]. This method is renowned for its extremely high accuracy and is used in high-security applications such as airport security and national ID programs. One of the main benefits of iris recognition is its non-intrusiveness and the ability to work from a distance. However, the technology can be costly, and accuracy can be affected by factors such as lighting and movement.

Facial recognition, on the other hand, is favored for its balance of accuracy, convenience, and non-intrusiveness. It has seen significant advancements in recent years, driven by improvements in image processing and machine learning algorithms. The process involves capturing an image of the individual's face, extracting distinctive features, and matching these features against a pre-existing database. Key steps in this process include image acquisition, pre-processing, feature extraction, and matching [10]. High-resolution cameras and controlled lighting conditions improve the accuracy of image acquisition, while advanced pre-processing techniques enhance the quality and alignment of the captured images. Feature extraction methods, such as Principal Component Analysis (PCA), Local Binary Patterns for Texture (LBPT), Eigenfaces, and Scale-Invariant Feature Transform (SIFT) [11] and deep learning models, identify and encode unique facial features, which are then matched using various similarity measures.

Despite its potential, the implementation of facial recognition technology in attendance systems faces several challenges. Ensuring consistent accuracy across different lighting conditions, angles, and facial expressions is a significant hurdle. Privacy concerns also arise due to the sensitive nature of biometric data, necessitating robust data protection measures. Additionally, the cost of deploying high-quality facial recognition systems can be prohibitive for some institutions. Addressing these challenges requires ongoing research and development to improve the robustness, accuracy, and affordability of facial recognition technology.

The proposed project aims to develop a facial recognition-based attendance system that addresses these challenges. The system is designed to automate the attendance process, reducing the time and effort required for manual roll calls and minimizing disruptions during lectures. By eliminating the need for physical contact or specific access devices, the system enhances hygiene and user convenience. The project involves creating a comprehensive database of student images, implementing advanced image processing algorithms for feature extraction, and developing a reliable matching mechanism to generate accurate attendance records.

This project holds significant potential for improving attendance management in educational institutions. By leveraging facial recognition technology, the system can provide a more efficient, accurate, and user-friendly solution compared to traditional methods. The successful implementation of this system is expected to reduce fraud, streamline administrative processes, and contribute to a more effective learning environment. Moreover, the project's alignment with SDGs underscores its broader impact on promoting innovation, responsible consumption, and quality education.

2. RELATED WORKS

Numerous methods have been used in the area of face recognition for attendance control as summarised in Table 1. A face recognition attendance system that makes use of deep learning convolutional neural networks (CNNs) is the suggested method in one study [12]. The significance of facial recognition in attendance management and access control systems is emphasized by the writers, who also highlight its widespread use as a biometric authentication method. The authors have utilized transfer learning by using three CNNs that have already been trained in order to obtain excellent prediction accuracy and an acceptable training duration. In a different study [13], the researchers provide a cutting-edge software program for face identification in difficult environmental circumstances that blends biometric and hybrid technologies. The suggested system combines the properties of a Discrete Cosine Transform Compressed based Log Gabor Filter (DCTLGF) and a Laplace of Gaussian filter-based Discrete Wavelet Transform (LGDWT). A Multiclass Support Vector Machine (MSVM) classifier uses these unique characteristics to categorize individual faces. The system is evaluated using a dataset of twenty-five people with two hundred facial photos taken with a low-resolution web camera. The results show how successful the system is, with accuracy varying between 91% and 96% based on the parameters.

A facial recognition system was created [14]. The inventors of the system concentrate on using Local Binary Patterns (LBP), a potent method for characterizing local structures, in the context of face detection in a video stream. In order to improve the identification system's accuracy, the suggested technique combines skin, eye, and nose detection into one integrated Haar cascade file for face detection. The technology also permits the generation of a face dataset for further recognition needs. The experiment findings show that the suggested approach outperforms previous techniques, producing a recognition accuracy of up to 96.5%.

