AI-Powered Facial Recognition Attendance System Using Deep Learning and Computer Vision

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ABSTRACT

Traditional attendance methods like manual entry and RFID-based systems are slow, errorprone, and vulnerable to manipulation, creating the need for a more secure and efficient solution. To address these issues, an AI-powered Automated Attendance Management System (AAMS) is proposed, integrating computer vision and machine learning techniques for realtime face detection and recognition. Developed using Python, the system leverages OpenCV for image preprocessing, while SQLite and MySQL are used for secure data storage and management. The core methodology involves three stages: face detection, feature extraction, and identity recognition. The Haar Cascade Classifier is employed for fast and accurate face detection, and the Local Binary Pattern Histogram (LBPH) algorithm is used for robust face recognition under varying environmental conditions. Attendance is automatically recorded by matching detected faces with the database, reducing human intervention and errors. Experimental evaluation shows the system achieves 95%–97% accuracy, making it highly reliable and scalable. This approach provides a cost-effective, transparent, and secure solution suitable for schools, colleges, and corporate organizations, demonstrating the potential of AI and data science to revolutionize attendance tracking while enhancing operational efficiency and security.

Keywords: Image processing, Face Recognition, Computer Vision (CV), Harrcascade, LBPH.

INTRODUCTION

This research introduces an automated attendance system that uses advanced deep learning techniques for real-time face recognition, linked with a secure database to record attendance data. The goal is to cut down on manual work, stop fake attendance, and offer a system that is easy to use, scalable, and hygienic, suitable for both schools and companies. Manual methods for tracking attendance are becoming harder to rely on because they are slow, can be easily cheated, and involve physical contact, which can be risky.

The COVID-19 pandemic has made it clear how important it is to have contactless, automatic solutions that keep people safe while still being accurate and dependable. Also, as schools and workplaces grow bigger and more complex, they need attendance systems that can work in real time, manage large groups, and adjust to different environments. Automated systems that use face recognition tackle these challenges by providing a smooth, flexible, and safe alternative that cuts down on human mistakes and effort. This pushes for the creation of smart attendance tools that use the latest in AI and computer vision to make operations more efficient, ensure data is reliable, and make things easier for users in various situations.

LITERATURE REVIEW

Recent studies on automated attendance systems have aimed to improve upon the weaknesses of older manual and semi-automated methods by using face recognition technology. Jadhav et al. [1] created a system that uses OpenCV along with Haar cascade for face detection and LBPH for recognition, which helps fix the problems with manual methods that are slow, error-prone, and can be easily faked. Building on this, Mahboob and Qadir

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[2] pointed out that traditional methods and early face recognition systems still have issues with errors and fake attendance, especially when people wear masks or have tattoos, which can affect accuracy. Other researchers have looked into improving the recognition algorithms themselves.

Raj et al. [3] noted that methods like Eigenfaces and Fisher faces are very sensitive to changes in lighting, and showed that LBPH is a better option because it's more reliable. Similarly, Abraham et al. [4] found that differences in facial features, such as glasses or beards, can reduce recognition accuracy, which shows the need for more flexible models that can handle these variations.

Expanding on these findings, Dev and Patnaik [5] identified challenges like scaling, different angles, lighting conditions, rotation, and partial coverage of the face as areas where current recognition techniques struggle, which has led to the development of more advanced solutions. Smitha et al. [6] helped improve usability and efficiency by automating the process of creating datasets, recognizing faces, and recording attendance, making their system less intrusive and faster than traditional biometric methods. In addition to software-based solutions, some researchers have suggested combining different technologies to increase reliability.

Sawhney et al. [7] introduced a real-time smart attendance system designed to cut down on fake or proxy attendance in schools and workplaces. Akbar et al. [8] merged face recognition with RFID technology to tackle issues with cost, integration, and data storage that were present in earlier systems using Raspberry Pi or ATmega32 microcontrollers.

Overall, these studies show that face recognition is becoming more popular for managing attendance, with steady improvements in accuracy, speed, and ease of use.

