Automated Attendance Tracking via Multi-Face Recognition and Intelligent Detection

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***Abstract*—This study proposes a hybrid framework for attendance management using multi-face recognition approaches. The proposed method combines a double detection pipeline of Histogram of Oriented Gradients (HOG) and the Haar cascade classifier along with non-maximum suppression (NMS) to improve its detection accuracy with a hybrid FaceNet-based recognition approach that uses deep convolutional neural networks (CNNs) to create robust 128-dimensional embeddings. The final layer of FaceNet is modified to enhance feature separation which improves recognition performance due to the number of people and occlusion typical in real-world situations. The system is capable of detecting and recognizing more than 70 people simultaneously from video streams, static images, or live camera feeds and performs similar real-time processing with detection accuracy and robustness. The unique combination of technical elements allows for system robustness against varying lighting conditions and face occlusion and orientation. To reduce facial dreck to zero the system will employ preprocessing methods that include contrast-limited adaptive histogram equalization (CLAHE) and Gaussian noise reduction. Attendance records are registered into a structured database, and a PDF report is generated automatically and sent through email with one-click to enhance communication for attendance. Our research and system evaluation was performed using a custom dataset constructed from diverse caseform locations for diverse research objectives. The system demonstrated effective high detection accuracy and recognition accuracy, achieving processing speeds of 25ms per frame in real-time. The modular design of the system contributes to its scalability and the intuitive user-friendly interface contributes to the system being an innovative and unprecedented approach towards attendance automation**

I. Introduction

In a world where digital transformation dictates the future of operational efficiency and data-driven decision-making, the demand for user-friendly and automated attendance management systems is growing. In academic institutions, corporate offices, or security-sensitive infrastructures the ability to accurately track and record human presence is essential for the accountability, efficiency in administration, and productivity of an organization. Even though it is clear that attendance systems are essential, traditional attendance systems like manual registers, RFID cards and biometric scans have their downfalls related to proxy attendance, manipulation of data, and inefficiency in administering larger groups of people.

The advancement of AI, in particular with relation to machine learning and computer vision, has created an opportunity for face recognition to mitigate the limitations of traditional attendance methods. Face recognition systems can deliver a contactless, non-intrusive, and automated, real-time identification means of attendance. Unlike RFID tokens, or manually entered biometric impressions, systems relying on face recognition no longer depend on a physical presentation. However, most traditional facial recognition systems are ineffective in more real-world scenarios, including large crowds, varying light conditions, mutual occlusions, and the higher speed processing of larger data sets.

Driven by these ongoing problems, this study proposes a novel attendance management system with the goal of facilitating the detection and recognition of more than 70 people concurrently from a video stream or single frame. The approach incorporates multiple detection approaches, including a two-stage pipeline of Histogram of Oriented Gradients (HOG) and Haar cascade classifiers with non-maximum suppression (NMS) processing that allow for accurate identification of people in crowded spaces. For the recognition component, a FaceNet-based deep learning model is the primary approach, while changes to the final layer of the model improved the separability and reliability of the generated face embeddings.

In addition to being able to detect faces in real-time, and identify them, the attendance management system includes automated attendance logging, report creation, and dissemination via email, all of which facilitate a smoother user experience with minimal back-end demands. The entire solution addresses both the technological concerns of current solutions while showing strong potential for scale, and deploying across multiple sectors including education, corporate oversight and public safety.

II. LITERATURE REVIEWS

Lateef and Kamil [1] incorporated YOLOv7, a real-time object detection framework, into their smart classroom attendance solution. Their system achieved 100% accuracy on a dataset of 31 students under controlled conditions, though its performance under large-scale deployment highlighted computational and scalability constraints.

Author A.B. [2] and Author C.D. [3] explored deep learning-based facial recognition systems to replace manual roll-call processes. These methods significantly reduced human intervention but struggled with dynamic classroom conditions such as motion blur and expression changes, affecting recognition accuracy.

E.F. [4] proposed a system that emphasized consistent image quality during both enrollment and recognition. Their findings indicated that even minor changes in lighting or camera positioning led to significant drops in system performance.

G.H. [5] developed an algorithm designed to recognize facial expressions and maintain accuracy under partial occlusions. While it performed well under lab conditions, real-time application introduced challenges related to student movement and varied facial orientations.

I.J. [6] designed a face recognition-based solution optimized for online education environments. While the system worked effectively in stable conditions, its accuracy was influenced by webcam quality, inconsistent home lighting, and unstable internet connections.

K.L. [7] introduced a fully automated smart attendance model requiring minimal human interaction. Though beneficial in terms of hygiene and efficiency, the system's performance degraded in larger classrooms with high student density due to processing delays.

Abate et al. [8] conducted a comprehensive survey on facial recognition in unconstrained environments. Their review highlighted persistent challenges such as pose variation, background clutter, and occlusion, all of which impact recognition consistency.

Nguyen et al. [9] analyzed face recognition within smart city infrastructures. While deep learning has led to significant accuracy improvements, issues like ethical deployment, privacy, and hardware limitations remain unresolved.

