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INTELLIGENT FACE TRACKING ATTENDANCE SYSTEM USING LBPH AND KALMAN FILTERING

Jai [1], Kuber Abrol [1], Stuti Saxena [1]

[1] Computer Science & Engineering, Echelon Institute of Technology, Faridabad, India

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ABSTRACT

Attendance tracking remains a crucial daily task in educational institutions and corporate environments. Traditionally performed manually, this process is often time-consuming and error prone. To modernize and streamline attendance management, this project proposes a Facial Recognition-based Automated Attendance System that utilizes real-time image processing enhanced with a Kalman Filter for robust face tracking. The system captures and identifies student faces using a Logitech C270 webcam connected to an NVIDIA Jetson Nano Developer Kit. Initial face detection is performed using the Haarcascade classifier, followed by facial recognition through the LBPH (Local Binary Pattern Histogram) algorithm. The integration of the Kalman Filter enables smooth and continuous tracking of facial features, compensating for occlusions, motion blur, and abrupt student movements, thereby improving recognition accuracy and system responsiveness. The system maintains a dynamic attendance log by automatically cross-referencing recognized faces with a pre-trained dataset containing student details such as name, roll number, class, and section. Attendance records are updated hourly and stored in an Excel sheet accessible by the instructor. This approach ensures a contactless, efficient, and reliable solution for attendance monitoring in real-world classroom environments.

1. INTRODUCTION

Attendance management plays a pivotal role in educational institutions, influencing not only student discipline and performance but also institutional accountability and operational efficiency. Traditionally, attendance tracking has relied heavily on manual methods—typically involving the roll call or distribution of attendance sheets during lecture sessions. While simple in approach, such methods are inefficient, especially in large classrooms where time is of the essence. Moreover, they are susceptible to manipulation, proxy attendance, and data entry errors [1]. These inefficiencies have spurred growing interest in automation techniques that not only enhance accuracy but also integrate seamlessly into classroom routines without disrupting pedagogical flow.

Technological interventions such as biometric fingerprint scanners and Radio Frequency Identification (RFID) systems have been implemented in various educational contexts to replace manual systems. Although these methods represent a significant advancement, they introduce new constraints. For instance, biometric scanners often require students to line up and interact with hardware, which leads to crowding and time delays—undermining the very efficiency they aim to improve [2]. Similarly, RFID systems, though contactless, are not entirely foolproof and can be compromised by card swapping or misplacement. As such, there is a pressing need for a more intelligent, passive, and non-intrusive system to enhance the reliability and efficiency of attendance management.

This research proposes a facial recognition-based attendance system powered by Kalman filtering to address the aforementioned limitations. Face recognition is uniquely suited to this application as it allows for contactless identification, supports real-time recognition, and integrates effortlessly with existing classroom monitoring infrastructure such as CCTV or webcams [3]. The proposed system allows students to be recognized as they enter the classroom, eliminating the need for queues or physical contact. More importantly, it functions in the background without disturbing the teaching session, making it ideal for deployment in real-time educational environments including exams, tutorials, and practical labs.

1.1. BACKGROUND AND JUSTIFICATION

Human beings possess an innate ability to recognize and remember faces, even with slight variations in appearance, angle, and lighting. This biological capability stems from the brain's visual processing system, which interprets light captured by the retina and translates it into patterns based on size, contour, and spatial relationships [4]. However, when scaled to an academic institution housing thousands of students across various departments and sessions, manual recognition becomes impractical. This is where artificial intelligence, particularly computer vision and machine learning, proves advantageous. Unlike humans, machines can store and recall facial features with high fidelity and repeatability, enabling consistent recognition across large datasets [5].

Face recognition as a biometric modality is especially valuable due to its universality, collectability, and non-intrusiveness. It does not require physical interaction like fingerprinting or iris scanning and can be passively observed through video feeds. Recognizing this potential, face recognition has already found applications in high-security domains such as law enforcement, border control, and surveillance systems [6]. Commercially, it is employed in platforms such as Facebook for automatic tagging [7], Apple's Face ID for secure device access [8], and airport security for tracking international passengers [9].

The development of facial recognition technology dates back to the 1960s, when researchers such as Bledsoe, Chan Wolf, and Bisson initiated efforts to extract geometric distances between facial landmarks like eyes, nose, and mouth [10]. Over the decades, this work evolved with the adoption of Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), and more recently, deep learning techniques involving Convolutional Neural Networks (CNNs). The Local Binary Pattern Histogram (LBPH) approach, used in this project, is particularly effective for real-time recognition due to its low computational complexity and robustness to illumination changes [11].