By integrating facial recognition technology into an Android-based attendance system, Bhat et al.'s suggested method [15] aims to overcome the drawbacks. A QR code containing course material is created and put up at the front of the classroom to ensure student attendance. With cellphones, students may take a selfie and show the QR code. The server receives the taken picture and processes the attendance. Based on linear discriminant analysis, the experimental findings demonstrate that the proposed attendance system achieves a 97.29% face recognition accuracy. Furthermore, the technology requires a mere 0.000096 seconds to identify a face photograph stored on the server.

A group method [16], offers a face attendance system based on smartphones that is useful and reasonably priced for colleges and educational institutions. The technology makes use of cellphones' excellent cameras to take group photographs and automatically record attendance. The system uses one-shot learning-based facial recognition techniques, which allow it to recognize new users from a single picture, increasing its robustness and effectiveness. The proposed solution is composed of an Android application that is completely functional and a backend system architecture that is easily deployable without requiring expensive infrastructure. The efficiency of the proposed model is supported by empirical results, which show an accuracy level of around 97% on the LFW dataset and 85% on a dataset of student class photos that is accessible to the public. By doing away with the risk of phony or proxy attendance practices, this innovative strategy provides a safe and effective alternative for attendance control. To free up critical time for teaching and learning activities, it meets the requirement for simplified administrative responsibilities during lectures.

In order to create an automatic attendance system for use in university classes, Fu et al. [16] described a unique method that combines two deep learning techniques: Multi-Task Cascade Convolution Neural Network (MTCNN) for face identification and Center-Face recognition. Based on a large number of experimental data, the system is able to identify absence, tardiness, and early exit as the three classroom disciplinary infractions for automatic attendance. Following class, the system creates an attendance table that includes information about each student's learning progress. The suggested method identifies faces with an amazing accuracy rate of 98.87% while using just 100 milliseconds each frame. With a true positive rate of 93.7% and a true false rate of less than 1/1000, the model is impressive.

Table 1. Comparison of advantages and disadvantages of various face recognition attendance systems

References	Advantages	Disadvantages
[12]	Utilizes pre-trained CNNs, leading to excellent prediction accuracy.	Deep learning models like CNNs can require substantial computational power, which may not be feasible for all institutions.
[13]	Combines DCTLGF and LGDWT, enabling the system to capture unique characteristics for better face classification.	The combination of DCTLGF and LGDWT adds algorithmic complexity, potentially leading to higher processing times [17].
[14]	LBP is effective for recognizing textures and local structures, boosting the system's reliability in varied lighting.	LBP may struggle with significant changes in facial expressions or extreme variations in lighting conditions [18, 19].
[15]	Combines QR code scanning with facial recognition, adding a layer of verification for attendance.	The system depends on students using smartphones, which may not be feasible in all educational environments.
[16]	Capable of recognizing new individuals from a single image, making it flexible for new attendees.	The system shows reduced accuracy (85%) when using publicly available student class photos, suggesting variability in real-world conditions.
[17]	Processes each frame in 100 milliseconds, making it suitable for real-time applications and also delivers an impressive accuracy.	The combination of MTCNN and Center-Face can be computationally demanding, requiring high-performance hardware [20].