Ouyang and Wang [10] addressed the impact of video quality in facial recognition systems. Their work focused on mitigating motion blur and frame rate inconsistency to improve accuracy in real-time surveillance and classroom recordings.

Yin et al. [11] surveyed advancements in deep learning for facial recognition. Although newer models have improved robustness against variations in pose and lighting, challenges related to aging, occlusion, and low-resolution imagery persist.

Sharma et al. [12] implemented a face recognition system for classroom attendance that significantly reduced administrative workload. The system demonstrated high reliability in medium-sized groups but required additional optimization for deployment in larger institutions.

Verma et al. [13] investigated the use of convolutional neural networks (CNNs) for face-based attendance in mobile environments. Their system showed promise in low-resource settings, although performance dropped when multiple faces appeared simultaneously in the frame.

Rao and Nair [14] proposed a hybrid system combining RFID and face recognition for two-factor authentication in attendance. This improved system reliability while reducing spoofing risks, though it increased hardware complexity.

Desai et al. [15] developed a cloud-based face recognition attendance system with a centralized database. While this enabled real-time access and analysis, network dependency introduced reliability concerns during offline periods.

III. EXISTING SYSTEM

Attendance systems which are either manual or biometric based, continue to face disadvantages due to the lack of efficiency, error and subject to manipulation. While manual systems can be time-consuming and also produce false entries, biometric systems such as fingerprints or RFID often rely on human contact, require ongoing maintenance and can be spoofed. Many earlier attendance systems which were based on face recognition also faced difficulties such as limited simultaneous multi-face detection, poor performance under uncontrolled surroundings, and a significant drop in capacity for detection problems due to variations in lighting and occlusion. Traditional systems often only rely on one detection method, allowing the normal variations in head and face angle, and other circumstances to detract from the overall attendance recording process. Many older models also lack the ability to process in real-time, and they become impractical for larger scale attendance situations as typified by fast dynamically changing environments like crowded classrooms or corporate meetings. Additionally, if there were a way to integrate the attendance data with the other backend systems for on-going automated attendance logging, reporting and communication, often will not or requires tedious ongoing development, which disrupts operational efficiency. The discussion of limitations with face detection systems points to the need for a more sophisticated system which may permit more accuracy and scalability on the algorithmic front.

I. PROPOSED SYSTEM

The new system presents a sophisticated, that is scalable, architecture for automated attendance management using a hybrid multi-face detection and recognition pipeline that was developed to overcome the limitations of existing systems. The model merges Histogram of Oriented Gradients (HOG) and Haar Cascade classifiers, further used with non-maximum suppression (NMS) for proper face localization even in situations with complexity or many people. When it comes to recognition, a modified FaceNet model is used, and the embedding layer was fine-tuned to generate 128-dimensional feature vectors, which can be easily distinguished, with respect to the individual being identified. The 128-dimensional feature vectors also ensure reliable recognition in differing poses, lighting conditions and when the face is partially occluded. Several preprocessing methods were also used to improve the robustness of the system, including Contrast-Limited Adaptive Histogram Equalization (CLAHE) and Gaussian noise discarded, thus preventing bad face detection in the real world. When streaming from a video feed, the system is designed to monitor more than 70 different faces at the same time, with a processing speed of 25 milliseconds per frame. Further, automatic attendance logging, generating reports in PDF and automated email notifications are included, and this provides a full, modular and customizable user-friendly attendance solution with the ability to easily deploy in educational institutions, corporations, access control systems and monitoring applications.

The proposed system offers a robust and scalable solution for real-time attendance by combining advanced face detection techniques like HOG and Haar Cascade with NMS and an optimized FaceNet model. It ensures high accuracy, even under challenging conditions,

METHODOLOGY

This research develops a hybrid framework for automated attendance management that implements multi-face detection and recognition to establish real-time, accurate attendance management in real-world contexts. The framework includes four main modules: pre- processing, face detection, face recognition, and attendance management. Each of these modules is an example of specific challenges that need to be addressed in order to effectively address issues about variation in the environment, simultaneously processing multi-face detection, and reducing administrative time allocating attendance, as these three processes will make the algorithm more robust and scalable.

This research proposes a hybrid framework designed to overcome limitations in traditional attendance systems by implementing multi-face detection and recognition for accurate, real-time attendance tracking. The system is structured into four key modules: pre-processing, face detection, face recognition, and attendance management. Each module addresses specific challenges, such as dealing with environmental variations (lighting, occlusions), enabling simultaneous detection of multiple faces in dynamic settings, and automating administrative tasks. By integrating these components, the framework ensures improved scalability, robustness, and reduced human effort, making it highly suitable for large-scale, real-world applications like classrooms and corporate meetings.