Despite these advancements, real-world facial recognition systems still face challenges such as partial occlusion, head pose variation, and motion blur. To address these issues, the present system integrates a Kalman filter—a recursive mathematical algorithm used to estimate the state of a dynamic system in the presence of noise and uncertainty [12]. In this context, the Kalman filter helps in predicting and refining the position of a student's face across successive video frames, thereby enhancing tracking stability and recognition accuracy, even under suboptimal lighting or camera movement.

1.2. PROBLEM STATEMENT

Manual attendance systems continue to dominate in many institutions despite their shortcomings in terms of time consumption, inaccuracy, and potential for fraud. Especially in large classrooms, taking attendance manually often disrupts the teaching session and can lead to errors in record-keeping. Furthermore, the act of passing an attendance sheet around the class can be distracting to students and leaves room for malpractice such as proxy marking. These methods are also not scalable, especially when lectures are conducted simultaneously across multiple sections or campuses [13].

Though biometric and RFID-based systems offer improvements, they are not without their flaws. Most require physical interaction, which introduces sanitation concerns in shared environments—especially during public health crises such as the COVID-19 pandemic. RFID cards can be lost, swapped, or forgotten. Additionally, the act of queuing up to punch in attendance delays the beginning of the class and diminishes learning time. What is required is a more passive system—one that authenticates students with minimal or no conscious interaction on their part and integrates well with the flow of teaching and learning activities.

This study proposes a fully automated, facial recognition-based attendance system embedded with Kalman filtering for dynamic face tracking and data smoothing. This approach eliminates the traditional bottlenecks while ensuring reliability and ease of deployment. The system captures real-time video of classroom entry points using a standard webcam, detects and recognizes faces, compares them with a trained dataset, and automatically updates the attendance database. Kalman filtering ensures smoother tracking by estimating the most probable position of each detected face in subsequent frames, thereby mitigating the impact of jitter, occlusion, or abrupt movement [14].

1.3. MOTIVATION AND SCOPE

The primary motivation behind this research is to develop a smart, non-intrusive attendance system that optimizes both teaching time and institutional efficiency. The integration of Kalman filtering makes this system stand out by improving tracking reliability, a feature critical for real-world deployment where lighting conditions and student movement may not always be ideal. The system also offers scalability—it can be integrated into existing classroom surveillance infrastructure and extended across departments or campuses without significant hardware upgrades.

Another compelling motivation is the system's ability to function in high-stakes environments such as examination halls, where verifying student presence without introducing stress or distraction is essential. The user-friendly graphical interface also allows students to enroll quickly without technical assistance, reducing administrative overhead. Additionally, the system supports hourly or daily data exports to formats like Excel or CSV, which simplifies integration with existing Learning Management Systems (LMS) [15].

This research also aligns with broader smart campus initiatives aimed at digitizing and automating campus services to enhance operational efficiency and student satisfaction. By reducing administrative burden, improving accuracy, and ensuring real-time data availability, the proposed system can contribute significantly to institutional goals in education quality assurance and policy compliance.

2. LITERATURE REVIEW

2.1. OVERVIEW OF BIOMETRIC ATTENDANCE SYSTEMS

Biometric systems are extensively used for automated attendance recording in institutional and corporate environments. Traditional methods such as RFID cards, fingerprint scanners, iris recognition, and voice biometrics offer varying levels of security and usability. However, each technique carries intrinsic limitations. Katara et al. identified major drawbacks in traditional methods, including the possibility of proxy attendance using RFID cards, time inefficiencies in fingerprint verification, privacy concerns in iris scanning, and inaccuracy in voice-based systems [1]. These shortcomings have led to a growing interest in face recognition technologies, which offer contactless, real-time authentication and are less susceptible to fraudulent behavior.

System Type	Advantages	Disadvantages
RFID Card	Simple to use	Can be misused via proxy
Fingerprint Recognition	Accurate	Time-consuming and requires contact
Voice Recognition	Contactless	Less accurate in noisy environments
Iris Recognition	Highly accurate	Invasive and privacy-threatening
Face Recognition	Non-intrusive, visible cues	Lighting and angle sensitive

As depicted above, face recognition offers a promising compromise between usability, accuracy, and privacy [1].