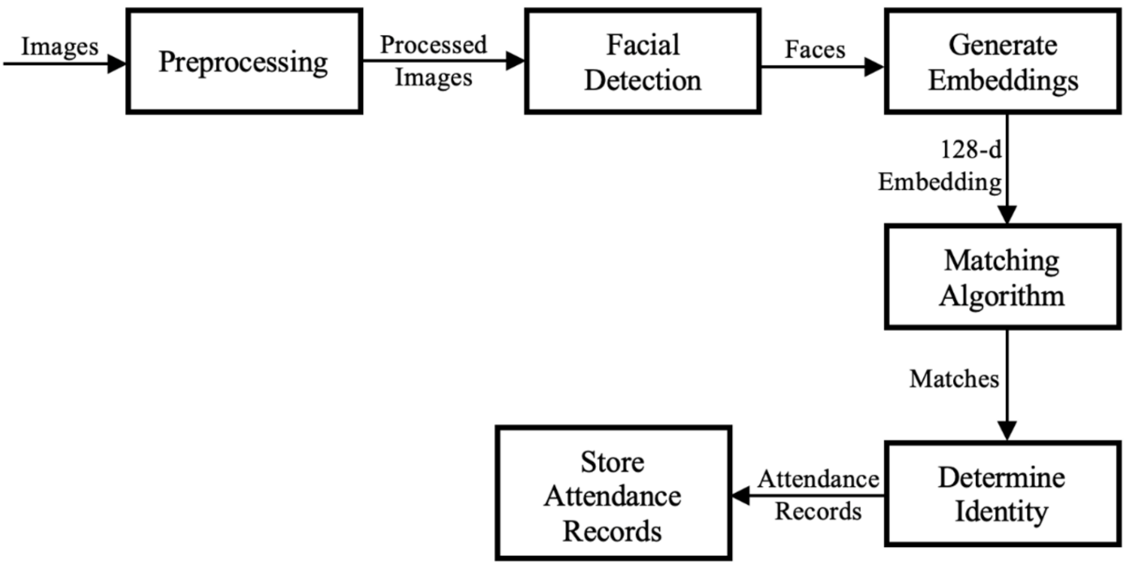


Figure 1. System design

3. METHODOLOGY

As depicted in Figure 1, the methodology for developing the system involves several key phases including preprocessing, facial detection, embedding generation and matching to determine identity and storage of attendance records in a database.

Preprocessing involves preparing input images to ensure consistency and suitability for facial detection and recognition. This process includes converting video frames or uploaded images into the appropriate format for further processing. Initially, the frames are converted to a NumPy array, ensuring that the image can be manipulated using OpenCV and other image processing libraries. Subsequently, the images are typically converted to the BGR color space, which is the default format for OpenCV.

Facial Detection focuses on identifying and locating faces within an image, crucial for subsequent facial recognition steps. The InsightFace API, utilizing the Buffalo SC model, is employed for robust and efficient face detection. This model comprises of the RetinaFace-500MF detection model and a recognition model pretrained with the WebFace600K dataset which is composed of images representing 600,000 unique identities. This process begins with loading the InsightFace model for face detection. Once the model is initialized, it is used to detect faces in the input image, providing bounding boxes that outline the detected faces.

Embedding generation transforms detected faces into high-dimensional numerical representations, capturing unique features of each face for comparison in the matching algorithm. The InsightFace model generates 512-dimensional embeddings for each detected face to encapsulate distinct facial features. The underlying ArcFace algorithm optimizes these embeddings using a method called Additive Angular Margin Loss. This approach works by mapping face images onto a hypersphere where the feature vectors are normalized. The distance between these features is measured as angles to enforce intra-class compactness and inter-class separation.

ArcFace operates by calculating the cosine of the angle between a feature vector and its class center, applying an additive angular margin to increase the geodesic distance between different classes on the hypersphere. This method enhances discriminative power and stabilizes training by maintaining a linear margin across the full angle range, which leads to high accuracy in recognition tasks. The resulting embeddings are then stored for future comparisons with existing ones, enabling effective face recognition and verification [21]. The matching algorithm is pivotal in comparing the generated embeddings with stored embeddings to identify the most similar matches, thus recognizing the identity of detected faces. Cosine similarity is employed to compare embeddings, measuring the cosine of the angle between two vectors to quantify similarity. This process includes converting stored embeddings to a NumPy array for comparison, calculating cosine similarity between the test vector and stored embeddings, and identifying matches with a similarity score above a predefined threshold. Eq. (1) below is a representation of cosine similarity, where f_1 and f_2 are two vectors which would be the feature embeddings to be compared in this case. Cosine similarity ranges from -1 to +1, where values closer to +1 indicate higher similarity between vectors.

$$(f_1, f_2) = \frac{f_1 \cdot f_2}{\|f_1\|\|f_2\|} = \frac{\sum_{i=1}^{n} f_{1i} f_{2i}}{\sqrt{\sum_{i=1}^{n} f_{1i}^2}\sqrt{\sum_{i=1}^{n} f_{2_i}^2}} \tag{1}$$

The determination of the identity is based on the similarity scores obtained from the matching algorithm. If the highest similarity score exceeds a predefined threshold, the corresponding name is assigned to the detected face; otherwise, the identity is marked as "Unknown." This thresholding on cosine similarity scores aids in determining if the face matches any stored faces, with the highest score above the threshold indicating the identified person. The process involves identifying the person if the highest similarity score is above the threshold and marking the identity as "Unknown" if no similarity score exceeds the threshold.