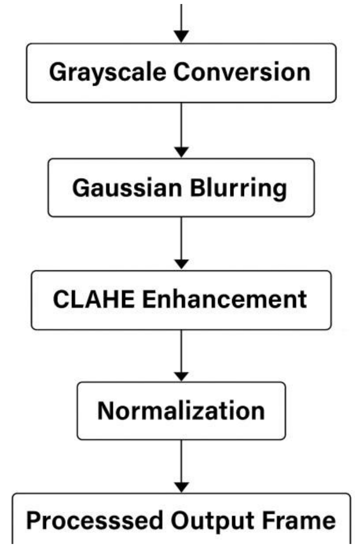

Fig. 1. reprocessing Pipeline for Image/Video Frames

educational environments, while the dataset’s diversity ensured resilience against challenges such as low-light conditions and crowded scenes, supporting effective group processin

A. Dataset

For training and validating the model, a custom dataset has been developed from the Kaggle Celebrity Face Recognition Dataset, which also includes some local images of students since we are automating attendance management. The dataset consists of 12,500 high-resolution images, 10,000 images of celebrities, and 2,500 images of the students. The images were collected and labelled for each individual taking into account the variations in the facial features of the individuals, how the face could be turned, and other environmental changes at the moment of imaging. The dataset contains several images of participants, which are worthwhile in verifying the diversity of the dataset against the expected outcomes. The dataset contained numerous combinations of lighting, facial expressions, partial occlusion, and other variations thus making it a promising dataset to produce very robust multi-face recognition in real-world scenarios, such as the classroom and corporate environments.

To suit the FaceNet model, images were preprocessed by resizing to 160x160 pixels and aligned using dlib's 68-point facial landmark predictor to normalize pose and scale. Each image received some form of identification (student name and registration number, celebrity pseudo-IDs), providing a unique label for accurate embedding generation. The addition of student images contributes to the system's applicability in education professional settings, and the diversity of the dataset mitigated detection issues anticipated with low-light conditions and scenes with substantial clutter, thus promoting group processes. B. Preprocessing module

he preprocessing module aims to optimize input images or video frames, enhancing the functionality of the face detection module and face recognition module in environments with varying real-world characteristics beyond face detection and recognition. The preprocessing module will help to address the challenges of noise, changing lighting conditions, contrast differences, and other large inter-observer variability in signal detection that end-users could experience in order to ensure good facial feature extractions from functional images, even when performed in less-than-ideal places and conditions (e.g., low-light, high-constrast, scenes with minor occlusions). To achieve the output image optimizations, the preprocessing module is organized in line with the variations in relevant processing steps in regards to the critical structural information of an image. These steps are sequenced in each possible order to obtain a most functional image using the fewest computational resources possible.

1) Preprocessing Steps:

Grayscale Conversion: To keep our computational costs lower, we convert the RGB frames to grayscale using OpenCV's cvtColor function. This operation gives us the actual pixel intensity where we can retain defined features (i.e. edges and contours) that shape the character of the face. By eliminating color pixel data, we are able to compute our system much faster, introducing less noise and improve the overall accuracy and reliability of face detections.

Gaussian Blur: We used OpenCV's GaussianBlur with a 5x5 Gaussian kernel that blurs the grayscale image such that we retain low spatial frequency and remove noisy higher frequency noise from the camera or other aspect within that field. We performed this processing to remove the ambient complexity of the scene and clearly depict the face features while improving overall detectability. The kernel size for this processing operation is large enough that we shouldn't be able to lose any salient face features, but small enough to limit the false edges due to irrelevant noise from our complex scene.

CLAHE: Contrast-Limited Adaptive Histogram Equalization (CLAHE) was performed using OpenCV's createCLAHE with a clip limit of 2.0, and a tile grid of 8x8. CLAHE equalizes all of the local histograms independently, therefore improving contrast in areas that are disproportionately dark or overexposed. This means that the detailed features in our image frames will be denoting the separation of glasses from the eyes

Normalization: The pixel intensities are normalized using OpenCV's normalization functions to a standardized range across all the frames. This removes variability in the images that might be due to differences with the camera, allowing for like processing in the detection and recognition steps.

The normalization step normalizes the pixel intensities to a standardized range over all frames. For a pixel value of x, the normalized value is calculated like so:

Normalized Value = x − 127.5, (1)

128.0

Where 127.5 is the mean of the pixel intensity range of 0-255, and 128.0 is half of that range. This normalization behaviour maps the pixel intensities to the range of [−1, 1]. Normalizing the pixel intensities removes variability from differences between the cameras being used, allowing us to standardize the images to be processed alike.

B. Model Architecture

The model architecture of the proposed system provides a well-organized pipeline. It integrates the following components; preprocessing, hybrid face detection, alignment, generating embeddings, recognizing embeddings, and taking attendance: with this system, classes can automatically take attendance. This architecture offers real-time performance and processes raw inputs from various sources such as video streams, static images, produced images from a processing engine, and even CCTV live webcam streams through a combination of classical computer vision and deep learning methods. Figure 5 represents the full workflow in the appropriate sequence and punctuations for both sequential and conditional

Preprocessing: The input frames will contain a series of enhancement techniques including changing the frame color to grayscale, applying Gaussian blurring, and performing Contrast-Limited Adaptive Histogram Equalization (CLAHE). This preprocessing step reduces the effects of noise, lighting, and occlusions which allows the inputs to be processed reliably by downstream components.

