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Face Recognition and Authentication Using Dlib for Examination Attendance System

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Abstract:
Facial recognition technology enables the identification and detection of individuals based on unique facial features. based on various labels such as name, ID number, etc. In this research, a face recognition system for examination attendance is implemented using the DLIB library. Since manual attendance is a tedious and time-consuming task, this research aims to automate the process, thereby increasing the integrity of examinations. The proposed solution reduces the workload of invigilators by eliminating the need to manually take attendance and fill out attendance sheets. The dataset for this research comprises a combination of student images captured by a camera and images from the database. The system utilizes the DLIB library to generate facial encodings, which are then used to identify students in real-time. Upon recognizing a student, the system logs their attendance by recording their name and the current timestamp in a CSV file. DLIB has pre-trained CNN models that can be used for face detection. This ensures accurate and efficient attendance tracking, providing a reliable record of student presence during examinations.

Keywords: Face detection, Face Recognition, DLIB Examination Attendance System (EAS), CNN.

1. INTRODUCTION

Biometric attendance systems have become increasingly prevalent, yet they often suffer from delays as individuals must queue to scan their fingerprints. To address this, we have proposed a technique to streamline attendance tracking. The human face, with its unique and distinct features, serves as a prime candidate for identification purposes. Each individual possesses a set of facial characteristics that differentiate them from others. The proposed system utilizes this unique feature to accurately identify individuals and mark attendance. Facial recognition entails analyzing and comparing facial features against a database of stored faces, making it a reliable method for verifying identity. In this paper, high-performance facial recognition, utilizing convolutional neural network, DLIB, to achieve real-time recognition is proposed offering a seamless and efficient solution for organizations and institutions across various sectors.

2. LITERATURE REVIEW

J. Cai, et.al. presented an improved D-S face detection algorithm designed for detecting facial fatigue signs in complex environments. Notably, it addresses challenges related to lighting and partial occlusion. The algorithm achieves an impressive accuracy rate of 93.8%.[1]

S. M. Anzar, et.al. introduced RIAMS, a novel multimodal attendance management system designed for post-COVID virtual learning. RIAMS combines various modalities, including facial recognition, voice recognition, and keystroke dynamics, to accurately track student attendance. The system addresses the challenges posed by remote learning and ensures reliable attendance monitoring. The proposed approach enhances the integrity of virtual classes and provides a seamless experience for both students and educators. The algorithm achieves an impressive accuracy rate of 99.38% but only static weights for face recognition and ancillary modalities are considered and it also incurs scalability issues. [2]

F. Albalas, et.al. proposes a novel approach for occluded face detection using deep graph-based convolutions. By learning discriminant spatial features, the model effectively handles occlusions in face images. The graph-based convolutions capture contextual information and improve detection accuracy. The proposed method enhances face detection performance, especially in challenging scenarios with partial occlusions. The algorithm achieves an impressive accuracy rate of 86% but Therefore, predicting the category of the detected face remains challenging. [3]

W. Sun, et.al. proposes a face spoofing detection method that combines domain adaptation and lossless size adaptation. The method aims to improve the robustness of face anti-spoofing systems. Key components include domain adaptation to handle domain shift (e.g., different lighting conditions, camera sources) and lossless size adaptation to address variations in face image sizes. By leveraging both techniques, the proposed method achieves better performance in detecting face spoofing attacks. The algorithm achieves an impressive accuracy rate of 50% but requirement of external data is its major limitation.[4]

E. Kim, et.al. introduces a method for detecting fake faces generated by deep neural networks. It combines content and trace feature extractors to identify inconsistencies in facial features. The proposed approach aims to expose deep fake images by analyzing both visual content and subtle traces left during the generation process. The algorithm achieves an impressive accuracy rate of 85.50%.[5]

H. Qi, et.al. proposes a real-time face detection method that leverages blink detection. By analyzing eye blink patterns, the system identifies faces in video streams. The approach aims to improve real-time performance and reduce false positives. The algorithm achieves an impressive accuracy rate of 95.32%.[6]

N. Li, et.al. proposes a Chinese face dataset specifically designed for face recognition in uncontrolled classroom settings. The dataset aims to address real-world challenges such as varying lighting conditions, occlusions, and diverse facial expressions. The algorithm achieves an accuracy rate of 70% but does not achieve good results in the recognition of Chinese faces.[7]