To store the attendance record involves recording attendance information, including the detected person's name and the current timestamp. This data is stored in a Redis database for later retrieval and analysis. Attendance records are logged and stored using Redis, a fast and efficient in-memory database, as key-value pairs where the key is the person's name and the value is the timestamp. The process includes logging the attendance by appending the person's name and timestamp to the logs and saving these logs to the Redis database, ensuring no duplicates.

4. RESULTS AND DISCUSSION

The first step was to test the pretrained model and for this some form of data was needed. Various angle face photographs of the individuals were the needed data. Since a pretrained model with high accuracy was being used, the photos used were clean i.e. devoid of noise, and the number of images per subject was few. These images were photos of celebrities acquired online. The frontal view photographs of the faces were thought to be the most crucial. For the purpose of feature extraction in this model, every picture was enlarged to a standard 600 by 600 size. The facial embeddings of each picture were collected, and the average was found and stored for each person.

Next, to test the model, test photos which included the subjects who were already stored in the system were passed through the model to get the embeddings of the faces in the photo and then match these embeddings to the data that was stored. This matching was done with the use of distance metrics.

After the model was tested, a face recognition script was created to integrate various functionalities such as embedding extraction from frames of live feed or uploaded photos, face recognition and interaction with the Redis database.

Next, Streamlit was used to develop the user interface where the face recognition script was imported to make the functionalities of the script easily accessible for users. The web app consists of four pages as shown in Figures 2 to 5: home page, registration page, real time prediction page and report page.

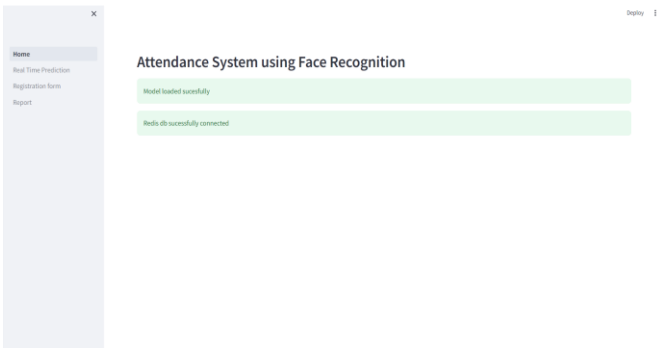


Figure 2. Home page

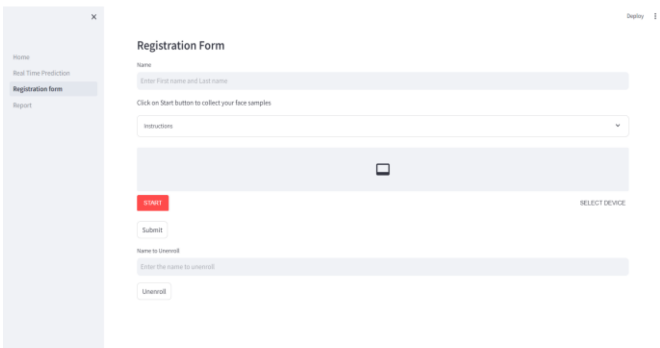


Figure 3. Registration page

The system was able to recognize the face of one of the authors who was enrolled on the system as seen in Figure 6, and the attendance report was also exported as a CSV file. As shown in Figure 7, the CSV file contains the matriculation number of students with a corresponding 1 or 0 to indicate if a student was captured or not.