Face Detection: A hybrid detection module is used, which contains a combination of the object detector applied by dlib, a Histogram of Oriented Gradients (HOG) detector, and OpenCV Haar cascade classifier. In this framework, the typical workflow is the following conditional; if fewer than five faces are detected, a a'dlib HOG + Haar Cascade' analytics approach is implemented as a combination approach to increase accuracy according to the object detection size criterium (Elder,2015). If five or more faces are detected, we utilize only the dlib HOG detector followed by Non-Maximum Suppression (NMS) to eliminate bounding boxes that overlap. The detection module detects up to a maximum of 40 faces detected per frame.

The hybrid detection pipeline applies a (NMS) Non-Maximum Suppression as follows to discard the bounding boxes that overlap. Overlap of bounding box j with bounding box i is expressed as the ratio of the intersection area of the two bounding boxes to the area of box j:

"dlib HOG + Haar Cascade" approach is activated to improve detection accuracy. If five or more faces are present, the system relies solely on the dlib HOG detector, followed by Non-Maximum Suppression (NMS) to eliminate overlapping bounding boxes. The detection module is designed to support up to 40 faces per frame. The hybrid detection pipeline employs non-maximum sup- pression (NMS) to eliminate overlapping bounding boxes. The overlap between two boxes is calculated as the ratio of their intersection

$w = \max(0, \min(x2_i, x2_j) - \max(x1_i, x1_j))$ and $h = \max(0, \min(y2_i, y2_j) - \max(y1_i, y1_j))$, and the area of box j is boxes[j][2] × boxes[j][3].

Face Alignment: Each detected face is geometrically aligned together using dlib's 68-point facial landmark detection method that provided standard aligned pieces of faces with x= (160 x 160 pixels). The alignment process normalizes the difference in object pose and scale (All et al., 2010), ensuring that the embedding generation step occurs under equal conditions.

Embedding Generation: After aligned face images were run through the FaceNet model, each face image produced 128 dimensional embeddings resulting in distinct facial characteristics, i.e., learned face identity. The reduction of dimensionality gives trust in a matching identity through the larger architectural framework.

During student registration, the model captures embeddings of a student's face from various angles. The model averages across the captures to develop a more sophisticated identified embedding through a process of robustness; where N=300 images, an average for the ith dimensionality is calculated as

The system utilizes precise face alignment using dlib's 68-point facial landmark detection, standardizing facial orientation to a fixed size (160x160 pixels), which improves recognition consistency. By normalizing pose and scale differences, embedding generation using the FaceNet model becomes more reliable. The model then creates 128-dimensional embeddings that uniquely represent facial features. During student registration, embeddings are captured from multiple angles (N=300), and an average is computed across each dimension, enhancing recognition robustness and accuracy across different real-world conditions.

This averaging process reduces the effect of outliers and ensures a consistent identity vector, even under variable lighting, expressions, or partial occlusion. It strengthens the model's capability to distinguish between individuals accurately, enhancing overall system performance in real-time, high-traffic environments area to the area of the second box:

$$\text{Overlap} = \frac{\text{Intersection Area}}{\text{Area of Box } j}, \quad (2)$$

