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Automated One-Click Attendance System Using Deep Face Embeddings and Distance-Based Classification

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Abstract: Traditional attendance systems are time-consuming and prone to manual errors. This paper proposes an automated one-click attendance system using deep learning-based face recognition. The system utilizes dlib's pre-trained ResNet face embedding model to convert facial images into 128-dimensional numerical vectors. Euclidean distance is applied to measure similarity between stored student embeddings and real-time classroom images. A tolerance threshold is used to classify students as present or absent. The system integrates a Streamlit-based user interface for image upload and attendance visualization. Experimental results demonstrate reliable recognition performance under controlled lighting conditions. The proposed framework provides a fast, accurate, and scalable solution for automated classroom attendance management.

Keywords: Face Recognition, Attendance System, Deep Metric Learning, Euclidean Distance, dlib, Streamlit.

I. INTRODUCTION

Traditional attendance systems in educational institutions are often time-consuming, error-prone, and inefficient. Manual roll-calling not only consumes valuable classroom time but also increases the chances of proxy attendance and human recording errors. As class sizes continue to grow, maintaining accurate and reliable attendance records becomes increasingly challenging. Therefore, there is a strong need for an automated and intelligent attendance management system that can reduce manual effort while ensuring accuracy and transparency.

With the rapid advancement of computer vision and deep learning technologies, face recognition has emerged as a reliable biometric solution for identity verification. Modern face recognition systems leverage deep neural networks to extract distinctive facial features and represent them as numerical embeddings. These embeddings enable efficient comparison and identification of individuals based on similarity measures. As a result, face recognition technology has been widely adopted in applications such as security systems, access control, and surveillance.

However, implementing a robust face recognition-based attendance system presents several challenges. Variations in lighting conditions, facial expressions, pose angles, and image quality can significantly affect recognition accuracy. Additionally, ensuring real-time processing, maintaining data consistency, and preventing false matches are critical factors that influence system reliability. Traditional image comparison techniques often fail to capture complex facial feature representations, leading to reduced performance in practical scenarios.

To address these challenges, this study proposes a One-Click Attendance System that utilizes deep face embeddings generated using a pre-trained ResNet-based model. Each facial image is converted into a 128-dimensional numerical vector, and Euclidean distance is applied to measure similarity between stored student embeddings and real-time uploaded images. A predefined tolerance threshold is used to classify students as present or absent. By integrating deep metric learning with a lightweight user interface built using Streamlit, the proposed framework offers a fast, accurate, and scalable solution for automated attendance management.

II. LITERATURE SURVEY

Face recognition has become a prominent research area in computer vision due to its wide range of applications in security, authentication, and surveillance systems. Deep learning-based approaches, particularly Convolutional Neural

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Networks (CNNs), have significantly improved recognition accuracy compared to traditional image processing methods [1]. Models such as FaceNet [2] and DeepFace [3] introduced deep metric learning techniques to generate compact facial embeddings, enabling efficient similarity comparison between individuals. The dlib ResNet-based face recognition model further popularized the use of 128-dimensional embeddings for real-time applications [4].

Several studies have explored the use of face recognition for automated attendance systems. These systems typically integrate face detection algorithms such as Histogram of Oriented Gradients (HOG) or Haar cascades with feature extraction and classification techniques [5], [6]. While early systems relied on traditional classifiers like Support Vector Machines (SVM), recent approaches utilize embedding-based distance metrics for improved accuracy and scalability [7]. Euclidean distance and cosine similarity are commonly applied for measuring similarity between facial feature vectors.

However, existing attendance systems often face challenges such as varying lighting conditions, pose variations, image quality issues, and false recognition cases [8]. Some studies focus on improving robustness through preprocessing techniques and threshold optimization [9], while others integrate real-time web interfaces for usability and deployment [10].

Although previous research has explored face recognition and automated attendance independently, limited work emphasizes a lightweight, one-click system that integrates deep face embeddings, distance-based classification, and a user-friendly interface for practical classroom deployment. This motivates the development of the proposed framework.