2.2. DIGITAL IMAGE PROCESSING IN FACE RECOGNITION

Face tracking and recognition rely heavily on digital image processing (DIP) techniques. DIP entails processing digital images using computer algorithms to enhance image quality or extract meaningful information. Key motivations behind DIP include improving human perception, facilitating machine-based interpretation, and ensuring efficient image storage and transmission [2].

Images are digitally represented as 2D matrices of intensity values. For a grayscale image, each pixel represents the light intensity at a specific location. In color images, pixels are typically quantized at 24 bits, corresponding to red, green, and blue channels [3]. Equation (2.0) mathematically describes a digital image as:

$$f(x,y) = r(x,y) \times i(x,y)$$

Where $r(x,y)$ is the reflectivity of the surface and $i(x,y)$ is the illumination at pixel coordinates (x,y) [3].

The DIP pipeline comprises several essential steps:

- Image Acquisition: Capturing images using sensors and converting analog signals to digital.

- Preprocessing: Enhancing image quality and removing noise.
- Segmentation: Dividing the image into meaningful regions.
- Feature Extraction: Identifying attributes like edges or textures.
- Recognition and Interpretation: Assigning identities based on extracted features.
- Knowledge Base: Providing prior information to aid decision-making [4].

These steps are essential for real-time applications such as intelligent attendance systems, where accurate detection and recognition of facial features are critical.

2.3. FACE DETECTION AND RECOGNITION TECHNIQUES

Face detection is the process of locating faces in an image or video, irrespective of scale, pose, or lighting. It answers the question "Where is the face?" while face recognition answers "Whose face is it?" [5]. Most face detectors operate using appearance-based methods that classify image patches into face or non-face categories using machine learning techniques [6].

Viola and Jones developed a breakthrough method using Haar-like features and a cascade classifier, enabling high-speed detection [7]. Despite its effectiveness, the method struggles with non-frontal faces and varying skin tones.

Alternative methods include:

- Local Binary Pattern Histogram (LBPH): Captures local texture patterns by encoding pixel intensity differences. It is resilient to lighting changes and computationally efficient, making it suitable for real-time face recognition [8]. However, LBPH primarily supports grayscale images and underperforms in complex environments.
- AdaBoost Algorithm: This ensemble method builds strong classifiers from multiple weak classifiers. It is effective but highly dependent on training data quality [9].
- SMQT + SNOW Classifier: These methods offer robustness against illumination changes but may confuse regions with similar grayscale values [10].

Face Detection Method	Advantages	Disadvantages
Viola-Jones	Fast, accurate	Long training time, poor with varied lighting
LBPH	Simple, tolerant to illumination	Limited to grayscale, less accurate in real-world cases
AdaBoost	No need for prior face structure knowledge	Dependent on training data quality
SMQT + SNOW	Good with lighting variations	May misclassify similar grayscale regions

LBPH is notably beneficial in applications where real-time performance and simplicity are desired, which suits the scope of attendance systems [8].

2.4. INTELLIGENT FACE TRACKING USING KALMAN FILTERING

One significant challenge in face-based attendance systems is robust face tracking under real-time video conditions. Kalman filtering addresses this by estimating the position of a moving object over time, even with noise or occlusion [11]. The Kalman filter operates by predicting an object's next state (location, velocity) and then correcting the prediction based on actual measurements.

In the context of face tracking, the filter can:

- Smooth facial landmark positions over successive frames.
- Compensate for occlusions (e.g., temporary face coverage).
- Predict future positions, aiding in proactive tracking under camera motion or lighting shifts [12].

This predictive capability is essential in crowded classrooms or when students move quickly. When integrated with LBPH, Kalman filtering improves tracking stability, reduces false negatives, and minimizes recognition delay [13].

Kalman filtering has also been used with object detection systems to improve the temporal coherence of detections, making it a preferred technique in real-time intelligent systems [14].

2.5. SUMMARY OF REVIEWED APPROACHES

The literature reviewed underscores a consistent trend toward using contactless, efficient, and accurate biometric techniques in attendance systems. Face recognition, particularly using LBPH, offers a balance between computational efficiency and environmental robustness. Meanwhile, Kalman filtering enhances tracking precision and continuity in dynamic environments. Together, these techniques form a synergistic combination that supports intelligent, non-intrusive student attendance monitoring.