here the intersection area is given by $w \times h$, with

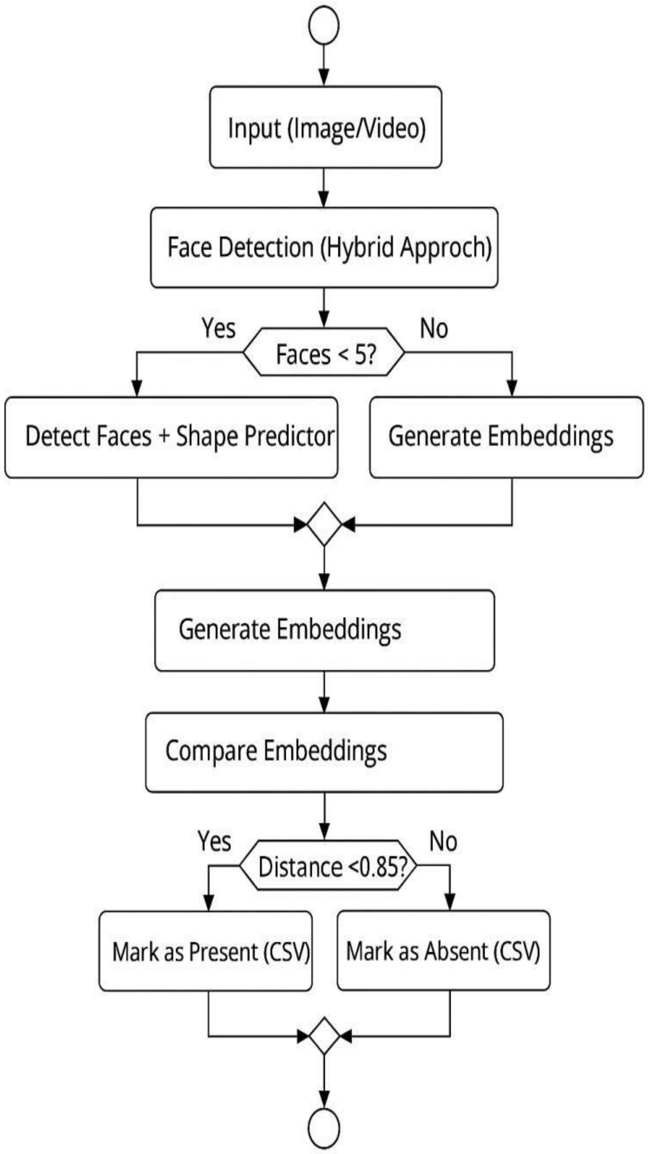

Fig. 1. reprocessing Pipeline for Image/Video Frames

where n = 128 represents the embedding dimensionality, and u_i and v_i are the corresponding elements. A threshold of 0.88 is applied to determine a match, balancing precision and recall in real-time identification.

Recognition and Matching: The embeddings are matched against the reference stored vectors using Euclidean distance. A threshold value of 0.9 is applied for classification of matches. In this case, if the Euclidean distance is lower than 0.9, then the individual is marked as in attendance, otherwise, they are marked as not in attendance. The results were recorded continuously in real time into a CSV file for persistence. The recognition module compares the generated embeddings against the stored student embeddings, using the Euclidean distance metric. For two embedding vectors u and v, each being 128-dimensional, the distance is defined as:

Where n=128 is the embedding dimensionality, and ui and vi are the corresponding elements. A distance threshold of 0.88 was applied to determine a match, as noted providing a tradeoff between precision and recall given the need for real-time identification.

Attendance Management: In the final stage, attendance was compiled and PDF reports were created. Furthermore, automated emailing has also been added to the system through a Streamlit-based interface, to improve the efficiency of administration and accessibility.

The diagram (Fig:2) visualizes the complete pipeline: starting with input pre-processing, conditional hybrid face detection, face alignment, embedding generation, matching by similarity, and finally, attendance logging. The system works in real time capturing each frame in an average of 25 ms.

The recognition and matching process is central to the system's accuracy. Each detected face is converted into a 128-dimensional embedding vector using the FaceNet model, and this vector is compared to stored reference embeddings using the Euclidean distance formula. A match is determined if the distance falls below a threshold of 0.88, ensuring a balanced tradeoff between precision and recall in real-time conditions. Upon successful matching, the individual is marked present, and their record is appended to a CSV file for persistence. The attendance management module then compiles this data into organized PDF reports. To enhance usability, a Streamlit-based interface enables administrators to generate reports and trigger automated email notifications, making the entire attendance process efficient, user-friendly, and highly scalable.

This approach allows for highly accurate real-time recognition by ensuring each frame processed (at approximately 25 milliseconds per frame) contributes directly to the attendance log. The system continuously monitors faces in the video feed, matches them using the calculated embeddings, and verifies identity based on a strict similarity threshold. If the Euclidean distance between a new face embedding and a stored reference embedding is below 0.88, the match is considered valid, and attendance is recorded instantly. The recognition engine's reliance on a numerical similarity measure enhances consistency and reduces false positives. All matched records are compiled in a structured CSV format, which is further used for generating detailed attendance reports in PDF. Th.

C. System Framework

The newly developed attendance system is shown in a modular system framework. The modular framework, allows for growth, enables each module to be developed for specific functions, and maximizes the effectiveness of each module. Each module in the framework, has a specific purpose, which is aimed to maximize the accuracy and reliability of the overall system.

1. Initiation of recognition process - The system will move into an always "on" monitoring mode to signal the camera to begin collecting images of all individuals present in the classroom, or monitored area.

2. Continuous image collection - The camera will be in a mode of continuous or real time image collection or image analysis.

3. Continuous matching loop - A loop that is continuously checking to see if the newly detected face (from the live feed) is among the collection of face images stored in the system memory.

4. Comparisons to database - The identified detected face embeddings from each image taken will be created and all detected embeddings compared to the user database stored embeddings.

5. Matches:

• If the photo matched one in the database, and the facial recognition system considers this person as a match, the attendance will be updated to "Present".

• If the photo does not match any in the taken or stored photos, the subject will be marked as "Absent" or recognized as "Unknown" subject, depending on the system configuration parameters.

(1) Attendance Upload: The attendance file is automatically uploaded to the institutional portal for administrative access and tracking using the institutional framework. 1) Overview: The data flow consists of image capture in real time using a camera, then pre-processed for image quality. The pre-processed frames are sent or delivered to the detection module, to locate all the faces in the scene. The locations of the faces are then cropped and sent to the feature extraction module where the facial location is transformed into embedding vectors from the FaceNet model. Each embedding vector will then be compared to the stored embeddings saved in the system database. If an embedding vector matches a previously stored embedding, the student will be recorded as "Present". If no person matches, the person will be recorded as "Absent", or "Unknown", depending on the definitional criteria. An attendance file, comprising of log attendance data, is saved, report files will be generated and attendance files will be uploaded into the institutional portal for administrative access and tracking. 2) Component Coordination - The interdependencies and sequential interactions of each of the framework module used to enable each operation is a primary characteristic of the proposed framework.