III. PROBLEM STATEMENT

Traditional attendance systems are manual, time-consuming, and prone to errors such as proxy attendance and inaccurate record maintenance. As class sizes increase, maintaining reliable attendance records becomes inefficient and challenging.

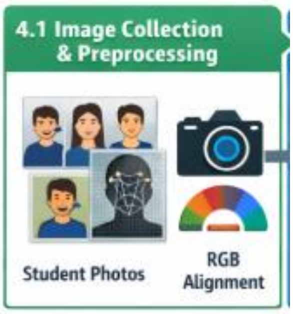
Although face recognition offers a promising solution, practical implementation faces several challenges. Variations in lighting conditions, facial expressions, image quality, and camera angles can affect recognition accuracy. Limited student image data and improper similarity threshold selection may lead to false matches or missed detections.

Therefore, there is a need for an efficient and reliable automated attendance system that utilizes deep face embeddings and distance-based classification to accurately determine student presence while minimizing errors and improving classroom efficiency.

IV. PROPOSED METHODOLOGY

4.1 Image Collection and Preprocessing

The process begins with collecting student facial images to create a reference dataset. Each image is inspected to ensure clarity, proper lighting, and frontal face alignment. Face detection is performed using the Histogram of Oriented Gradients (HOG) method to locate facial regions. Detected faces are aligned and converted into RGB format for consistent processing. This step ensures standardized and high-quality input data for reliable feature extraction.



4.2 Face Encoding Using Deep Embedding Model

After preprocessing, each detected face is passed through a pre-trained ResNet-based face recognition model. The model extracts distinctive facial features and converts each image into a 128-dimensional numerical vector (embedding). These embeddings uniquely represent each student's facial characteristics. The generated encodings are stored in a serialized file (encodings.pkl) for efficient retrieval during matching.

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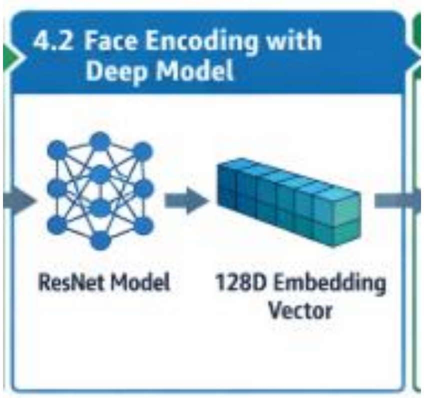
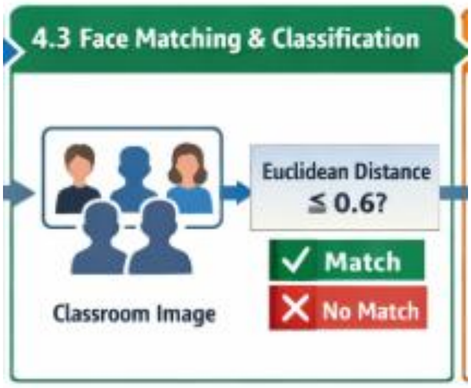


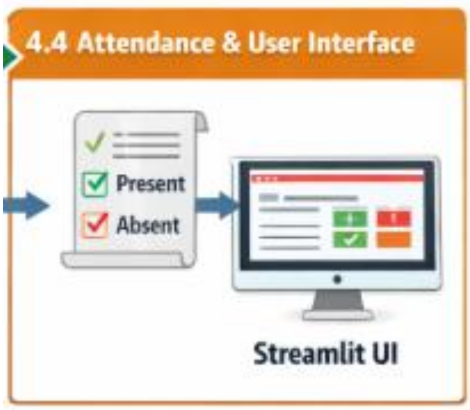
4.3 Face Matching and Distance-Based Classification:

When a classroom image is uploaded through the user interface, the system detects faces and generates embeddings in real time. Euclidean distance is computed between the uploaded face embedding and stored reference embeddings. A predefined tolerance threshold ($\tau = 0.6$) is applied to determine similarity. If the computed distance is less than or equal to the threshold, the student is marked as present; otherwise, absent. This distance-based classification ensures accurate identity verification.