R. Qi, et.al. proposes a face detection method based on cascaded networks. The approach leverages a multi-stage architecture to improve face detection accuracy. The cascaded structure consists of multiple convolutional networks, each refining the face detection results. The method achieves better performance by iteratively adjusting the bounding boxes and reducing false positives. The algorithm achieves an accuracy rate of 95.3%.[8]

H. -B. Kim, et.al. presents a high-precision recognition of criminal faces from uncontrolled video footage. By

leveraging advanced face recognition techniques, the system aims to identify criminals accurately in challenging scenarios. The algorithm achieves an accuracy rate of 90%.[9]
F. You, et.al. proposes the algorithm aims to accurately identify drowsy drivers by analyzing features such as eye closure duration, blink frequency, and head movement. By accounting for individual variations in baseline behavior, the system enhances detection performance. The algorithm achieves an accuracy rate of 94.6% but there are scalability issues with this model.[10]

3. PROPOSED SYSTEM

Our proposed solution leverages advanced face recognition technology for automated attendance marking. The system begins by loading training images from a specified directory, extracting class names, and generating facial encodings for each image. A webcam captures real-time video frames, which are processed to detect and recognize faces. As shown in Figure 2, the confusion matrix demonstrates the distribution of correctly and incorrectly classified instances, giving a clear view of the model's performance. Detected faces are matched against the known encodings to identify individuals. When a match is found, the system draws a rectangle around the face, displays the name, and logs the attendance with a timestamp in a CSV file. The system operates efficiently in real-time, providing a seamless and accurate method for tracking attendance automatically.

4. METHODOLOGY

The face recognition and attendance marking system begins with loading training images from a specified directory. This process entails converting each image to RGB format and using a face recognition model to generate facial encodings. These encodings, which represent unique features of each face, are appended to a list for later comparison. With the training data prepared, the system initializes the webcam by opening a connection to it. The main loop of the system starts by capturing a frame from the webcam. This frame is resized and converted to RGB format to facilitate face detection and recognition. The system then identifies face locations and generates face encodings for the detected faces within the frame. For each detected face, the system compares its encoding with the known encodings from the training images. It computes the distances between the current face encoding and the known encodings to find the best match. If a match is found, the system retrieves the name associated with the matched encoding. A box is placed around the identified face and the name is displayed on the frame. Simultaneously, the system marks attendance by logging the recognized person's name and the current timestamp into a CSV file. The processed frame, now annotated with rectangles and names, is displayed in a window. The system continuously checks for an exit condition, such as a key press 'q', to terminate the loop. Upon exiting, the system performs clean-up by releasing the webcam and destroying all OpenCV windows, ensuring that resources are properly freed. In the Face Recognition and Authentication system using DLIB the algorithm is based on the DLIB library for facial recognition, specifically using Convolutional Neural Networks. DLIB uses a CNN-based model to generate facial encodings, which convert the facial features into a 128-dimensional vector.