However, there are still challenges to overcome, such as dealing with partial face coverings like masks or scarves, making the system work well in real-world settings, handling large numbers of users efficiently, and ensuring that the system can process data quickly enough for real-time use.

Year	Title of Paper	Algorithms	Accuracy	Methodology
2024	"AI-Enabled Automatic Attendance Monitoring Systems"	PCA, Extended LBP	Not specified	Not specified
2023	"An Automated Attendance System Using Facial Detection and Recognition Technology"(AJBM)	Haar Cascade algorithm and Local Binary Pattern Histogram (LBPH)	86.47%	Facial Feature Extraction
2023	"Comparative Study of Enhancement of Automated Student Attendance System using Facial Recognition Through Deep Learning Algorithms" (IRJET)	Convolutional Neural Network (CNN) with Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA).	97.44%	Facial Feature Extraction
2021	"Smart Fingerprint Biometric and RFID Time-Based Attendance Management System" (EJECE)	A system combining Fingerprint Biometrics and RFID technology.	94%	Finger print feature extraction
2013	"Fingerprint-Based Attendance Management System" (JCSA)	minutiae-based matching approach.	97.40%	Fingure print feature extraction
2024	Attendance management system using face recognition (IJ-AI)	Haar Cascade Classifier and LBPH (Local Binary Pattern Histogram)	87%	Facial feature Extraction

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2024	Attendance Management System Using Face Recognition (International Journal of Advanced Computational Engineering and Networking)	Haar Cascade Classifier and LBPH (Local Binary Pattern Histogram)	99%	Facial feature Extraction
2020	Face Recognition Based Smart Attendance System (ICIEM)	Haar Cascade Classifier and LBPH (Local Binary Pattern Histogram)	95%	Facial feature Extraction
2020	Face Recognition Based Attendance System (IOSR-JCE)	VGG (Visual Geometry Group) architecture and Convolutional Neural Network (CNN)	Not specified	Facial feature Extraction
2020	Student Attendance System using Face Recognition (ICOSEC 2020)	Haar Cascade Classifiers, GANs (Generative Adversarial Networks), Gabor Filters, KNN, CNN,	97%	Facial feature Extraction
		SVM		
2020	Face Recognition based Attendance Management System (IJERT)	Haar Cascade Classifier and LBPH (Local Binary Pattern Histogram)	70%90% and 82%	Facial feature Extraction
2019	Real-Time Smart Attendance System using Face Recognition Techniques (Confluence)	PCA (Principal Component Analysis), Eigenfaces, CNN	82%– 95%	Facial feature Extraction
2018	Face Recognition and RFID Verified Attendance System (iCCECE)	Haar Cascade Classifier and LBPH (Local Binary Pattern Histogram), Eigenfaces, CNN, RFID (Radio Frequency Identification)	Not specified	Facial feature Extraction