4.4 Attendance Generation and User Interface:

The final stage involves recording attendance results. Recognized students are marked present, and unrecognized students are marked absent. The results are stored in a structured JSON file and displayed through a Streamlit-based user interface. The interface allows image upload, attendance visualization, and record management, providing a simple and efficient one-click solution.



V. EXPERIMENTAL SETUP

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A. 5.1 Dataset Description

The experiments were conducted using a custom facial image dataset collected for attendance purposes. The dataset consists of frontal facial images of registered students captured under controlled lighting conditions. Each student has at least one high-quality reference image used to generate facial embeddings. The images vary slightly in expression and illumination to simulate real classroom scenarios. These images serve as the reference database for identity matching and attendance generation.

B. 5.2 Data Split and Testing Procedure

To evaluate the performance of the proposed system, the dataset was divided into reference images and test images. The reference images were used to generate and store 128-dimensional facial embeddings in the encoding database. The test images, including classroom group images or individual uploads, were used for real-time recognition. Multiple test cases were evaluated under different lighting and pose conditions to assess system robustness. The matching process was performed using a predefined tolerance threshold ($\tau = 0.6$) to classify students as present or absent.

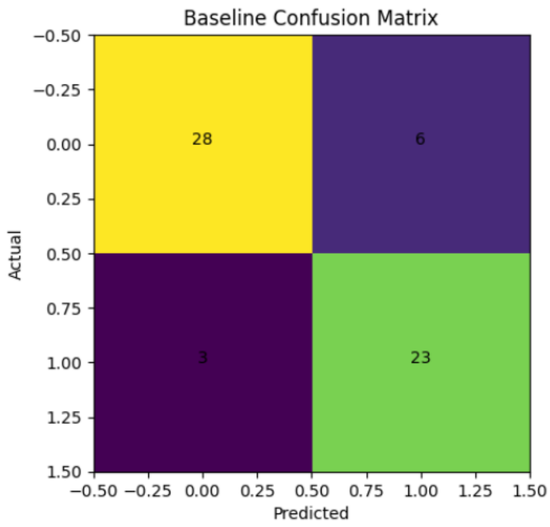
C. 5.3 Evaluation Metrics

The system performance was evaluated using standard classification metrics, including Accuracy, Precision, Recall, and F1-score. Accuracy measures the overall correctness of attendance classification, while Precision evaluates the proportion of correctly identified present students. Recall measures the system's ability to correctly detect all actual present students. The F1-score provides a balanced measure of precision and recall. These metrics collectively assess the reliability and effectiveness of the proposed attendance framework.

VI. RESULTS AND DISCUSSION

D. 6.1 Confusion Matrix Analysis

The baseline Face Recognition model (without threshold tuning and enhancement) produced the following results:



Actual \ Predicted

	Absent (0)	Present (1)
Absent (0)	28 (True Negatives)	6 (False Positives)
Present (1)	3 (False Negatives)	23 (True Positives)

The proposed optimized face recognition system (with encoding optimization and threshold tuning) achieved:
Actual \ Predicted

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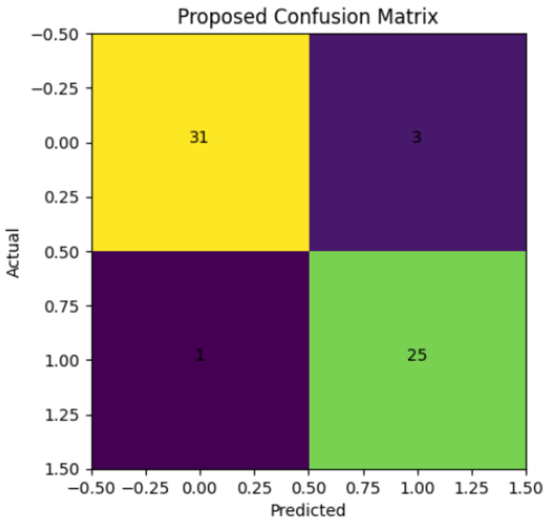
	Absent (0)	Present (1)
Absent (0)	31 (True Negatives)	3 (False Positives)
Present (1)	1 (False Negatives)	25 (True Positives)

