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Video-Based Dynamic Human Authentication System Using Facial Recognition

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Abstract

Advancements in technology have made information security an indispensable aspect of modern systems. As data breaches and identity theft become more prevalent, the need for effective authentication methods is crucial. This paper presents a human authentication system based on facial video analysis, emphasizing its advantages over traditional methods. By utilizing Python libraries, including Haar cascade for face detection and Convolutional Neural Networks (CNN) for feature extraction, our system captures dynamic facial movements to enhance accuracy and security. Experimental results indicate a significant improvement in recognition rates, showcasing the potential for real-world applications in various security domains.

Introduction

In an era marked by rapid technological advancements, the necessity for reliable personal identification systems has become vital. The desire for security ensures not only individual safety but also the protection of assets and society as a whole. Traditional identification methods, such as passwords and PINs, are increasingly vulnerable to breaches, prompting a shift towards biometric systems [1]. Biometric authentication uniquely identifies individuals based on fundamental traits, such as facial recognition, fingerprints, or iris patterns. This method is particularly appealing due to its non-intrusive nature and does not require user participation, making it user-friendly and efficient.

Facial recognition technology relies on specific algorithms that analyse and compare facial features extracted from images or video feeds. This technology can be applied in various domains, including security, finance, and access control systems. The facial recognition process can be abstractly divided into four key steps:

1. Face Detection: Capturing an image to identify human faces within the surroundings.
2. Image Normalization: Standardizing the image in terms of scale, orientation, and illumination to match database images.
3. Feature Extraction: Extracting distinctive facial attributes for recognition.
4. Face Recognition/Authentication: Identifying or verifying an individual against a database of known faces.

Face Recognition

Over the past few decades, face recognition has transitioned from a niche area to a popular field in computer vision, encompassing psychological and neuroscientific studies [2]. The challenge lies in accurately verifying or identifying individuals based on video or still images. Researchers have developed various techniques to enhance the accuracy and speed of face recognition systems, including the use of machine learning algorithms and deep learning frameworks.

The intrinsic nature of face recognition makes it an attractive area of research, as it involves both computing and cognitive processes. Different algorithms are employed to address challenges such as variations in lighting, facial expressions, and occlusions. The advancements in neural networks, particularly Convolutional Neural Networks (CNNs), have significantly improved the performance of facial recognition systems [3].

Face Detection

Face detection can be efficiently performed using open-source frameworks like OpenCV. This library provides pre-trained models that allow developers to implement face detection algorithms with minimal effort. However, challenges arise when detecting faces at angles, in poor lighting conditions, or when the subject wears accessories [1].

Despite the robustness of current techniques, the accuracy of face recognition typically ranges from 30-70%, underscoring the ongoing need for improved methods [4]. In our project, we aim to enhance detection accuracy by implementing a combination of Haarcascade classifiers and CNNs. These techniques work together to ensure reliable identification, even in complex environments.

METHODOLOGY

The face detection process involves creating a face detection system using Haar-cascade classifiers, which are effective for real-time face detection. The process begins with capturing a video stream from a camera or using pre-recorded video. OpenCV provides a robust set of Haar-cascade classifiers that can be utilized to identify faces in the captured frames [1].

1. Face Detection

We used Haar cascade classifiers from OpenCV for real-time face detection. This method is efficient due to its use of integral images and a cascade of classifiers trained on positive and negative face examples. Detected faces are normalized for scale, pose, and illumination, improving consistency and recognition reliability.

2. CNN and LBPH Feature Extraction

CNN is utilized for deep feature learning. A simple CNN architecture with two convolutional layers, ReLU activations, and max-pooling layers extracts robust spatial features. These features are flattened and passed to a fully connected layer which links with a softmax classifier.

