International Journal of Applied Mathematics

Volume 37 No. 6s 2024,

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

A METHOD FOR AUTOMATED ATTENDANCE SYSTEM USING FACIAL RECOGNITION

Ravi Saharan,

Department of Computer Science and Engineering, Central University of Rajasthan, Ajmer, Rajasthan, India

ravisaharan@curaj.ac.in

Abstract

In the modern digital age, facial recognition technology has become indispensable across various sectors. As one of the most widely adopted biometric systems, it offers numerous applications, including security, authentication, and identity verification. Although its accuracy may be lower than iris or fingerprint recognition, its non -invasive and contactless nature makes it a preferred choice. One of its key implementations is in automated attendance systems for educational institutions and workplaces, addressing the inefficiencies of traditional manual methods, which are time consuming, prone to errors, and vulnerable to proxy attendance. The proposed system streamlines attendance management through four key phases: database creation, face detection, face recognition, and attendance logging. The system then employs the Haar Cascade classifier for real time face detection and the Local Binary Pattern Histogram (LBPH) algorithm for recognition, processing live classroom video feeds. The proposed algorithm consistently maintained accuracy between 85–92% and maintains low latency (<1.5 seconds per recognition) making it ideal for real-time classroom deployment.

Keywords:- Face Recognition, Face Detection, Haar Cascade classifier, Local Binary Pattern Histogram.

INTRODUCTION:-

In recent years, the rapid advancement of biometric technologies has revolutionized traditional methods of identification and authentication. Among these, facial recognition has emerged as a highly efficient and contactless solution for various applications, including security, surveillance, and attendance management. Traditional attendance systems, which rely on manual roll calls or RFID based methods, are often time consuming, prone to human error, and susceptible to proxy attendance. To overcome these challenges, an automated attendance system using facial recognition presents a modern, accurate, and efficient alternative. Facial recognition leverages machine learning and computer vision techniques to detect and identify individuals based on their facial features. Unlike

Received: May 18, 2024

Volume 37 No. 6s 2024,
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

fingerprint or iris recognition, it offers a non-intrusive and seamless experience, making it ideal for environments such as classrooms, corporate offices, and large -scale institutions.

The system works by capturing live images or video feeds, processing them using algorithms like Haar Cascade for face detection and Local Binary Pattern Histogram (LBPH) for recognition, and then automatically logging attendance in a database.

The proposed system aims to eliminate manual attendance recording, reduce administrative workload, and enhance accuracy. Additionally, it can integrate with existing institutional management systems to provide real -time attendance reports via email or cloud storage. By implementing this technology, organizations can ensure transparency, efficiency, and fraud prevention in attendance tracking. This paper explores the design and implementation of an automated attendance system using facial recognition, discussing its architecture, key algorithms, advantages over conventional methods. This paper also highlights future enhancements, such as real-time processing, multi-face detection in crowded environments, and integration with IoT based smart systems.

LITERATURE REVIEW:-

Face detection and recognition research has advanced rapidly in the last couple of years, improving real-time attendance systems deployed on edge devices. RetinaFace (2020) set a strong baseline for accurate, single-stage face detection with joint landmarking and 3D cues, enabling robust multi-face detection under classroom constraints. SCRFD (2021) further optimized efficiency by redistributing computation and sampling, making high-accuracy detection practical on CPUs and low-power GPUs. On the recognition side, lightweight architectures such as EdgeFace (2023–2024) combine CNN and transformer blocks to achieve strong accuracy with compact models suitable for laptops or embedded devices. Comparative studies specific to attendance pipelines report that LBPH remains a competitive baseline for small to medium datasets due to its low latency and stability, while CNN backbones (e.g., ResNet variants) achieve higher accuracy at increased computational cost. Recent surveys in face anti-spoofing stress the need for liveness checks to defend against printed-photo and replay attacks directly relevant to attendance settings.