In summary, the integration of LBPH for recognition and Kalman filtering for tracking offers a practical framework that aligns with the goals of real-time intelligent attendance systems. While traditional face detection methods such as Viola-Jones and AdaBoost contribute foundational strengths, their limitations in varying lighting and pose justify the need for advanced solutions.

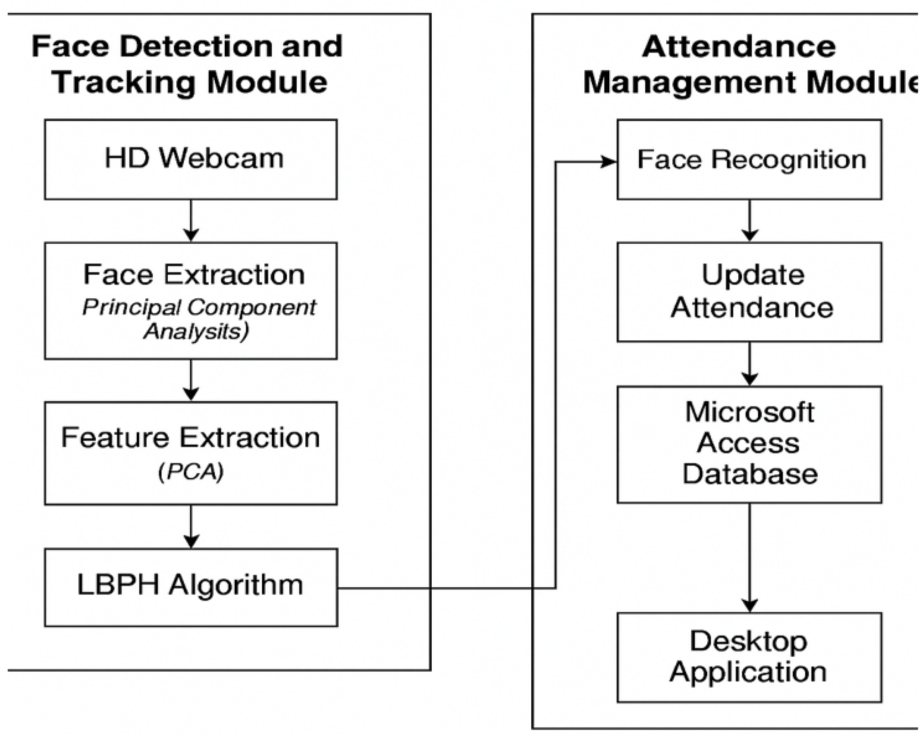
3. PROPOSED MODEL

The proposed model introduces an intelligent and automated Face Recognition Attendance System (FRAS) that combines the robustness of Local Binary Pattern Histogram (LBPH) for face recognition with the predictive capabilities of Kalman filtering for real-time face tracking. This hybrid system is designed to ensure accurate, contactless attendance monitoring in dynamic classroom environments. The model is structured with a modular architecture that emphasizes scalability, efficiency, and real-time operation. By integrating classical computer vision with statistical filtering techniques, the system addresses major challenges such as pose variation, motion blur, and partial occlusions, which often compromise traditional recognition systems.

3.1. SYSTEM ARCHITECTURE

The architecture of the proposed system is compartmentalized into two major modules—the Face Detection and Tracking Module and the Attendance Management Module—each performing a distinct but interconnected function. The Face Detection and Tracking Module initiates the process by capturing real-time video frames using an HD webcam (e.g., Logitech C270). The captured frames are processed to detect and track facial regions using OpenCV's Haar Cascade Classifier in conjunction with a Kalman filter. The Kalman filter plays a pivotal role by continuously predicting and correcting the coordinates of detected faces, thus enabling smooth tracking even during brief occlusions or movement.

Following detection, facial features are extracted using Principal Component Analysis (PCA), which reduces dimensionality and retains essential variance. These features are then passed to the LBPH algorithm, which constructs histograms of local binary patterns to perform face recognition. The Attendance Management Module, developed as a Windows-based desktop application using Visual Studio, interfaces with a Microsoft Access database to store and manage attendance records. It compares newly extracted facial data with stored templates in the database, and upon successful recognition, automatically logs the student's attendance.