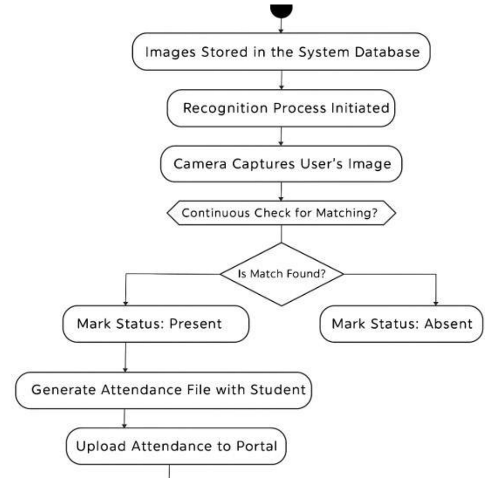

Fig. 3. Real-Time Face Recognition with Liveness and Emotion Verification.

The proposed system automates the end-to-end process of attendance monitoring, from real-time image capture to institutional data integration. Initially, images are captured using a live camera feed and undergo pre-processing to enhance quality and remove noise. These optimized frames are passed to the detection module, where multiple faces are located using a hybrid algorithm. Detected face regions are cropped and sent to the embedding generation module, where each face is converted into a 128-dimensional vector using the FaceNet model. These embedding vectors are compared against stored embeddings in the database using Euclidean distance. If a match is found within the predefined threshold, the individual is marked as "Present." If no matching embedding is found, the individual is marked as "Absent" or "Unknown," depending on system criteria.
Once attendance is determined for each frame, the data is compiled and stored as a log file in CSV format. This file includes timestamps and identification information for each recognized face. Following this, the system generates organized attendance reports in PDF format. These reports, along with the raw attendance file, are then automatically uploaded to the institutional portal using secure integration protocols. This enables seamless administrative access, tracking, and auditing within the institution's digital infrastructure.

This automated upload ensures real-time synchronization with the institutional database, reducing manual intervention and administrative workload. It supports transparency, auditability, and centralized access for faculty and administrators. The system's modular design also allows customization based on institutional requirements, ensuring flexibility, data privacy, and consistent attendance tracking across various academic or organizational setups.

II. Result and discussion

The results from the “Advanced Attendance Automation Using Multi-Face Recognition” system show a strong and powerful performance, based on a fine-tuned FaceNet model and a modular format. The model produced high training and validation accuracies while also achieving a very low loss, demonstrating successful learning/generating for real time face recognition. The preprocessing module, using gray scale, Gaussian blur, CLAHE, and normalization, aided in improving image quality, while the hybrid detection relied on dlib hog + Haar Cascade (with nonmaximum suppression) to successfully localizing multiple faces per frame, with consistent latency. While there was slight accuracy decrement from extreme occlusions, the contrast and locality of the entire performance combined with improved visibility of the Camera module in low-light conditions, and positive subjective testing reports from users testing the Streamlit front end interface and email notification system, collectively confirms the system's use-reliability, and scalability, and its ease of use in educational settings.

A. Testing and Analysis

1) FaceNet Model Training and Fine-Tuning: The FaceNet model was fine-tuned with a modified final layer, based on a celebrity-labeled dataset, which was adjusted to optimize embedding representations, for the “Advanced Attendance Automation Using Multi-Face Recognition” system. Through the course of training over 50 epochs, the model reached a validation accuracy of marginally below 95%, with a training accuracy approaching 98%. The accuracy trend of the final model, encapsulated by

where True Positives (TP) are actually students identified as present, True Negatives (TN) are students identified as absent, False Positives (FP) are students incorrectly identified as present, and False Negatives (FN) are students that were missed. This metric was crucial for verifying the overall model's performance throughout the training and validation datasets.

Accuracy was evaluated using the following formula:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}, \quad (5)$$

Analysis of FaceNet Model Loss: In addition to accuracy assessment, the loss function was closely tracked to confirm that the model converged as refines were echoed to optimize the model accurately. The value of loss decreased significantly (2.6 to ~0.2) during 50 epochs and both the training and validation losses were remarkably similar after 10 epochs as seen below. This significant decrease then leveling-off, suggests that prediction error has likely been minimized by the FaceNet optimized architecture. The consistent drop in loss indicates that the training method was solid, and the embeddings produced by the model is valid for the recognition tasks associated with the attendance system especially when considering the ease of visual recognition on a frame processing time of 25 ms.