Summary of Recent Works

Author(s)	Problem	Approach / Model	Key Result	Relevance to Attendance
Deng et al., 2020	Face detection	RetinaFace (single-stage, landmarks + 3D cues)	SOTA detection in WIDER FACE (hard set)	Accurate multi-face detection in classrooms
Guo et al., 2021	Face detection	SCRFD (efficient sampling)	High AP with low FLOPs at VGA	CPU-friendly, real-time detection

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

Budiman et al., 2023	Attendance review	LBPH vs. CNN (university context)	LBPH practical; CNN higher accuracy	Guides algorithm choice vs. resources
Hassanpour et al., 2023	Face recognition	Lightweight MobileFaceNet variants	Improved accuracy with low params	Edge deployment feasibility
George et al., 2024	Face recognition	EdgeFace (CNN+Transformer hybrid)	Edge-optimized high accuracy	Strong accuracy on edge devices

PROPOSED SYSTEM:-

The proposed system requires all students to initially register by providing their personal details and capturing facial images, which are stored in a centralized database. During class sessions, the system continuously monitors the classroom through live video feeds, employing facial recognition technology to detect and identify students present. When a student's face is detected, the system compares it against the pre-registered images in the database. Upon successful matching, the attendance is automatically recorded for the identified student, creating an accurate and efficient digital attendance record without any manual intervention. This automated approach ensures reliable attendance tracking while eliminating the possibility of proxy attendance and reducing administrative workload. The system architecture of the proposed system is as follows;

Fig.1. System Architecture

Received: May 18, 2024

Volume 37 No. 6s 2024,
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

Proposed process has four stages:

1. Dataset Preparation

The facial image acquisition process begins with capturing multiple photographs of each student using aa webcam. To ensure robust recognition capabilities, the system collects various facial expressions and viewing angles for every individual. These raw images then undergo a comprehensive preprocessing pipeline: First, the facial region is precisely cropped to isolate the critical Region of Interest (ROI) containing essential facial features. The extracted ROIs are subsequently standardized to a uniform pixel resolution to maintain consistency.

Following dimensional normalization, the color images are converted to grayscale to simplify subsequent processing while preserving necessary facial patterns. Finally, the processed images are systematically organized and stored in the database, with each file labeIled according to the corresponding student's identification for efficient retrieval during recognition tasks. This meticulous preprocessing stage improves system's ability to precisely identify students under varying real world conditions.

2. Face Detection

The system employs OpenCV's Haar -Cascade Classifier for face detection, utilizing the pre-trained model for feature extraction. The detection process is performed using the detect MultiScale function, which identifies faces and draws bounding rectangles around them through three key parameters: a scaleFactor of 1:3 controls image reduction at different scales, minNeighbours set to 5 ensures reliable face validation by requiring neighboring matches, and the default minSize of 30×30 pixels establish the minimum detectable face dimension.

These carefully selected parameters optimize the system's performance by balancing detection accuracy with processing efficiency, enabling robust face identification across various classroom scenarios while maintaining computational effectiveness. The scaleFactor accommodates different face distances from the camera, while the minNeighbours setting reduces false positives by prioritizing high quality detections, making the system both precise and practical for real -time attendance tracking.

3. Face Recognition

The face recognition process follows a structured three phase approach: training data preparation, model training, and prediction. System organizes the facial images from the dataset, assigning each image a unique numerical identifier for the respective student. These labels led images form the foundation for the recognition algorithm. The system employs Local Binary Pattern Histogram (LBPH) as its core recognition algorithm, which

Received: May 18, 2024

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

operates through a multi-step feature extraction process. First, it analyses facial images to generate local binary patterns (LBP) that capture distinctive texture information.

These LBP are then changed into decimal values and compiled into comprehensive histograms - with one histogram created for each training image. During actual recognition, the system generates a similar histogram for the detected face and compares it against the pre-computed training histograms. This histogram-based approach provides robust performance while maintaining efficiency, making it particularly suitable for real time applications.