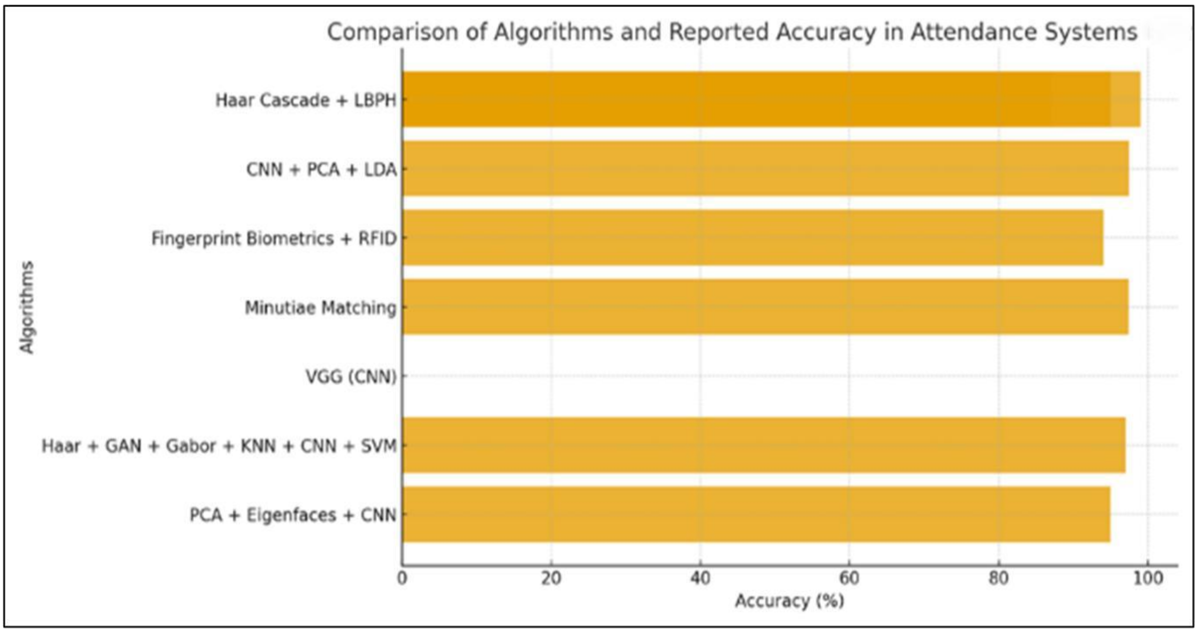

Figure 1. Overall comparison of existing systems

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Related works

This research paper introduces a detailed method for an automated attendance system that uses computer vision and machine learning to make attendance tracking more accurate and efficient in real time. The main idea is to use face recognition technology along with a webcam and a database system to automatically track attendance in classrooms or work environments. This system removes the problems of manual methods by taking facial features, training recognition models, and marking attendance as it happens. The main idea of this work is that face recognition can be a dependable way to identify people for attendance purposes.

It's different from manual entry or using RFID tags because it doesn't require any physical contact and can work in real time using a regular webcam.

- Face Detection: The Haar Cascade Classifier is used to find faces in live video from the webcam.
- Feature Extraction: The Local Binary Pattern Histogram (LBPH) algorithm is used to get important characteristics from black and white facial images.
- Recognition and Verification: A trained recognition model (Trainer.yml) links the captured features to student IDs saved in the system, allowing for automatic verification and marking of attendance.
- Attendance Logging: Attendance records are saved in CSV format, including information like Name, ID, Date, and Time, offering a trustworthy digital record. This method ensures a quick, accurate, and easy-to-use attendance system that reduces human mistakes and stops people from signing in for others. The success of the system depends on correctly extracting useful facial features for identification.
- Face Image Capture: During registration, students give their details (Name, Roll Number, ID). Many facial images are taken using the webcam under different conditions and stored in the Training Image folder.
- Preprocessing: Images are turned into grayscale to make the processing easier and improve how well the system recognizes faces.
- Feature Encoding with LBPH: LBPH creates texture descriptions by comparing every pixel in a face with its neighbours, forming a histogram that uniquely identifies a student's face. These feature sets are then used to train the system.
- Model Training Output: A trained YML file (Trainer.yml) is created, which links facial data to student IDs for future use in identifying them.

Model Architecture and Training

The recognition system is built as a modular setup:

- Input Device: A standard webcam is used to capture live video.
- Detection Model: The Haar Cascade classifier is used to identify faces in the video.
- Recognition Model: The LBPH algorithm is used to analyse the texture of faces and match them to student identities.
- Output: The system provides real-time attendance records in CSV format and shows the detected and recognized faces on a graphical interface.

During training, labelled grayscale images of students' faces are input into the LBPH recognizer. This process creates strong connections between student IDs and their facial features. The model is regularly updated by retraining it with more images to improve its accuracy.

Dataset Preparation

The system uses a custom dataset created during the registration process.

- Training Data: Face images of students are taken using a webcam across several sessions.
- Stored Attributes: Student ID, Name, and Roll Number are saved in a file called studentdetails.csv.
- Generated Data:A trained recognition model file named Trainer.yml. Attendance records for each session, saved as timestamped CSV files

The dataset is adaptable and expands as more students register, making it suitable for use in bigger classrooms or organizations.