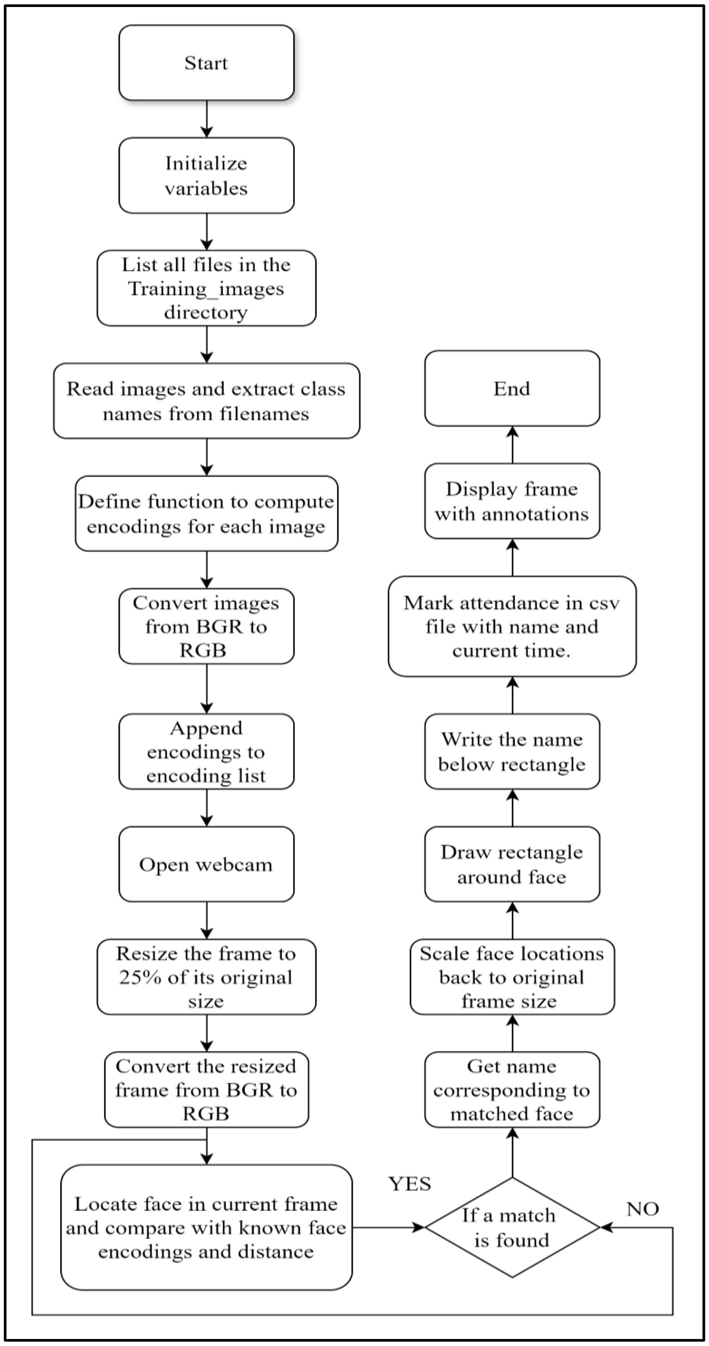

Figure 1: Flowchart of Methodology

CNN algorithm on a dataset of 680 instances, Typically, datasets are split into training and testing sets. A common split is:

- 80% for training (used to train the model),
- 20% for testing (used to evaluate the model).

Let’s apply this split for your dataset of 680 instances.

Training dataset:

Training Data = 80% × 680=0.80 × 680 = 544 instances

Testing dataset:
Testing Data = 20% × 680=0.20 × 680 = 136 instances
Thus, 544 instances will be used for training the model, and 136 instances will be used for testing the model's accuracy.
The system workflow is represented in Figure 1, where the flowchart maps out the core steps of the process This real-time face recognition and the attendance marking system demonstrates the practical application of computer vision techniques used in the automating identity verification and tracking.

5. RESULT AND DISCUSSION

The Images are detected and classified in their specific custom-made classes. Confusion Matrix is created and Accuracy of **97.32%** is achieved.
The is a key element to evaluate the execution of the model. This compares the actual outcomes (e.g., whether a student is truly present or not) with the predicted outcomes (whether the system identifies a person as present or absent). Here are the formulas related to the matrix, which can be utilize evaluate the accuracy and performance of your Dlib-based face recognition and authentication system:

- Step 1: **Accuracy Formula**

Given: Accuracy = 97.32% Total numbers of Students= 680
Subtitle in the accuracy formula:

$$0.9732 = \frac{\mathrm{TP} + \mathrm{TN}}{680}$$

Rearrange to calculate TP+TN: TP+TN =0.9732×680 = 662.5
This means that 663 instances were classified correctly.

- Step 2: **Calculating Incorrect Classifications (FP + FN)**

The number of incorrect classifications is:
FP+FN=680−(TP+TN)
Substitute the values:
FP+FN= 680−663 = 17
So, there are 17 incorrect classifications.

- Step 4: **Final Confusion Matrix Values**
  Based on these calculations, we have:
  - True Positives (TP) = 332
  - True Negatives (TN) = 331
  - False Positives (FP) = 9
  - False Negatives (FN) = 8

- **Accuracy:** It measures the effectiveness system by showing in percentage of accurate identification out of all attempted identifications.

$$\text{Accuracy} = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}}$$

$$= \frac{332+331}{332+331+9+8}$$

$$\text{Accuracy} = \frac{663}{680} = 0.9732 \times 100 = 97.32\%$$

- **Precision:** It shows the proportion of true positives out of all positives identified by the system. A high precision means that when the system identifies a face as a student, it is highly likely to be correct.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} = 0.9736$$

- **Re-Call:** Utilization is crucial when the system's main concern is to ensure that every registered student is correctly identified. A huge recall means the system correctly identify most of students, reducing the chances of marking a student as absent when they are present.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} = 0.9765$$

- **F1-Score:** The metric is the harmonic mean of precision and recall. It helps balance the need to avoid both misidentifying unauthorized individuals (false positives) and failing to recognize authorized students (false negatives). A high F1-Score indicates a well-rounded system.