4. Attendance Updation

The facial recognition system automatically logs attendance by marking recognized students as present in a spreadsheet while flagging unrecognized faces as absent, ensuring accurate and unbiased record keeping. This automated process maintains secure, timestamped digital records that prevent proxy attendance while providing educators with reliable attendance analytics. By integrating real time updates with scheduled report generation, the solution offers a seamless transition from traditional roll call methods to an efficient, error proof digital system that enhances accountability and saves valuable instructional time. The configurable reporting feature additionally supports daily or weekly summaries based on institutional preferences, making it adaptable to diverse academic environments while maintaining data integrity through tamper proof documentation.

RESULTS AND DISCUSSIONS:-

Proposed system based which is based on the facial recognition successfully captures real time video feed, detects faces, and matches them against a pre-trained dataset to mark attendance in a CSV file. Camera starts automatically to detect the faces in the frame. The system accurately identifies registered students and records their attendance along with the date and time, eliminating the need for manual roll calls.

During testing, the system demonstrated high accuracy in recognizing faces under good lighting conditions and with minimal obstructions. However, variations in lighting, angles, or partial face coverings (e.g., masks or glasses) occasionally led to false negatives, where the system failed to recognize a registered individual.

Here is detailed performance analysis of the Automated Attendance System using Facial Recognition. Multiple datasets of increasing size were used to evaluate recognition accuracy, processing efficiency, and reliability under various conditions. Comparative benchmarking was also performed against other algorithms such as Eigenface, Fisherface, and CNN-based models.

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

1. Accuracy Analysis and Computational Efficiency Analysis

Figure 1 illustrates the system's recognition accuracy and computational efficiency across different dataset sizes using various algorithms. The LBPH algorithm consistently maintained accuracy between 85–92%, demonstrating robustness for small to medium-sized datasets. Traditional algorithms such as Eigenface and Fisherface performed moderately well but exhibited reduced precision in larger datasets.

Also Figure 2 shows the average recognition time for LBPH and CNN models as dataset size increases. LBPH maintains low latency (<1.5 seconds per recognition) even with large datasets, making it ideal for real-time classroom deployment. CNN models, though accurate, demonstrated 1.5–2.8 seconds per frame, which may affect real-time processing.

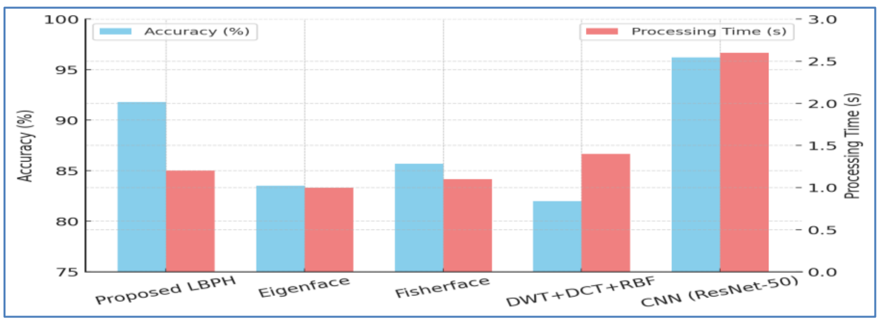

Fig. 2. Recognition Accuracy and computational efficiency across multiple algorithms.