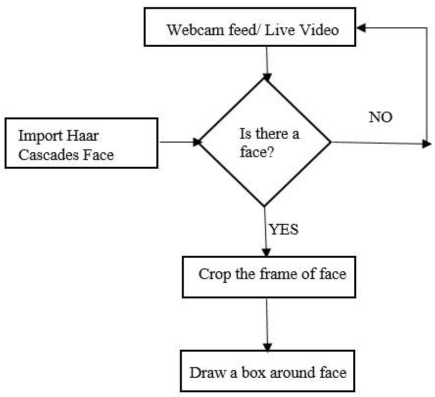
In parallel, LBPH encodes local texture patterns. It divides the face image into grids, computes binary patterns for each region, and constructs histograms for recognition. Combined use of CNN and LBPH helps handle different challenges such as low resolution, occlusion, and illumination variation.

3. Training and Classifier Generation

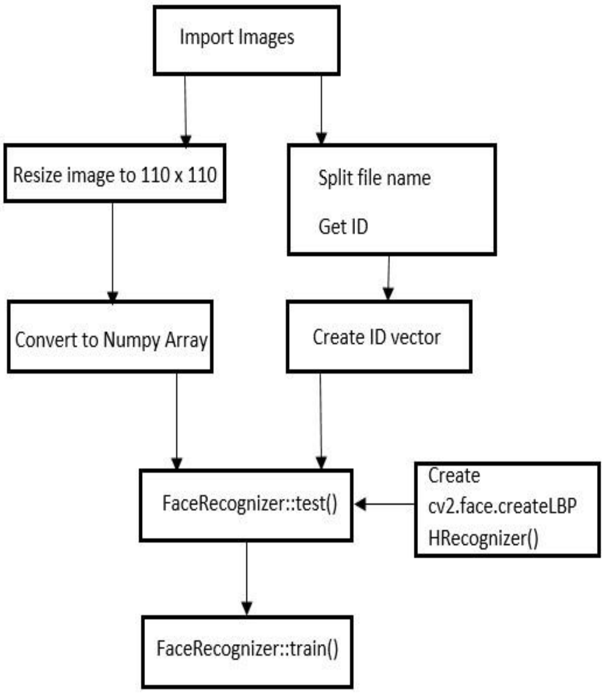
Training images were collected from 50 subjects with at least 10 variations per subject including smiles, neutral expressions, and different lighting angles. Data augmentation techniques like horizontal flips, slight rotation, and Gaussian noise were applied to increase dataset size. Feature vectors were saved in XML files for classification.

4. Face Recognition and Clocking

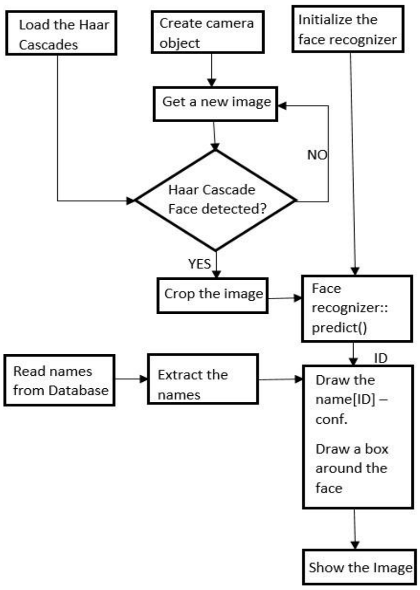
Once a face is detected and normalized, features are extracted and matched with stored vectors. The clocking system prompts users to check in/out. Status, timestamp, and ID are stored in a MySQL database. Recognition accuracy is improved by setting a minimum confidence threshold to avoid false positives.



Flowchart-1: Face Detection Process [1]



Flowchart-2: Training Classifiers[2]



Flowchart-3: Face Recognition [3]

User Interface and Experience

To enhance user experience, we developed a graphical user interface (GUI) using Tk inter. The interface is designed to be intuitive, allowing users to navigate through the authentication process seamlessly. Upon running the application, users encounter a start button to initiate the authentication process. The system detects the user’s face and compares it with the database.