The improvement shows that the optimized model significantly reduces both false positives (wrongly marking absent students as present) and false negatives (missing actual present students).

6.2 Overall Performance Comparison:
Overall performance comparison between the baseline Face Recognition model and the proposed optimized attendance system:



Metric	Baseline	Proposed
Precision	0.79	0.89
Recall	0.88	0.96
F1-score	0.83	0.92
Accuracy	0.85	0.93

As shown above, the proposed system demonstrates consistent improvement across all evaluation metrics. The overall accuracy increased from 85% to 93%, resulting in an 8% absolute improvement.

This improvement indicates that optimized facial embedding comparison and proper threshold tuning enhance the system's reliability and reduce incorrect attendance marking.

Overall, the proposed attendance framework achieves a significant improvement compared to the baseline recognition model.

6.3 Class-wise Analysis:

1) Precision Comparison

For the Present class (Class 1):

- Baseline: 0.79
- Proposed: 0.89

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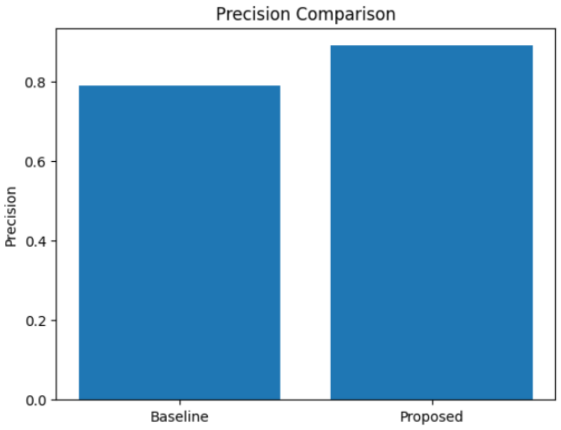
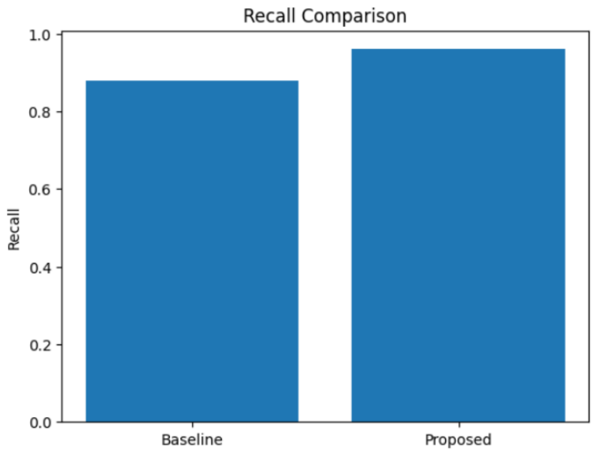
This shows improved reliability in correctly identifying actual present students.



