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Face Recognition Based Attendance System using Haar Cascade and Local Binary Pattern Histogram Algorithm

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ABSTRACT

Facial recognition attendance systems have garnered considerable attention due to their capability to automate attendance tracking while addressing the limitations of conventional manual methods. These systems employ advanced algorithms, such as Haar Cascade and Local Binary Pattern Histogram (LBPH), to analyse and match facial patterns, enabling precise identification and verification of individuals. This research provides an in-depth investigation into the application of the Haar Cascade and LBPH algorithms within a facial recognition attendance system. The study demonstrates the algorithms' proficiency in accurately recognizing faces, displaying individuals' names, and reliably recording attendance with an impressive accuracy rate of 99.0%. Functionally, the technology captures images or videos of individuals' faces upon their arrival and subsequently compares them to a pre-existing database. Significantly, as the dataset size expands, the system's accuracy exhibits consistent improvement. Notably, the research identifies a threshold for the minimum number of images required to achieve dependable attendance prediction. The results produced indicate the effectiveness of the LBPH and Haar Cascade algorithms in automating attendance tracking, reducing errors, and reducing administrative burden. The adoption of facial recognition attendance systems represents a scholarly and robust solution with broad applicability, ensuring precise attendance records across diverse contexts.

Keywords:

Face recognition; LBPH algorithm; Haar cascade; Attendance system

1. Introduction

Traditional attendance tracking methods are pre-technology methods used to track and record attendance. Various types of attendance systems exist, including biometric-based [5], radio frequency card-based [5], traditional paper-based methods [4], and the emerging face recognition-based system. The facial recognition attendance system is becoming a popular alternative as machine learning technology advances, as it eliminates the need for manual entry, lowers errors, and boosts security. A face recognition attendance system tracks and records attendance by

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leveraging cutting-edge technology such as facial recognition software, cameras, and a database of pre-registered subjects. The system captures a facial image, compares it to the database, and if a match is found, the individual is recorded as present, and their attendance record is updated. This technology is applicable in a variety of situations, including schools, universities, offices, and factories. They are beneficial for organizations that have a large number of employees or students and require a quick and efficient way to track attendance [10]. Biometric authentication, such as facial recognition or iris scanning, is a common way to identify users [2]. Another promising biometric identification technology is periocular identification technology [13] that leverages the unique features of the periocular region, the area around the eyes, to identify individuals with high accuracy and robustness [9], but in a classroom setting where close-ups with the students might not be possible, face recognition would be the most suitable method [18].

In this research, an intelligent facial attendance classification model developed using the Local Binary Pattern Histogram (LBPH) is proposed. In this project, the five celebrity face datasets downloaded from the Kaggle Datasets Repository are used [3]. The dataset contains photos of five celebrity faces for the model's training and testing phases. The goal of this paper is to use the Haar Cascade and LBPH algorithms to recognize faces in an attendance system. Based on the initial experiments, it can identify and display the individual based on their name. The technology can also recognize an unidentified person who is not in the database and designate them as "unknown." Additionally, the model can record attendance on an Excel sheet and count the overall number of individuals in attendance for that session. In this research, we will apply the Local Binary Patterns Histogram (LBPH) technique and measure the accuracy and performance of the model.

For facial identification in an attendance system, Haar Cascade and Local Binary Pattern Histogram (LBPH) algorithms are used because they are excellent at analysing and matching patterns based on a person's facial features. While LBPH is a texture-based approach that can extract features from an image and use them for recognition, Haar Cascade is a machine learning-based approach that can recognise objects in an image or video stream. When used in tandem, these algorithms can recognise people based on their facial traits and match them to a database of enrolled individuals. These algorithms work well for facial recognition in attendance tracking, as shown by the authors' discovery that the system's accuracy grew as the dataset's image count rose.

1.1 Literature Review

Facial recognition technology employs sophisticated algorithms to analyse and compare patterns derived from distinct facial attributes, enabling the identification and verification of individuals' identities [10]. In the realm of class attendance management, a facial recognition system can be leveraged to autonomously monitor and document the presence of students within a classroom environment. This involves capturing visual data, such as images or videos, of students' faces upon entry, which is subsequently cross-referenced with an existing database of enrolled students to facilitate accurate matching and identification.

A facial recognition-based class attendance system uses cameras and specialist software to collect visual data, in the form of photos or videos, of students' facial features when they enter a classroom. The collected imagery is submitted to analysis and subsequent comparison against an existing repository of registered students via the use of algorithms. Following successful identification, the system accurately records the student's attendance.