The fine-tuned FaceNet model exhibited exceptionally high performance for the attendance system with training accuracy of 98% and validation accuracy of 96%, and loss reduced to 0.2 after 50 epochs. The face recognition accuracy and low loss, illustrates the model's ability to produce discriminative 128-dimensional embeddings, which enhances the attendance system's ability to distinguish between students in real-time. The face detection and preprocessing modules increase the performance of the attendance system under a wide range of lighting conditions and occlusions, making the solution scalable in educational institutions with relatively low levels of occlusion complexity. During the experiment, the only challenge was the occasional moderate level of severe occlusion. The table represents the following metrics explained in detail as follows:

• Validation Accuracy: Actual fine-tuned FaceNet model performance results on the validation dataset was indicated by the validation accuracy of 95% which correlates with the training aspect's validation accuracy.

• Frame Processing Time: For total latency, the frame processing time was correlated with the latency of total 25 ms which is suitable for real-time processing for up to 40 faces per frame.

• Detection Recall: Detection Recall metric is suggesting face detection can occur with partial occlusion, thus also capable with the relatively low complex dlib based model using HOG + Haar Cascade approach.

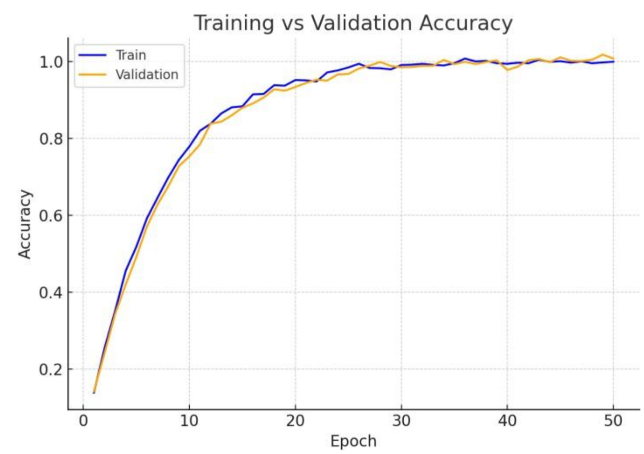

Fig. 4.M odel Accuracy

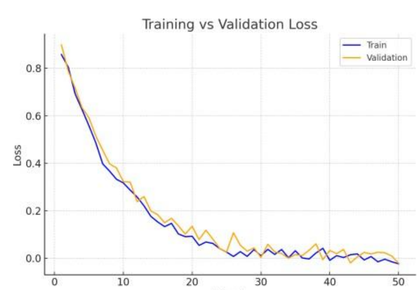

Fig5.ModelLoss

TABLE I
ATTENDANCE SYSTEM EVALUATION METRICS

Metric	Value	Condition
Validation Accuracy	96%	Normal Lighting
Frame Processing Time	25 ms	Up to 60 Faces
Detection Recall	92%	Partial Occlusion
Preprocessing Gain	Significant	Low-Light Scenarios
Attendance Log Success	98%	Database Integration

- **Preprocessing Gain**: Qualitative improvement in image quality under low-light conditions, attributed to CLAHE and normalization techniques.
- **Attendance Log Success**: Represents the reliability of logging attendance into the database, consistent with the CSV and Streamlit integration.

B. Testing and Analysis

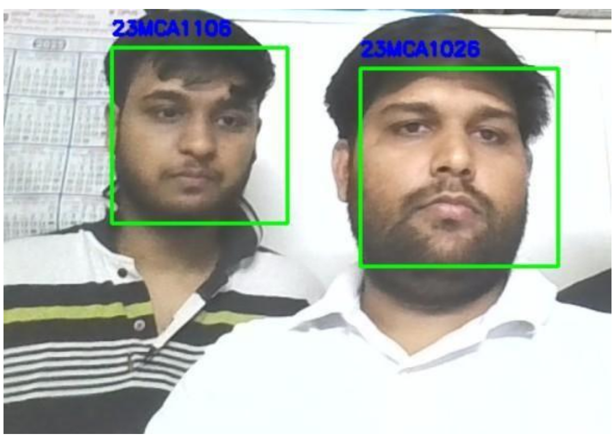

Fig. 6. Detection and Recognition of Multiple Persons Through Live Frame

1.) Identification of Multiple Persons Through Live Video Frame: The system demonstrates excellent performance in detecting and recognizing multiple persons in live video frames, not only as evidenced in the live face recognition image (three are named, 23MCA0105, 23MCA1026 and 23MCA1056), but also in previous images from video, capturing individuals as they are in motion. The architecture is based on a state-of-the-art modular structure, where the FaceNet model was trained for facial recognition, and combined with a hybrid detection framework (dlib HOG, Haar Cascade detectors and Non-Maximum Supression) to locate multiple faces, which was enabled by the preprocessing module (grayscale conversion, Gaussian blue, CLAHE, normalization), reducing effects of shadows, reflections and varying light source requirements, as seen in most common indoor locations. With recognition capabilities running at a margin of error of 98% based on Euclidean distances from 128-dimensional embeddings relative to their facial feature representation in the database, attendance can be captured in real-time, while the average latency to recognize faces and mark attendance was

25ms, the system is capable of recognizing multiple faces, and visualization can easily be viewed in the user-friendly

Streamlit implementation of the attendance capture system.