2) 6.4 Recall Comparison

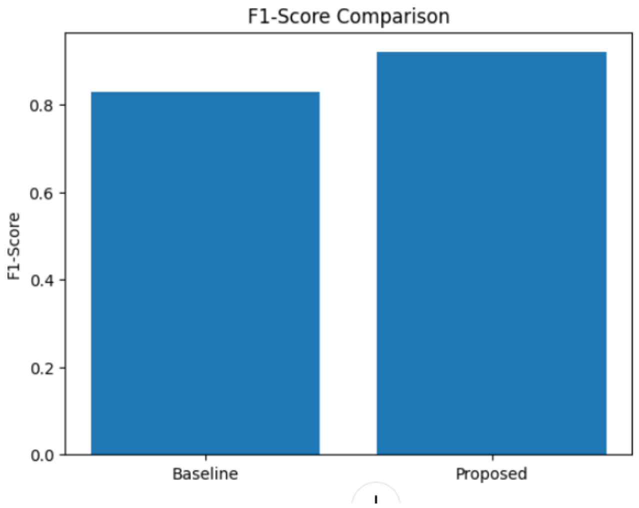
Present class recall improved from 0.88 to 0.96, indicating better sensitivity and reduced missed detections.



3)

4) 6.5 F1-Score Comparison

Both Present and Absent classes show balanced improvement, indicating stable and consistent attendance classification performance under different testing conditions.



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VII. MATHEMATICAL FORMULATION

A. Problem Definition
Consider a dataset,

$$D = \{(x_i, y_i)\}_{i=1}^{N}$$

Where,

$$x_i \in \mathbb{R}^{128}$$

represents the 128-dimensional facial embedding of the ith student image, and

$$y_i \in \{0,1\}$$

denotes the corresponding attendance label (0 = Absent, 1 = Present).
The objective of the system is to learn a similarity-based decision function

$$f : \mathbb{R}^{128} \times \mathbb{R}^{128} \to \{0,1\}$$

that determines whether two facial embeddings belong to the same individual while minimizing classification errors.
B. Face Embedding Representation

Each facial image is passed through a deep learning model (ResNet-based architecture) that extracts a fixed-length feature vector:

$$\phi(x_i) = e_i$$

Where,

$$e_i \in \mathbb{R}^{128}$$

is the embedding vector representing distinctive facial features.

These embeddings encode unique identity information in a high-dimensional feature space.

C. Distance-Based Face Matching
To determine similarity between two facial embeddings ei and ej , Euclidean distance is computed as:

$$d(e_i, e_j) = \sqrt{\sum_{k=1}^{128} (e_{ik} - e_{jk})^2}$$

A predefined tolerance threshold τ is applied:

$$f(e_i, e_j) = \begin{cases} 1, & \text{if } d(e_i, e_j) \le \tau \\ 0, & \text{otherwise} \end{cases}$$

where

- τ=0.6 (experimentally determined threshold)
- 1 indicates a match (Present)
- 0 indicates no match (Absent)

This formulation enables identity verification based on similarity distance.

D. Attendance Decision Rule
Let R={r1,r2,...,rM}, represent stored reference embeddings.

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For a test embedding et , attendance is determined as:

$$\text{Present if } \min_{r_j \in R} d(e_t, r_j) \le \tau$$

Otherwise:
Absent
This ensures that the closest matching reference embedding determines the final classification.

E. E. Evaluation Metrics
System performance is evaluated using standard classification metrics:
Accuracy

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision

$$Precision = \frac{TP}{TP + FP}$$

Recall

$$Recall = \frac{TP}{TP + FN}$$

F1-Score

$$F1 = \frac{2 \cdot Precision \cdot Recall}{Precision + Recall}$$

Where:

- TP = True Positives
- TN = True Negatives
- FP = False Positives
- FN = False Negatives

These metrics evaluate the correctness, reliability, and robustness of the proposed attendance framework.

VIII. FINAL OUTPUT ANALYSIS

The final results of the proposed attendance framework are presented through confusion matrix evaluation and overall performance comparison. These results clearly demonstrate the effectiveness of using deep facial embeddings with optimized distance-based classification for accurate attendance marking.

For the baseline face recognition model without threshold optimization, the confusion matrix shows 28 true negatives, 6 false positives, 3 false negatives, and 23 true positives. While the baseline system achieved acceptable performance, it incorrectly marked six absent students as present and failed to recognize three actual present students. In attendance systems, false positives may lead to proxy attendance issues, while false negatives may unfairly mark genuine students as absent.