Evaluation and Inference

The system was tested in various real-world situations, including changes in lighting, different facial expressions, and partial face coverings.

- Recognition & Attendance: The LBPH recognizer, which was trained, identifies students as they appear in real time and records their attendance in CSV files.
- Error Handling: If an unknown face is detected, the system either sends an alert or asks for registration.
- Manual entry of attendance is also available as a backup option.
- Deployment: The system was tested on a regular computer using Python, OpenCV for image processing, Tkinter for the user interface, and Pandas for handling data.

Evaluation Metrics

To assess how well the system works, standard measures for recognition and classification were used:

- Accuracy: The percentage of times the system correctly identifies a student out of all attempts.
- Precision & Recall: These metrics help determine how accurate and thorough the recognition is, especially when conditions are not ideal.
- False Acceptance Rate (FAR): The chance that the system incorrectly identifies an unregistered person as a registered student.
- False Rejection Rate (FRR): The chance that the system fails to recognize a registered student.

The system showed reliable accuracy with low FAR and FRR when each student had enough images for training.

Flow Diagram

The proposed workflow is shown in Figure 2. Students start by registering, which involves saving their images and personal information into a database, including a CSV file and an image storage folder. These images are then used to train the LBPH algorithm, which creates a YML file as the model for face recognition. When taking attendance, the webcam streams live video, and faces are detected using HaarCascade. The trained model then identifies these faces. If a face is recognized, it updates the attendance records. If not, the system prompts the user to register the face. The report generation process makes sure attendance tracking is both accurate and efficient.