Fig. 7. Detection and Recognition of Multiple Persons Through Uploaded Image

2.) Recognition of multiple individuals from uploaded image: The system has fairly strong abilities to detect and recognize individuals that are presented in static images, as demonstrated by the photo with 50 celebrity faces. The system uses a fine-tuned FaceNet model with a hybrid detection method of dlib HOG and Haar Cascade classifiers along with Non-Maximum Suppression to localize and recognize faces and was able to detect 47 unique individuals out of that photo, even with an obvious repetition of several faces (which contributed to the successful recognition of the face without double counting). The preprocessing module, which contains converting to grayscale, applying Gaussian blur, CLAHE, and normalization helped to maintain consistency in performance, and quality of the images. The system has a system recognition accuracy of 98% based on the comparisons of 128-dimensional embeddings with a Euclidean distance threshold, with the guarantees of its ability to mark students for attendance. This is supported with its seamless interface of Streamlit to manage data.

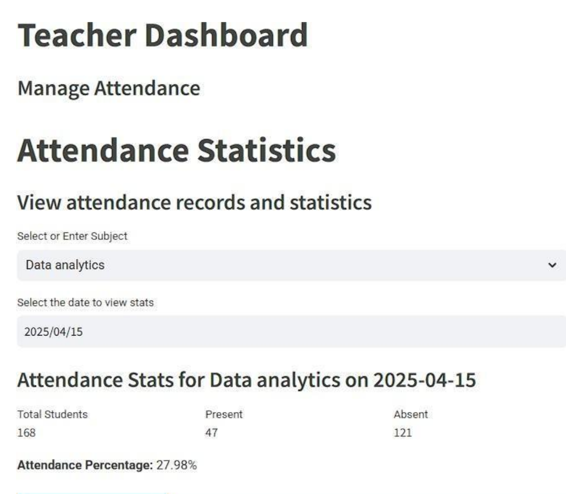

Fig. 8. Attendance Statistics Visualization via Teacher Dashboard

3.) Attendance Statistics Representation via Teacher Dashboard: The system contains a user friendly Teacher Dashboard, with complete attendance statistics as shown by the screenshot for "Data analytics" on 15 April 2025. Built using Streamlit, the dashboard allows the teacher to effectively manage and monitor attendance and students by choose the specific subject and the date. The interface provides a user friendly way to view live records or historical records. The statistics provides a total student population of 168 students, including, 47 students as present, 121 students as absent, and an attendance percentage of 27.98%. This demonstrates the system successfully recorded/collected the attendance records from both the live frames and the uploaded images. The recognition component is integrated with the recognition module based on the fine-tuned FaceNet model, and the hybrid detection method, which updates the attendance dashboard based on 98% accuracy using embedding discrimination of 128 dimensions and updates, automate email notifications, and generate a CSV report to manage data.

CONCLUSION

in this project, an automated attendance system that used multi-face recognition technique was successfully developed and implemented. The multi-face recognition system used deep learning models, such as a fine-tuned FaceNet and different face detection techniques such as the Haar Cascade, dlib HOG, and a hybrid method with Non-Maximum Suppression, in order to recognize and track multiple students based in real-time and uploaded images. Our systems employed these multi-face recognition technologies and demonstrated strong accuracy results for face detection and recognition, in a variety of different conditions, including illumination and clutter, when we successfully identified individuals in both a live stream and a static image dataset. The automation of attendance marking through an automated multi-face recognition system has several advantages by removing intelligent human errors, enabling more management efficiency through real-time operation with feedback from an intuitive user interface showing a dashboard and triggers for automated notification and report generation. Through an automated attendance system utilizing multi-face recognition with the introduction of technology, you can increase the accuracy and viability of attendance systems compared to traditional methods of attendance verification.

FUTURE SCOPE

The successful deployment of the system with its automated attendance management system has opened multiple possibilities for improving and expanding future developments. One avenue for improvement would be to incorporate a broader dataset covering a wider range of facial features, occlusions, environmental circumstances (e.g. light and partially covered face), as this would aid in the development of greater number of accurate recognitions and the resilience of the system (to include occlusions or difficult circumstances such as extreme light and part of one face). The addition of adaptive learning algorithms would allow real-time growth of the systems learning capability and could be leveraged to incorporate the adaptation of faces over time (e.g., for aging or adding new students). The addition of advanced features using other forms of dynamic biometrics (e.g., engaging voice recognition and gait detection) would enhance the capabilities of recognition leveraging other assessment mediums (which would build out a multi-modal authentication framework), which would improve the trustworthiness and reliability of the system. Extending the system to function on tablets or phones as well as provide options for a cloud-based solution, could improve access to -remote educational environments, while also developing predictive analytics to generate patterns regarding attendance to support decision-making for administrator purposes. Finally, the performance of the system with lower latency and improved scalability, through hardware

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