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AUTOMATED ATTENDANCE SYSTEM USING DEEP LEARNING

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Abstract: This project introduces an automated attendance management system designed to modernize and streamline traditional manual attendance tracking. The system leverages Deep Learning-based Face Recognition using the LBPH (Local Binary Pattern Histogram) Face Recognizer as its core identification engine, with a Flask web framework providing a browser-accessible interface. The system captures student facial images via webcam, preprocesses them through grayscale conversion and histogram equalization, and compares extracted LBPH histograms against a stored database to identify students accurately. Attendance is automatically recorded with a timestamp in a MySQL database, eliminating human error and proxy attendance. The system incorporates an Admin Module for model training, attendance monitoring, and automated email/SMS parent notifications, and a Student Module for facial recognition check-in and academic record access. Experimental results demonstrate 94.3% recognition accuracy under standard lighting, with end-to-end processing latency of approximately 95 ms.

Index Terms: Attendance Management, Computer Vision, Deep Learning, Face Recognition, LBPH, Flask, MySQL, Biometric Systems.

INTRODUCTION

Manual attendance systems in educational institutions are time-consuming, error-prone, and susceptible to proxy attendance. Traditional roll-call methods consume an average of 7.2 minutes per class session, representing significant lost instructional time over an academic year. As educational institutions increasingly adopt technology solutions, automated biometric attendance systems offer a compelling alternative that simultaneously eliminates proxy attendance and reduces administrative burden.

The Local Binary Pattern Histogram (LBPH) algorithm, proposed by Ojala et al. (1994, 2002), provides a robust and computationally efficient solution for face recognition in constrained environments such as classrooms. LBPH encodes the local texture structure of facial images through a spatially-distributed histogram representation that is inherently robust to monotonic illumination changes—a key advantage in classroom settings where lighting conditions vary throughout the day.

This paper presents the design and implementation of a web-based automated attendance system built on the LBPH face recognizer, Flask web framework, and MySQL database. The system is designed for deployment on standard institutional hardware without specialized equipment, making it economically viable for resource-constrained institutions. Key contributions include a complete face recognition pipeline from image acquisition through attendance recording, an automated parent notification system via email and SMS, and a dual-module architecture serving both administrators and students.

LITERATURE SURVEY

The development of face recognition-based attendance systems has been an active research area over the past two decades. Azkal et al. [1] conducted an exploratory study of deep learning techniques for attendance systems, comparing CNN-based approaches with classical methods. Their findings highlighted the trade-off between accuracy and computational requirements, concluding that classical methods such as LBPH remain competitive for small-to-medium student populations.

Patil et al. [3] reviewed IoT-based face recognition attendance systems, identifying webcam-based systems as the most practical approach for indoor classroom environments. Their comparative analysis showed LBPH outperforming PCA-based methods under varying illumination conditions. Smitha et al. [5] implemented an LBPH-based attendance system achieving 91% accuracy, noting that training dataset diversity was the primary determinant of recognition performance.

Alhanaee et al. [6] evaluated deep transfer learning approaches using VGG-Face and FaceNet architectures, achieving 97.8% accuracy but requiring GPU hardware not available in typical institutional settings. Goswami et al. [7] proposed an OpenCV-based system using the Haar Cascade detector combined with LBPH recognition, demonstrating that end-to-end processing latency under 150 ms is achievable on standard hardware—a threshold identified as critical for user acceptance. Airij et al. [8] introduced a smart attendance system with physical presence verification and centralized database integration, emphasizing the importance of de-duplication logic to prevent multiple attendance recordings per session.

The reviewed literature consistently identifies four key challenges in face recognition attendance systems: illumination variation, pose variation, computational efficiency, and database scalability. The proposed system addresses the first two through preprocessing (histogram equalization) and dataset diversity protocols, and the latter two through the selection of LBPH over deep learning architectures.

SYSTEM ARCHITECTURE AND METHODOLOGY

A. System Architecture

The system follows a three-tier architecture: (1) Presentation Layer — Flask web interface serving HTML templates via Jinja2; (2) Application Logic Layer — Python-based face recognition pipeline and business logic; and (3) Data Layer — MySQL database. Four key components are interconnected: Admin Interface, Student Dashboard, Parent Notification Service, and MySQL Database.

The Admin Interface allows administrators to manage student records, capture training images, initiate model training, and trigger parent notifications. The Student Dashboard provides students with facial recognition check-in, attendance history viewing, and marks download. The Parent Notification Service dispatches automated email (SMTP/Flask-Mail) and SMS (Fast2SMS API) alerts when attendance falls below configurable thresholds.

B. Face Recognition Pipeline

The recognition pipeline comprises five stages: Image Acquisition, Preprocessing, Face Detection, Feature Extraction, and Recognition.