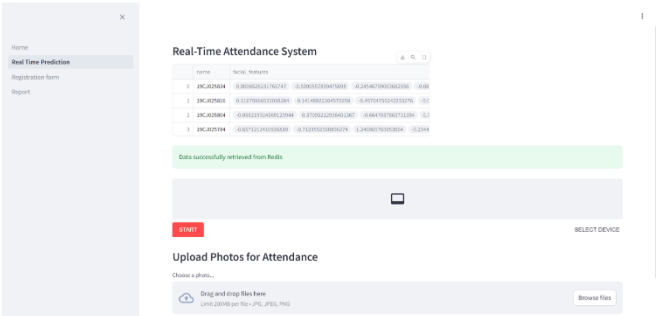


Figure 4. Real time prediction page

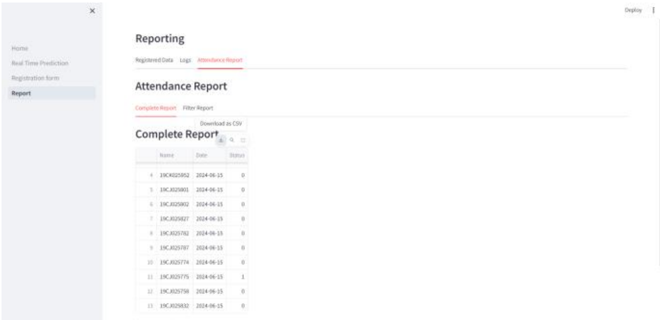


Figure 5. Report page

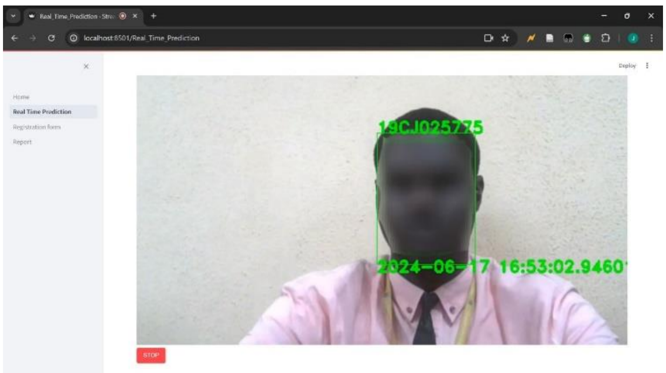
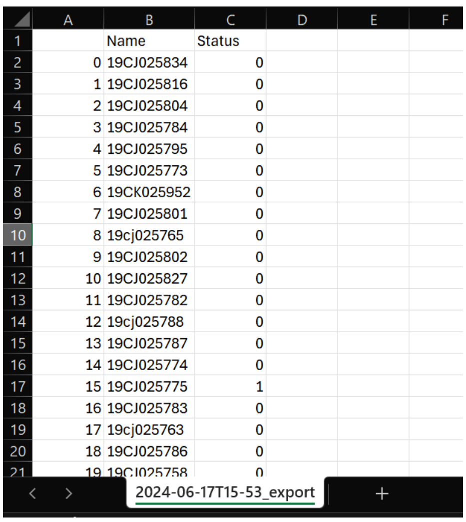


Figure 6. Attendance capturing



	A	B	C	D	E	F
1		Name	Status			
2	0	19CJ025834	0			
3	1	19CJ025816	0			
4	2	19CJ025804	0			
5	3	19CJ025784	0			
6	4	19CJ025795	0			
7	5	19CJ025773	0			
8	6	19CK025952	0			
9	7	19CJ025801	0			
10	8	19cj025765	0			
11	9	19CJ025802	0			
12	10	19CJ025827	0			
13	11	19CJ025782	0			
14	12	19cj025788	0			
15	13	19CJ025787	0			
16	14	19CJ025774	0			
17	15	19CJ025775	1			
18	16	19CJ025783	0			
19	17	19cj025763	0			
20	18	19CJ025786	0			
21	19	19CJ025758	0			

2024-06-17T15-53_export

Figure 7. CSV file containing the attendance report

The performance of the face recognition system was evaluated based on its ability to carry out its various functions effectively, including real-time attendance tracking, user registration, and attendance report generation. The system's performance was analyzed under different threshold values, lighting conditions, and camera quality to assess its robustness and accuracy.