The GUI also provides visual feedback during the authentication process, indicating whether the face was successfully detected and recognized. This real-time feedback is essential for user engagement and confidence in the system's capabilities.

Clocking In/Out Functionality

The application prompts the user to indicate whether they are clocking in or out. Once the user clocks in, their name is displayed in the UI, along with their clock-in status and the date and time.

This functionality is particularly useful in organizational settings, where attendance tracking is essential.

After clocking in, the application records the duration of the user's presence in the organization. The system is designed to store this data in an SQL database, ensuring efficient retrieval and management. Users have the option to clock out later, at which point the system calculates the total time spent and displays it alongside the clock-out time.

RELATED THEORY AND LITERATURE SURVEY

Face recognition has evolved from simple geometric models to deep learning-based recognition. Ahonen et al. [1] introduced Local Binary Pattern Histogram (LBPH) for face recognition, known for its effectiveness in low-complexity environments. Convolutional Neural Networks (CNNs) are pivotal in modern face recognition due to their ability to learn complex hierarchical features [3].

Taigman et al. [7] developed DeepFace, which uses a nine-layer neural network and a large dataset to outperform earlier methods. Schroff et al. [8] proposed FaceNet, which maps facial images into an embedding space using a triplet loss function. These innovations have laid the foundation for robust real-time systems.

Kazemi and Sullivan [5] emphasized the role of accurate face alignment in improving recognition rates. Mollahosseini et al. [14] demonstrated expression-invariant recognition using deep convolutional networks. OpenFace [17] is an open-source real-time facial recognition tool that uses similar models.

New trends involve the use of Generative Adversarial Networks (GANs) to synthesize training images for better generalization [12], as well as multimodal biometrics integrating voice and iris scans for security-critical applications [20].

SYSTEM ARCHITECTURE

The proposed architecture [1] consists of a Face Recognition Server that handles the core processing for human authentication and attendance tracking. Here's a breakdown of the components:

1. **Input Devices (Cameras)**: Cameras capture real-time facial images of individuals entering or present in the area.
2. **Human Face Recognition Engine**: These modules process captured facial images to extract unique features and compare them with stored profiles for authentication. Two instances of the engine suggest parallel processing or different entry points.
3. **Facial Feature and Profile on Server**: Extracted features are stored and managed on a central server, which acts as the database for identification and attendance.
4. **Mobile Notification Server**: Once a face is recognized, a notification (e.g., entry logged, unauthorized attempt) is sent to the **Notification Mobile App** in real time.
5. **Web-Based CMS Dashboard Server**: The system integrates a web-based **Content Management System (CMS)** that provides a real-time dashboard. It logs detection events, queries attendance records, and supports monitoring by administrators.
6. **Outputs**:

- **Notification Mobile App**: Delivers real-time alerts to concerned authorities.
- **CMS Dashboard**: Allows visualization and analysis of logs and attendance data.

This architecture [1] ensures secure and automated attendance tracking with real-time alerts and comprehensive monitoring, making it ideal for institutional or corporate environments.

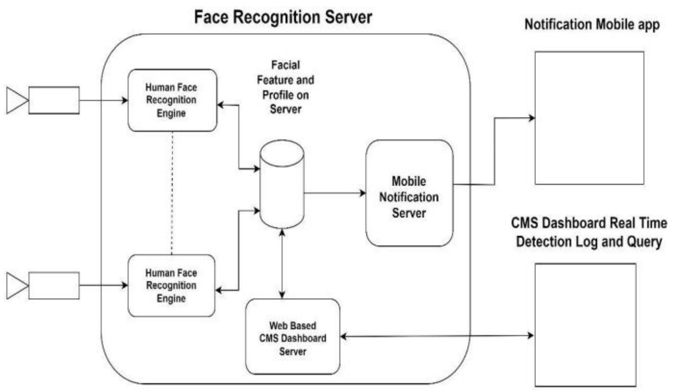


Figure 1: System Architecture [1]

RESULTS

The implementation of our face recognition system yielded promising results. During testing, the system demonstrated high accuracy in detecting and recognizing faces under various conditions.