- **Image Acquisition:** OpenCV's VideoCapture captures frames at 640×480 pixels, 30 fps from the webcam (device index 0).
- **Preprocessing:** Each frame undergoes BGR-to-grayscale conversion ($Y = 0.114B + 0.587G + 0.299R$) followed by histogram equalization using cv2.equalizeHist(), compensating for illumination variation.
- **Face Detection:** Haar Cascade Classifier detects face bounding boxes with parameters scaleFactor=1.1,minNeighbors=5, minSize=(30,30). Detected face regions are cropped and resized to 200×200 pixels.
- **Feature Extraction (LBPH):** The LBPH operator cmputes: $LBP(x,y) = \Sigma\, s(g_p - g^c) \cdot 2^p$, where g^c is the central pixel intensity, g_p is the p-th neighbor intensity, and $s(t) = 1$ if $t \geq 0$. The image is divided into an 8×8 grid; each cell yields a histogram of 256 LBP values. Concatenated histograms form the feature vector.
- **Recognition:** Euclidean distance $D(h_1, h_2) = \sqrt{[\Sigma_i(h_1(i)-h_2(i))^2]}$ compares the query feature vector against all stored vectors. The student with minimum distance below threshold T=70 is identified. Distance exceeding T results in an 'unknown' classification with no attendance recorded.

C. Training Dataset Protocol

For each enrolled student, the system captures a minimum of 50 training images over a 30-second automated session. Students are instructed to vary facial expression, head orientation, and camera distance during capture. Blur detection via Laplacian variance (threshold = 100) rejects motion-blurred frames. All accepted frames are cropped, resized to 200×200 pixels, histogram-equalized, and stored as PNG files in student-specific directories.

The LBPH recognizer's train() method is invoked on all collected images to build the initial model, which is serialized as a YAML file (~5–20 MB). New students are incorporated using the update() method without full retraining, supporting incremental enrollment throughout the academic year.

D. Attendance De-duplication and Security

De-duplication operates at two levels: an in-memory set provides O(1) lookups within each session; a database-level UNIQUE constraint on (RollNo, AttendanceDate) serves as a backstop. Authentication uses bcrypt password hashing (work factor 12) and Flask session management with HTTP-only, TLS-secured cookies. All database queries use parameterized statements to prevent SQL injection.

IV. DATABASE DESIGN

The MySQL schema comprises four normalized tables:

Students: Primary key RollNo (VARCHAR); fields Name, Branch, Section, ContactNo, ParentEmail, ParentPhone, ImagePath.

Attendance: AttendanceID (auto-increment PK), RollNo (FK), AttendanceDate (DATE), AttendanceTime (TIME), Status(ENUM:PRESENT/ABSENT/LATE). UNIQUE(RollNo, AttendanceDate).

Marks: MarksID (PK), RollNo (FK), SubjectCode, SubjectName, MarksObtained (DECIMAL 5,2), TotalMarks (DECIMAL 5,2).

AdminUsers: Stores admin credentials with bcrypt-hashed passwords and role identifiers.

V. RESULTS AND PERFORMANCE EVALUATION

A. Recognition Accuracy

Performance was evaluated on a dataset of 36 students (50 training images, 20 test images per student) under three lighting conditions. Under standard fluorescent classroom lighting, the system achieved True Acceptance Rate (TAR) = 94.3%, False Acceptance Rate (FAR) = 2.1%, and False Rejection Rate (FRR) = 5.7%. Under 50% reduced lighting, TAR decreased to 89.7%. Under bright window backlighting, TAR was 87.2%, with histogram equalization providing partial compensation.

Students with 50 training images achieved average TAR of 95.1%, compared to 88.4% for students with fewer than 30 training images, underscoring the importance of the automated minimum-sample capture protocol.

B. Processing Speed

End-to-end latency was measured on the target hardware (Intel Core i5-8250U, 8 GB RAM, Ubuntu 20.04):

Haar Cascade face detection: 42 ms/frame at 640×480. LBPH feature extraction: 18 ms/face at 200×200. Database lookup across 36 students: 23 ms. Database write (attendance record): 12 ms. Total end-to-end latency: ∼95 ms, yielding ∼10 recognition events/second — sufficient to process 60 students in approximately 6 seconds.

C. System Reliability

An 8-hour continuous operation test processed 1,482 recognition events across 6 simulated class periods. No crashes or unhandled exceptions were observed. Memory remained stable at ~450 MB. Database performance varied less than 5% over the test period. The system handled simulated network interruptions gracefully via local queuing with automatic database synchronization upon reconnection.

D. Comparison with Manual System

A four-week parallel pilot compared the automated system with traditional roll call in two sections (58 students each). Manual roll call required an average of 7.2 minutes per session; the automated system completed attendance in 2.1 minutes — saving 5.1 minutes per session (~51 hours of instructional time per section per academic year). The manual error rate was 3.8% (proxy attendance, transcription errors, missed entries); the automated system error rate was 5.7% (primarily false rejections), with zero proxy attendance incidents versus 8–12 estimated per month in the manual section.Parent communication: 34 low-attendance alerts were dispatched during the pilot; 28 parents responded within 48 hours (82% response rate). Post-pilot surveys showed 91% of parents preferred the automated notification system over the monthly physical mail reports.

VI. CONCLUSION AND FUTURE SCOPE

This paper has presented an automated attendance management system integrating LBPH face recognition, Flask web framework, and MySQL database. The system achieves ~94% recognition accuracy under standard classroom conditions with end-to-end processing latency of ~95 ms on standard hardware, eliminating manual roll calls and proxy attendance while providing automated parent notifications via email and SMS.

Future work will explore: (1) Migration to deep CNN architectures (FaceNet, ArcFace) for improved accuracy under challenging conditions; (2) Mobile application development for student and parent access; (3) Cloud deployment for multi-campus centralized management; (4) Liveness detection to prevent spoofing via photographs; and (5) Integration with institution-wide academic management platforms.

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