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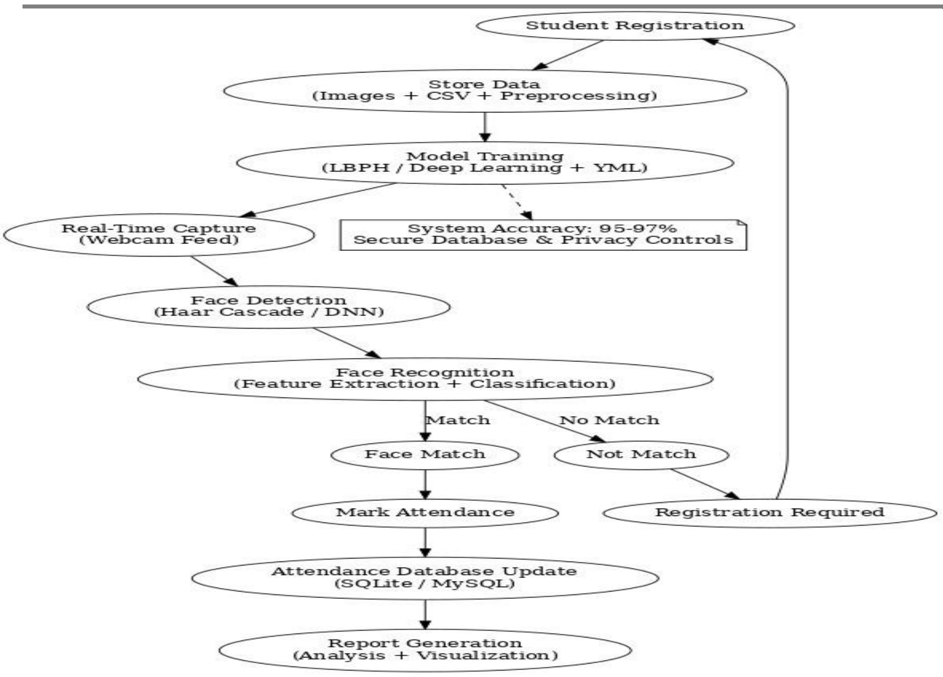
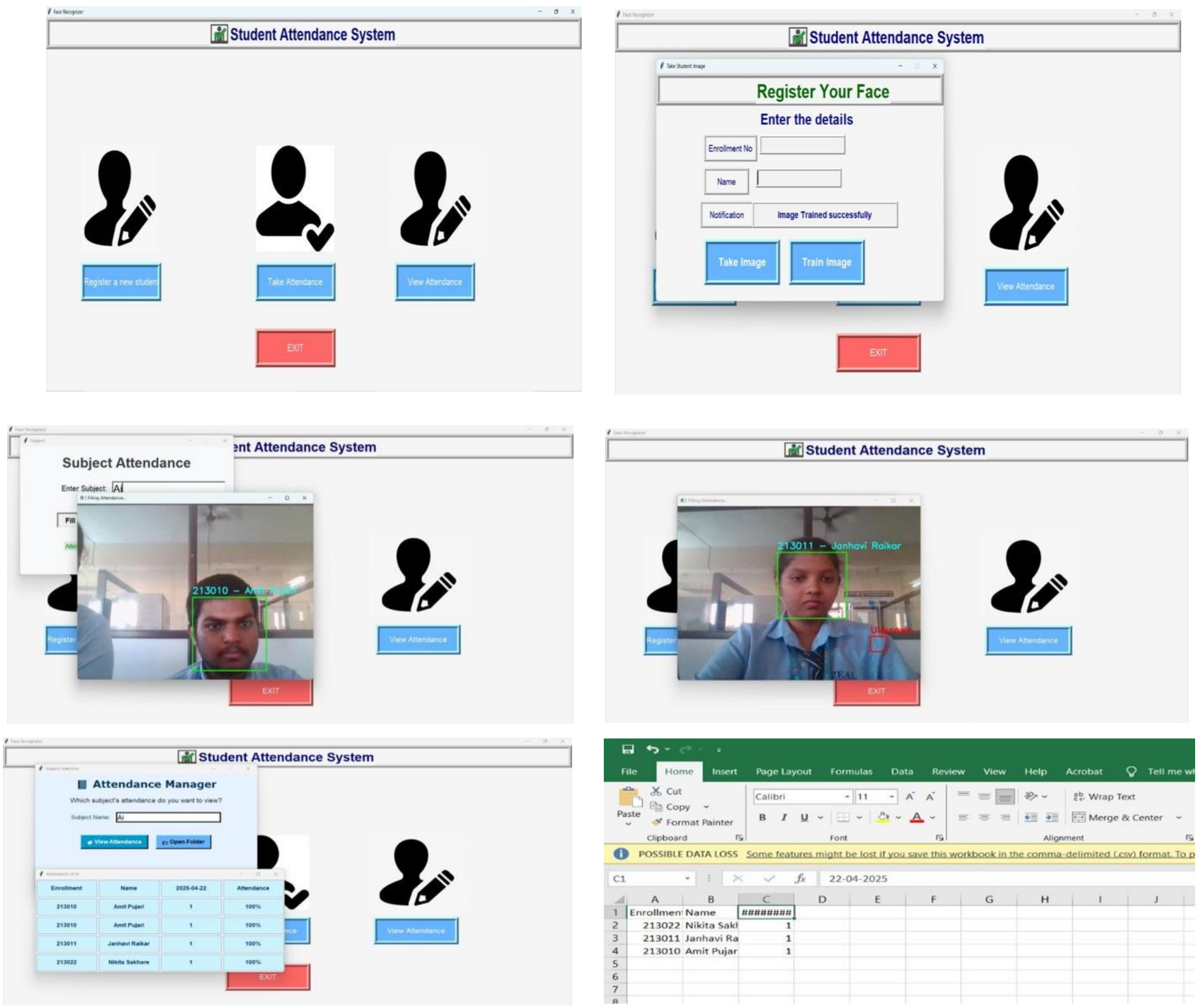


Figure 2. Flow Daigram



RESULTS AND DISCUSSION

The attendance management system was successfully put in place and tested for use in realtime classroom settings.