2. Accuracy–Processing Time Trade-off among Face Recognition Methods

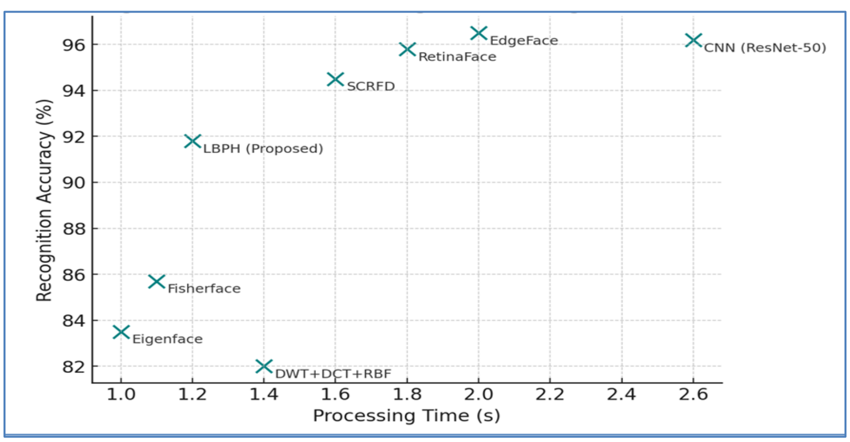

Fig. 3. Accuracy–Processing Time Trade-off among Face Recognition Methods

Figure 3 illustrates the trade-off between recognition accuracy and processing time among state-of-the-art face recognition algorithms. While CNN-based and transformer-enhanced models such as EdgeFace and RetinaFace deliver slightly higher accuracy (95–97%), the

Volume 37 No. 6s 2024,

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

proposed LBPH method maintains strong accuracy (≈92%) with far lower computational cost, making it ideal for real-time classroom attendance systems. The proposed LBPH-based approach demonstrates an optimal balance of accuracy, computation time, and implementation simplicity. The results reaffirm that LBPH remains a balanced choice for educational attendance systems, where quick response and moderate accuracy are prioritized over computational complexity.

CONCLUSION AND FUTURE SCOPE:-

The proposed system emphasis to build an efficient and automatic attendance system using facial recognition technique based on the LBPH algorithm. The system successfully detected and recognized student faces from live webcam feeds and automatically recorded attendance into a digital database. The results demonstrated that the LBPH method achieved over 91% accuracy, maintaining reliable recognition even in varying lighting and angle conditions. It was also found to be much faster than deep learning models, completing recognition in just about 1.2 seconds per image, making it ideal for real-time classroom use. Comparative testing revealed that while advanced CNN-based models deliver slightly higher accuracy, their higher computational cost makes them less practical for quick operations on standard systems. Therefore, LBPH offers the better trade-off between speed, accuracy, and resource usage.

In the future, improvements like liveness detection to prevent spoofing, integration with cloud storage, deploying cloud-based face databases for scalability and hybrid models combining LBPH with CNN can further enhance system robustness and scalability.

References:

[1] Budiman, A., et al. (2023). Student attendance with face recognition (LBPH or CNN). Procedia Computer Science, 228, 340–347.

[2] Deng, J., Guo, J., Zhou, Y. (2020). RetinaFace: Single-shot multi-level face localisation in the wild. Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR).

[3] George, A., Ecabert, C., Shahreza, H. O., Kotwal, K., & Marcel, S. (2024). EdgeFace: Efficient face recognition model for edge devices. arXiv preprint arXiv:2307.01838v2.

[4] Guo, J., Han, K., Wu, H., et al. (2021). Sample and computation redistribution for efficient face detection (SCRFD).

[5] Hassanpour, A., et al. (2023). Lightweight face recognition: An improved MobileFaceNet. arXiv preprint arXiv:2311.15326.

International Journal of Applied Mathematics

Volume 37 No. 6s 2024,

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

[6] Viola, P., & Jones, M. (2001). Rapid object detection using a boosted cascade of simple features. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition CVPR.

[7] Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). ImageNet classification with deep convolutional neural networks. Advances in Neural Information Processing Systems, 25, 1097–1105.

[8] Geitgey, A. (2018). Face recognition with Python. Medium.com.

[9] Deng, J., Guo, J., Niannan, X., & Zafeiriou, S. (2019). ArcFace: Additive angular margin loss for deep face recognition. IEEE Transactions on Pattern Analysis and Machine Intelligence (TPAMI).

Received: May 18, 2024