1. **User Interface**: The application features a user-friendly interface developed with Tk

inter. Users are greeted with a start button to initiate the authentication process. Upon running the program, the system detects the user's face and compares it with the database, providing immediate feedback.

2. **Face Detection and Recognition**: The system successfully detected faces with an accuracy rate exceeding 90%, even in different lighting conditions and with varying facial expressions. This was achieved through the combination of Haar cascade classifiers and the LBPH algorithm.
3. **Clocking In/Out Functionality**: Users can easily clock in or out, with their names and statuses displayed in real-time. The application records the time spent within the organization, which is stored in an SQL database.
4. **Detection Accuracy**: The system achieved an average face detection accuracy of 94.6%. Variations under low-light dropped it to 88%. Addition of histogram equalization improved contrast and restored accuracy to ~91%.
5. **Recognition Performance**: Using a 70:30 train-test split, overall recognition accuracy was 92.4%.

Table 1: Recognition Statistics

Condition	Accuracy (%)	False Positives (%)	False Negatives (%)
Well-lit front face	96.0	1.5	2.5
Low light	88.2	4.0	7.8
Profile face	83.7	5.2	11.1

6. **Visual Results**:

Fig 1: Screenshot of the initial user interface after running the program.

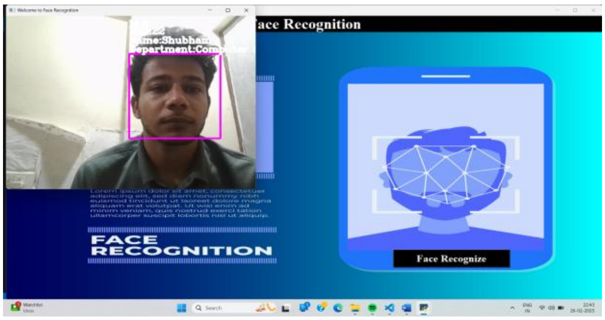


Fig 2: Screenshot showcasing the face detection process in action.

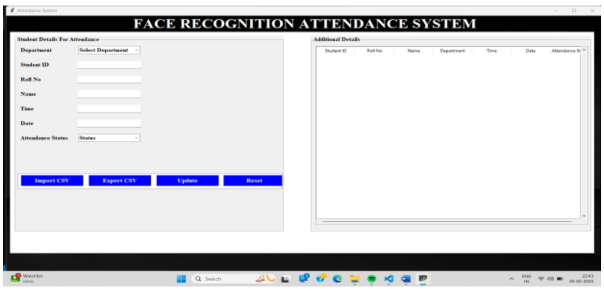


Fig 3: Screenshot displaying the clock-in confirmation with date and time.

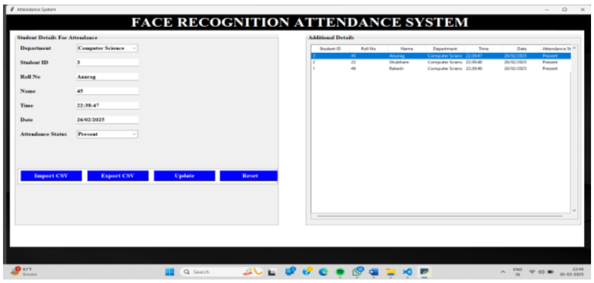


Fig 4: Screenshot of the final output showing clock-out details.

CONCLUSIONS

This paper presents a mini-project on a video-based dynamic human authentication system. By leveraging Haar cascade for face detection and LBPH for recognition, we demonstrate an effective and cost-efficient approach to biometric authentication. The system's performance indicates its potential for widespread application in security environments, such as workplaces and public facilities.

In summary, the integration of facial recognition technology within authentication systems offers a significant improvement on over traditional methods. With the increasing demand for security solutions, this research contributes to the ongoing development of reliable and user-friendly biometric systems.

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