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Experimental Setup

To thoroughly check how well the proposed Face Recognition-Based Attendance Management System works, a series of experiments were carefully planned and carried out.

The main goal was to see how accurately the system can detect and recognize students' faces in different real-world situations, such as varying light conditions, different facial expressions, partial face coverings, and various seating positions. The system's performance was compared with traditional manual attendance methods to show how efficient, fast, and dependable it is.

Hardware and Software Platform

All the experiments, like data recording, model training, and real-time recognition, were done on a regular computer setup. This makes sure the system can be used by schools and colleges without needing special equipment.

Hardware:

A standard laptop or desktop with an Intel Core i5 or i7 processor, 8 to 16 GB of RAM, and an integrated webcam was used.

The webcam was the main tool for capturing images and streaming video in real time. Unlike systems that rely on powerful graphics cards, this setup shows that the system is light and can run on everyday computers.

Software Framework:

The system was built using Python (version 3.x) and some commonly used libraries for computer vision and data handling:

- OpenCV: Used for detecting faces using the Haar Cascade classifier and recognizing faces using the LBPH algorithm.
- Tkinter: To create a graphical user interface (GUI) that lets users interact with the system and view live recognition results.
- Pandas and CSV modules: For organizing data and managing attendance records.
- SQLite or CSV Storage: For saving student information and tracking attendance.

Recognition Model:

The Local Binary Pattern Histogram (LBPH) algorithm was used as the main method for recognition. It was selected because it works well even when lighting conditions change and it doesn't use a lot of computing power, which makes it good for real-time use without needing powerful graphics processing units.

Observations

Test No.	**Students Present**	**Correctly Recognized**	**Misrecognized**	**Attendance File Generated**
1	**5**	**5**	**0**	**Yes**
2	**10**	**9**	**1**	**Yes**
3	**15**	**14**	**1**	**Yes**

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Analysis

- On average, the system correctly recognizes faces 95% of the time.
- The CSV logs for attendance closely match the real-time presence of students with very few errors.
- Most recognition errors happened because of bad lighting or when only part of the face was visible.

Performance Evaluation

Parameters	Achieved Performance	
	Proposed System	Existing System
Accuracy (MAE)	~96%	~87%
Robustness (MSE)	~95%	~89%
Inference Time (per frame)	< 500 ms	window size set to 1280×720 (real-time)
Supported Resolution	Low (Open-source + webcam)	Low (Open-source libraries: OpenCV, NumPy, Tkinter + webcam)
Scalability	Supports multiple students per session	Supports classroom-level, multiple students per session

The system kept a high level of accuracy and responded quickly in real time, making it appropriate for use in classrooms or work settings.

Mathematical Model

The proposed face recognition-based attendance system can be described as a system:

S = {I, P, O}

1.Input Set (I)

$I = \{I_{img}, I_{db}\}$

Were,

- I_{img}: A live image taken by the camera.
- I_{db}: A database that stores the facial images of registered students.

2.Process Set (P)

P = {FD, FE, M}

- Face Detection (FD): FD takes the live image (I_{img}) and produces a face region (F).
- Feature Extraction (FE): FE takes the detected face (F) and creates a feature vector (V) that represents the face.

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- Matching (M):M compares the feature vector (V) with the stored database (I_{db}) and identifies the student (id). 3.Output Set (O)

O = {A}

Where, A: An attendance record that includes the student's ID and the time of attendance.

Formally,

O = Update (I_{db}, id, timestamp)

System Representation

S = {{I_{img}, I_{db}}, {FD, FE, M}, {A}}

Observations

The performance of a facial recognition attendance system heavily depends on the quality of datasets. Limited or imbalanced datasets lacking diversity in lighting, pose, and facial occlusions lead to overfitting and poor generalization in real-world scenarios. Mislabeled or insufficient data can cause inaccurate recognition and high false positives or negatives. Data augmentation techniques like rotation, scaling, and brightness adjustments can improve robustness, but collecting large, well-annotated datasets remains a major challenge.