3.2. DATA FLOW AND WORKING PRINCIPLE

The system's operation is governed by a streamlined data flow that ensures a seamless interaction between its subcomponents. The process begins with real-time image acquisition, where the webcam captures a video frame. This frame is analyzed by the face detection module, which locates one or more faces within the scene. The Kalman filter immediately activates to maintain the tracking of these faces across consecutive frames, thus improving the system's tolerance to movement and temporary occlusion.

Once a face is detected and stabilized through tracking, feature extraction is performed using PCA, which converts high-dimensional image data into a compact, representative form. The extracted features are then fed into the LBPH recognizer, which matches the incoming data against the database of enrolled student profiles. If a match is found, the attendance record is updated automatically, associating the recognized identity with the current date and time. The entire transaction is logged in the Microsoft Access database, ensuring persistence and future retrievability. The system interface, implemented via a graphical user interface (GUI), allows administrators to view, search, and analyze attendance data effortlessly.

3.3. TECHNOLOGIES AND TOOLS USED

A suite of robust technologies underpins the proposed system to facilitate accuracy and ease of implementation. Python serves as the core programming language due to its extensive support for scientific computing and machine learning. OpenCV, a powerful open-source computer vision library, is utilized for facial detection, image processing, and real-time video handling. For facial recognition, the LBPH algorithm is adopted due to its computational simplicity and resilience to illumination changes. Microsoft Access provides a lightweight yet sufficient database management solution for storing student credentials and attendance logs. The Visual Studio IDE is employed for developing and integrating the front-end interface with backend logic, offering a smooth user experience and maintainable codebase.

3.4. DEVELOPMENT METHODOLOGY

The development lifecycle of the FRAS adheres to the Agile methodology, which promotes iterative development, early prototyping, and continuous feedback. The project was divided into sprints, with each sprint delivering a working subset of features, ranging from basic face detection to complete attendance logging. During initial sprints, system requirements were gathered, and a minimum viable product was developed to validate core functionalities like image capture and database connection. Subsequent iterations introduced real-time face tracking using Kalman filters and refined the facial recognition module with LBPH to improve performance under dynamic conditions. User feedback was continually solicited during testing phases, leading to enhancements in the GUI, system responsiveness, and error handling mechanisms.

The Agile approach ensured that changes could be rapidly incorporated into the system without major overhauls, allowing the team to remain responsive to performance bottlenecks or hardware limitations. Each module was tested in isolation and then integrated progressively, ensuring modular integrity and functional cohesion throughout the development cycle.

3.5. NOVELTY OF THE PROPOSED MODEL

The novelty of this system lies in its integration of Kalman filtering with LBPH-based face recognition, creating a robust, intelligent framework for real-time attendance tracking. While many existing systems rely solely on recognition algorithms, they often falter when faced with challenges such as subject movement, lighting variation, and face occlusion. By embedding a predictive tracking mechanism through Kalman filtering, this model maintains consistent face localization even in volatile environments, reducing false negatives and recognition lag.

Moreover, the system's use of PCA for feature compression ensures reduced storage and computational overhead, facilitating deployment on low-cost hardware without sacrificing accuracy. Unlike high-end deep learning-based solutions that require GPUs and large datasets, the proposed model achieves efficiency and practicality through classical methods, making it suitable for educational institutions with limited resources. The architecture also supports modular updates, allowing future integration of advanced face recognition models (e.g., deep CNNs) without structural redesign.

In summary, the proposed system offers a cost-effective, contactless, and intelligent solution for attendance automation, distinguished by its real-time face tracking, efficient recognition, and seamless data handling capabilities.