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} = 0.9744$$

The summary of these key performance metrics is presented in Figure 3, where accuracy and other relevant statistics are compared

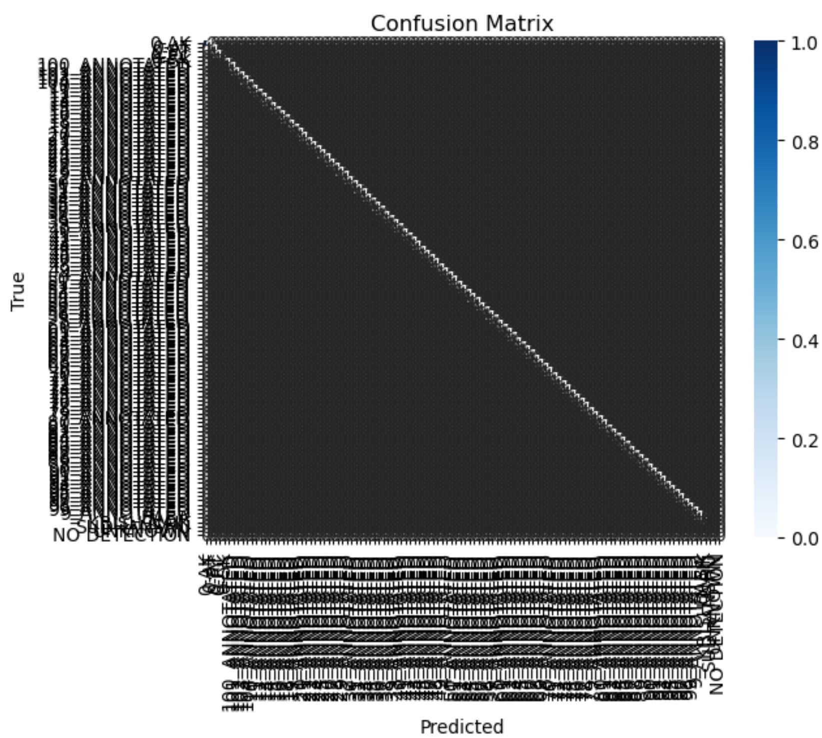

Figure 2: Confusion Matrix

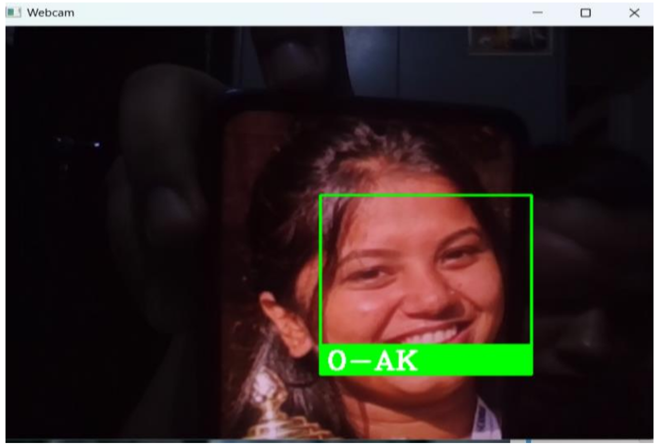

Figure 3: Face Recognition

	A	B
1	0-RC	19:03:24
2	0-AT	19:05:09
3	0-AK	19:07:12
4		

Figure 4: Attendance Sheet

Finally, The Figure 4, presents the attendance sheet, demonstrating the participant engagement during the study. This figure ensures that the transparency in participant tracking and underscores the importance of consistent data acquisition.

6. FUTURE SCOPE

The future scope of the face authentication model for exam and attendance systems is promising and is likely to evolve with advancements in technology and changing needs in education and organizations.

Barcode Scanner: - The addition of a barcode scanner in the Examination Attendance System will reduce the manual labor of maintaining supervisor sheets during examination. Scanning the barcode of answer sheets will automatically make an entry of extra supplement during examination.

Collaborating SIMS software: - The SIMS software is incubated at our own prestigious institution [KJSIT] which maintains attendance records of students dynamically and displays defaulter students. Thus, by collaborating with SIMS software, the integrity of examination can be maintained as defaulter students will not be marked as present.

7. CONCLUSION

The implementation of this face authentication using this mode for exam attendance system has substantial benefits in terms of protection, accuracy, performance, and experience. However, it requires continuous conscious attention to information privacy, ongoing maintenance, and model needs to be trained for each new academic year for the new set of data of students to keep it relevant and ongoing.

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