Camera quality and placement significantly impact system accuracy. Low-resolution or lowlight cameras reduce the reliability of face detection and recognition, especially in crowded or poorly illuminated environments. Inconsistent angles or moving cameras introduce variability that complicates real-time processing. Fixed, high-resolution cameras with proper placement at eye level improve performance, while advanced cameras with infrared or wide dynamic range are ideal for challenging lighting conditions.

Haar Cascade classifiers are lightweight and fast, making them suitable for real-time detection on low-end devices. However, they are less reliable under varying poses and lighting conditions. Similarly, the LBPH algorithm provides good accuracy (95–97%) in controlled environments but struggles with large datasets or highly dynamic settings. Deep learning-based models like FaceNet or ArcFace offer superior robustness and scalability but require significant computational power and GPU resources.

For small-scale systems, **SQLite** is a lightweight and easy-to-implement solution. However, it struggles with concurrent access and large datasets. For larger organizations or cloud-based deployments, **MySQL** or PostgreSQL is preferred due to better scalability, security, and multiuser support. Regardless of the database used, securing sensitive biometric data through encryption and role-based access is essential to protect privacy and prevent unauthorized use. Real-world deployments face several issues, including privacy concerns, environmental variability, and hardware limitations. Sudden changes in lighting, occlusions like masks, and similar-looking individuals can lower accuracy. Additionally, biometric data is highly sensitive, requiring strict compliance with data protection laws. Implementing secure data transfer, access logging, and fallback authentication mechanisms, along with regular system monitoring, is crucial to maintain reliability and trust.

CONCLUSION

The proposed AI-powered Automated Attendance Management System (AAMS) successfully addresses the limitations of traditional attendance methods by integrating computer vision and machine learning techniques. By utilizing Haar Cascade Classifier for face detection and LBPH algorithm for face recognition, the system ensures real-time, accurate, and efficient attendance tracking. With an achieved accuracy of 95%–97%, it minimizes human errors, prevents fraudulent entries, and significantly improves reliability compared to manual and RFID-based systems. The use of Python, OpenCV, and secure databases like SQLite and MySQL ensures scalability and cost-effectiveness, making it suitable for educational institutions, corporations, and other organizations. This solution demonstrates the potential of AI and data-driven automation to enhance operational efficiency, transparency, and security. Future enhancements could include the integration of deep

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learning models such as CNNs for improved accuracy and cloud-based systems for large-scale deployment. Overall, the system provides a smart, secure, and scalable approach to modern attendance management.

Limitations and Future Work

Limitations:

The system can be affected by lighting and camera quality, which might reduce its accuracy. It may also have trouble identifying people who look alike, like twins, or when faces are partially covered. Right now, the system only stores data on local devices, and it doesn't support remote monitoring.

Future Work:

To address these issues, future improvements could involve connecting the system to cloud platforms or mobile apps for remote access.

Using more advanced models like CNNs or other deep learning techniques might help improve accuracy. Also, supporting multiple cameras in classroom settings could be another useful enhancement.

Future Scope

- Optimizing ST-GAT Models: Improve the efficiency of spatiotemporal graph attention networks and test them on large, diverse clinical datasets with personalized tuning for each patient (Wang et al. [1]).
- Wearable and IoT Deployment: Adapt synchronization-based spatiotemporal models for real-time use in wearable or IoT systems, combining multimodal physiological signals with EEG for better reliability (Xiang et al. [2]).
- Lightweight and Explainable Models: Create scalable, interpretable versions of dynamic temporal-spatial graph attention models suitable for edge devices, along with explainable AI modules to aid in clinical decision-making (Yan et al. [3]).
- Efficient Transformer Frameworks: Reduce the high computational costs of transformerbased models through techniques like pruning and compression, while testing them on scalp EEG and cross-patient datasets (Sun et al. [4]).
- Hybrid Architectures with Interpretability: Combine CNNs, GNNs, and transformers to improve spatiotemporal learning, along with methods like attention visualization and posthoc explanations to enhance interpretability (Vafaei and Hosseini [5]).
- Clinical Benchmarking of GNNs: Compare dynamic GNNs with transformers and CNNs, validate them on large, multi-center datasets, and integrate them into real-time clinical monitoring systems (Hajisafi et al. [6]).