The real-time attendance tracking function was tested to measure its accuracy and reliability. Under optimal lighting conditions and with a high-quality camera, the system demonstrated high recognition accuracy.

The user registration function allowed new users to enroll by capturing the user’s facial features and storing the embeddings in the Redis database. The user interface, developed using Streamlit, was user-friendly, enabling users to enter names and capture facial samples effortlessly. The instructions provided within the app helped users understand the process, resulting in a smooth operation. The InsightFace model captured embeddings from registered individuals, consistently generating accurate embeddings even with varying facial expressions. Integration with Redis was seamless, with all captured embeddings being successfully stored and retrieved. The function to delete a user from the database also worked as expected, ensuring that users could be unenrolled when necessary.

The attendance report function provided detailed insights into attendance patterns and allowed for efficient tracking of individual attendance records. The system successfully retrieved logs from Redis and displayed the logs in a structured format using Streamlit, allowing users to view the complete attendance report. The attendance logs were updated in real time as new faces were recognized, ensuring that the reports reflected the latest data and provided an accurate and up-to-date view of attendance.

Different threshold values were tested to observe its impact on the system's performance. A lower threshold value of 0.3 resulted in higher recall but also increased false positives, meaning the system sometimes misidentified unregistered individuals as registered ones. The threshold value of 0.5 provided balanced performance, with a good recall rate and acceptable false positive rate, making it ideal for general use. A higher threshold value of 0.7 reduced false positives but also decreased recall, meaning some registered individuals were not recognized by the system.

The performance of the system was also affected by external factors such as lighting conditions and camera quality. The system performed best under natural or well-lit conditions, as poor lighting resulted in lower recognition accuracy due to insufficient facial feature capture. High-quality cameras with better resolution and frame rates provided clearer images, leading to more accurate recognition, whereas lower quality cameras introduced noise and reduced the system's ability to accurately capture facial features.

InsightFace, stands out when compared to the mentioned technologies due to its emphasis on highly efficient and accurate face recognition using advanced architectures like ArcFace for face embedding. Unlike traditional CNNs or feature extraction methods such as DCTLGF and LGDWT used in older studies, InsightFace employs well-optimized models that yield superior accuracy and robustness across diverse conditions. While methods like LBP or hybrid biometric techniques focus on local feature extraction or environmental adaptability, InsightFace excels with comprehensive feature representation, allowing it to handle complex variations in pose, lighting, and expressions more effectively. Moreover, unlike smartphone-based group recognition systems or lightweight implementations reliant on low-resolution cameras, InsightFace is designed for scalability and real-time performance, ensuring high recognition rates and minimal false positives in both controlled and uncontrolled settings. This makes it highly suitable for large-scale applications where reliability and speed are critical, surpassing traditional methods in terms of flexibility and accuracy.

5. CONCLUSION

The project aimed at building an attendance system utilizing face recognition technology to address the constraints of existing attendance systems in educational institutions. The technology was developed to collect and verify student IDs using face recognition, guaranteeing precise and fast attendance tracking. The research comprised an in-depth investigation of biometric systems, focused on face recognition, and the integration of multiple image processing algorithms to obtain the required outputs.

The implementation of this system revealed considerable advantages in terms of accuracy, efficiency, and security of attendance management. The initiative aligns with Sustainable Development Goals (SDGs) by supporting excellent education, stimulating innovation, and encouraging sustainable behaviours. However, future work should focus on improving the system's robustness under varying environmental conditions, such as different lighting and background noise, to enhance reliability. Additionally, incorporating more advanced machine learning techniques or better models could improve the system's adaptability and accuracy. Further research could explore the integration of multi-modal biometric systems to strengthen security and user authentication. Expanding the system's capability to support larger databases and real-time processing in more diverse settings could provide valuable insights for broader applications. The face embeddings and logs were saved and retrieved using Redis and the system was deployed using Amazon Web Services. In the future, we intend to secure ethical approval to engage hundreds of participants with the intention of capturing their face images and using to further improve the work done. At that point, user privacy protection and secure data storage will be taken very seriously as expected.

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