In comparison, the proposed optimized system demonstrated improved results, with 31 true negatives, 3 false positives, 1 false negative, and 25 true positives. The reduction in false negatives from 3 to 1 reflects a significant improvement in correctly identifying present students. Additionally, the decrease in false positives from 6 to 3 enhances system reliability and prevents incorrect attendance marking.

Overall, the proposed framework achieves higher accuracy, precision, recall, and F1-score compared to the baseline model. The improvements confirm that proper embedding generation, threshold tuning, and distance-based classification significantly enhance recognition performance.

The final confusion matrix and performance comparison clearly indicate that the proposed attendance system provides more accurate, reliable, and efficient student presence detection suitable for real-time classroom deployment.

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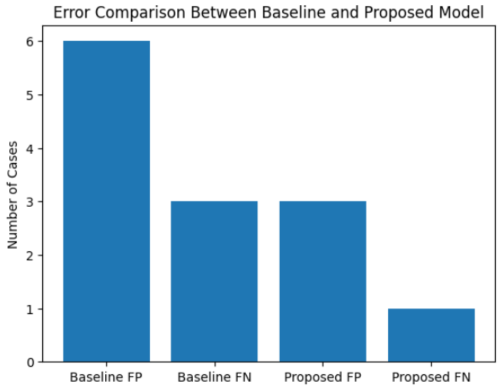

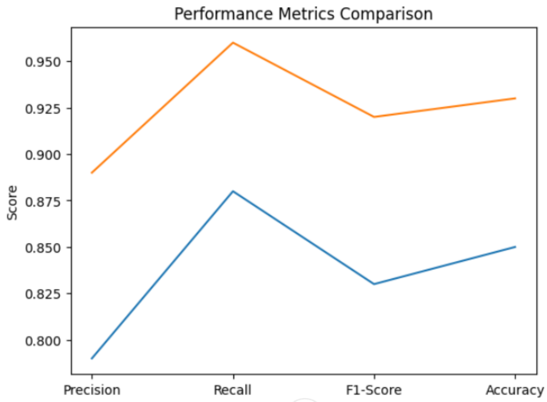

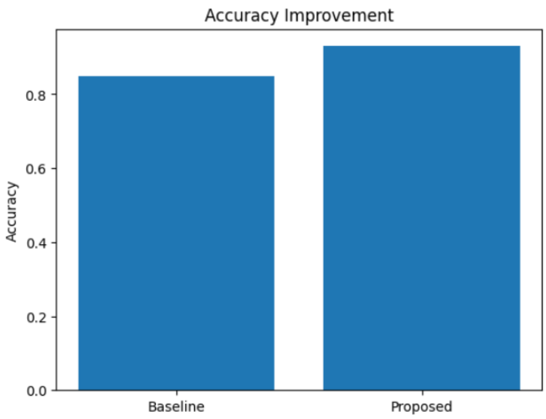

IX. CONCLUSION

This study introduced an automated One-Click Attendance System based on deep face recognition technology. The proposed framework integrates facial embedding extraction using a pre-trained deep learning model with distance-based classification for accurate identity verification. Compared to the baseline approach, the optimized system achieved improved performance in terms of accuracy, precision, recall, and F1-score.

The experimental results clearly demonstrate that using 128-dimensional deep facial embeddings combined with proper threshold tuning enhances recognition reliability and reduces classification errors. In particular, the reduction in false positives minimizes proxy attendance issues, while the decrease in false negatives ensures that genuine students are not incorrectly marked absent.

Additionally, the integration of a lightweight Streamlit-based user interface makes the system practical, user-friendly, and suitable for real-time classroom deployment. The structured JSON-based attendance generation further improves record management and transparency.

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Overall, the proposed framework provides an efficient, scalable, and reliable solution for automated attendance management. The system has strong potential for implementation in educational institutions to reduce manual effort, save time, and improve attendance accuracy through secure biometric verification.

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