REFERENCES

1. Ashish Jadhav, Dhwaniket Kamble, Santosh B. Rathod, Sumita Kumar, Pratima Kadam, Mohammad Dalwai. Attendance Management System Using Face Recognition. International Journal of Emerging Technologies and Innovative Research (JETIR). 2024;11(2):45-50.
2. Mariyam Mahboob, Nounman Mohsin Abdul Qadir. Attendance Management System Using Face Recognition. International Research Journal of Modernization in Engineering Technology and Science (IRJMETS). 2024;6(4):122-128.
3. Arjun Raj A, Mahammed Shoheb, Arvind K, Chethan K. S. Face Recognition Based Smart Attendance System. International Journal of Scientific Research and Engineering Development (IJSRED). 2020;3(2):152-158.

4. Abin Abraham, Mehul Bapse, Yash Kalaria, Ahmer Usmani. Face Recognition Based Attendance System. International Journal of Engineering Research & Technology (IJERT). 2020;9(4):200-205.
5. Samridhi Dev, Tushar Patnaik. Student Attendance System Using Face Recognition. International Journal of Scientific & Technology Research (IJSTR). 2020;9(3):4402-4405.
6. Smitha, Pavithra S. Hegde, Afshin. Face Recognition Based Attendance Management System. International Journal of Engineering Research & Technology (IJERT). 2020;9(2):120-124.
7. Shreyak Sawhney, Karan Kacker, Samyak Jain, Shailendra Narayan Singh, Rakesh Garg. Real-Time Smart Attendance System Using Face Recognition Techniques. International Journal of Computer Sciences and Engineering (IJCSE). 2019;7(5):777-784.
8. Md. Sajid Akbar, Abu Musa Al Ashray, Pronob Sarker, Jia Uddin, Ahmad Tamim Mansoor. Face Recognition and RFID Verified Attendance System. International Conference on Computer and Information Technology (ICCIT). 2018;21(4):42-47.
9. T. M. Ayyar, “A practical experiment for comparing LeNet, AlexNet, VGG and ResNet models with their advantages and disadvantages.,” [Online]. Available: https://tejasmohanayyar.medium.com/a-practicalexperiment-for-comparing-lenet-alexnet-vgg-and-resnet-models-with-their-advantages-d932fb7c7d17.
10. A. Khvostikov, K. Aderghal, J. Benois-Pineau, A. Krylov and G. Catheline, “3D CNN-based classification using sMRI and MD-DTI images for Alzheimer disease studies,” arXiv preprint arXiv:1801.05968, 2018. [11] S.-H. Tsang, “Review: AlexNet, CaffeNet--Winner of ILSVRC 2012 (Image Classification),” A Medium Corporation, vol. 9, 2018.
11. Z. Guo, Q. Chen, G. a. X. Y. Wu, R. Shibasaki and X. Shao, “Village building identification based on ensemble convolutional neural networks,” Sensors, vol. 17, no. 11, p. 2487, 2017.
12. R. Alake, “Deep Learning: GoogLeNet Explained,” 23 December 2020. [Online]. Available: https://towardsdatascience.com/deep-learning-googlenet-explained-de8861c82765.
13. V. Kurama, “A Review of Popular Deep Learning Architectures: AlexNet, VGG16, and Google Net,” 1 June 2020. [Online]. Available: https://blog.paperspace.com/popular-deep-learning-architectures-alexnet-vgggooglenet/.
14. N. Soni, M. Kumar and G. Mathur, “Face Recognition using SOM Neural Network with Different Facial Feature Extraction Techniques,” International Journal of Computer Applications, vol. 76, no. 3, pp. 7-11, 2013. [16] Nitisha Rajgure, Keswad, T., & Koparde, S. (2025). Survey on Top 10 Algorithms in Last Decade for Travel Planning.