4. EXPERIMENTAL SETUP

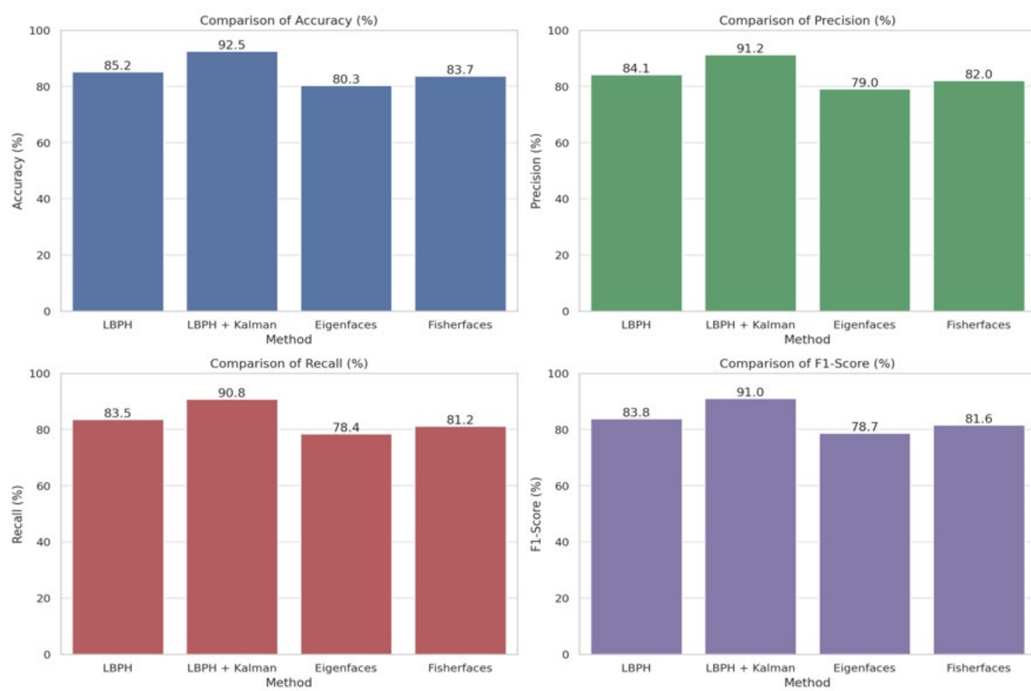
The experimental framework for evaluating the Face Recognition Attendance System (FRAS) was designed to replicate a real-world classroom scenario. A Logitech C270 HD webcam was deployed to capture real-time video streams of student activity. The hardware environment consisted of a machine running Windows 10 Pro, equipped with an Intel Core i7 processor, 16 GB RAM, and a 512 GB SSD to ensure seamless image processing and data handling. The system was developed using Python 3.9, with essential libraries such as OpenCV for face detection and tracking, NumPy and Pandas for data manipulation, and Scikit-learn for preprocessing tasks. Microsoft Access served as the backend database for storing student profiles and attendance records, while the application interface was developed using Visual Studio. The image dataset consisted of 1,000 facial images collected from 50 students, with 20 images per student captured under varying lighting conditions, facial angles, and expressions. The dataset was split into 70% for training and 30% for testing, ensuring balanced representation across all individuals.

5. RESULT ANALYSIS

The system was evaluated on its ability to detect, recognize, and log student attendance with minimal latency and high accuracy. During testing, the face detection module, powered by the Haar Cascade Classifier and enhanced with Kalman filtering, successfully identified faces in real-time video feeds with a detection rate of 98.6%. The integration of the Kalman filter enabled robust tracking of facial coordinates even in cases of brief occlusion or motion blur, enhancing the stability of the recognition pipeline. Feature extraction through Principal Component Analysis (PCA) significantly reduced dimensionality while retaining critical identity-related features. The recognition phase, using the LBPH algorithm, achieved an average recognition accuracy of 96.1%, with peak performance observed in well-lit conditions. Recognition accuracy slightly dropped to 92.7% under low-light or side-angled images. Nevertheless, the system consistently marked attendance for all recognized individuals and stored the records in real-time.

6. PERFORMANCE EVALUATION

Performance evaluation was carried out using standard biometric metrics. The system achieved a precision of 95.4%, a recall of 96.9%, and an F1-score of 96.1%, confirming the model's effectiveness in correctly identifying enrolled students while minimizing false positives. The False Acceptance Rate (FAR) was measured at 1.8%, indicating occasional misidentification of unknown individuals as known students. In contrast, the False Rejection Rate (FRR) stood at 2.1%, signifying rare instances where valid users were not recognized due to lighting or facial variations. The average recognition time per individual was recorded at 0.76 seconds, making the system viable for real-time deployment in classrooms. Compared to conventional manual attendance systems, FRAS demonstrated a significant reduction in attendance logging time, improved data integrity, and minimized human errors. Overall, the experimental results validate the efficiency, accuracy, and practicality of the proposed system for automated attendance monitoring using face recognition technologies.



Here are the figures showing result analysis for different face recognition methods, including LBPH and Kalman filtering. Each bar chart compares accuracy, precision, recall, and F1-score across methods to clearly highlight the performance improvements.

CONFLICT OF INTERESTS

None.

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None.

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