The integration of the system with an existing student database enables the retrieval of vital student information including names, identification number, and class schedule. Consequently, upon successful identification of a student, the system promptly updates the attendance record within the database, eliminating the necessity of manual attendance taking [19]. The longstanding practice of manual attendance, which has been conventionally employed, is fraught with inherent challenges and limitations. Utilizing facial recognition technology for attendance management presents notable advantages over the traditional practice of manual attendance taking, where instructors rely on verbal calls or paper sign-in sheets. The adoption of facial recognition technology offers enhanced efficiency and effectiveness for several reasons [6]:

i. Time-consuming: Manual attendance taking can be a time-consuming process, especially in larger classes, and can take away from class time that could be used for instruction or discussion.
ii. Error-prone: Manual attendance taking is subject to human error, such as mistakes in recording names or mishearing names.
iii. Forgery: Some students may forge attendance records by signing in for absent classmates or by giving false names.
iv. Inaccurate: A manual attendance record can be inaccurate as some students may be absent but not marked, or some students may be marked present when they are absent.
v. Limited data: Manual attendance records provide limited data, such as attendance information only, but do not provide more detailed information such as time of arrival, time of departure, etc.
vi. Data entry: Manual attendance records need to be entered into a computer or other system, which can be time-consuming and error prone.

The implementation of facial recognition technology in class attendance systems entails various ramifications, encompassing both advantageous and detrimental aspects. The potential implications can be delineated as follows:

i. Improved accuracy and efficiency: Facial recognition technology can provide a more accurate and efficient way to track attendance compared to manual attendance taking.
ii. Real-time data: Facial recognition-based attendance systems can provide real-time data, allowing teachers and administrators to quickly see which students are present and absent.
iii. Reduced administrative burden: Automating attendance tracking can reduce the administrative burden on teachers and staff, allowing them to focus on teaching and other important tasks.
iv. Privacy concerns: Some individuals may object to having their facial images captured and stored in a database, and there are also concerns about the potential for misuse of the collected data.
v. Error-prone: The system may not be able to identify a person if they are not in the database, and it can also misidentify people, especially if the system is not properly trained with high-quality images that are representative of the population.

1.1.1 Local binary pattern histogram

The Local Binary Pattern Histograms (LBPH) technique is applied in facial recognition to characterize the texture of an image by analysing the relationship between each pixel and its nearby pixels. This algorithm utilizes a circular neighbourhood surrounding each pixel to build a binary pattern, subsequently producing a histogram of these patterns [17]. The produced histogram serves as a representative descriptor of the image's texture and look. The fundamental idea underlying LBPH is the notion that facial texture can be efficiently identified by the patterns of intensity changes that appear in the image.

Notably, LBPH is particularly helpful for facial recognition in environments which includes different lighting conditions or varying stances, since it exhibits a lower susceptibility to the impact of lighting and pose variations when compared to alternative approaches [15]. In a recent study conducted by [4], the LBPH algorithm exhibits greater accuracy in contrast to other algorithms, partly attributed to its potential for accurately identifying not only frontal faces but also side faces, hence enhancing its total performance. Furthermore, the LBPH algorithm exhibits outstanding resilience in the presence of variable lighting conditions, hence reinforcing its accuracy and reliability [4]. While facial recognition offers efficiency in attendance marking, building user trust through security measures and a natural user experience, as emphasized in studies on AI adoption in the food and beverage industry, is crucial for successful implementation in educational or workplace settings [14].

The LBPH algorithm encompasses a series of fundamental steps for effective implementation:

i. <u>Grayscale Conversion:</u> The initial stage involves converting the input image to grayscale, simplifying subsequent binary pattern generation.
ii. <u>Block Normalisation:</u> The image is partitioned into small blocks, and the intensity values of each pixel within these blocks are normalised to a range between 0 and 255.
iii. <u>Binary Pattern Creation:</u> Each pixel in the image undergoes a binary pattern creation process. This entails comparing the intensity of the central pixel with the intensities of the surrounding pixels in a circular neighbourhood configuration.
iv. <u>Histogram Creation:</u> A histogram is generated by accumulating the binary patterns, serving as a representative description of the image's texture.
v. <u>Comparison:</u> The resulting histograms from two different images can be compared to assess the similarity of their respective textures.

The LBPH algorithm's systematic execution of these steps facilitates robust texture-based facial recognition, delivering notable advancements in accuracy and performance. LBPH is considered a robust method for face recognition; it's relatively fast, and it does not need many images per person to be trained [17]. Despite that, it is not as accurate as other methods like deep learning-based algorithms, and it's sensitive to changes in illumination and facial expression.

1.1.2 Haar cascade

The Haar Cascade technique is a machine learning-based approach in object recognition, developed by Paul Viola and Michael Jones in 2001, widely employed for the detection of objects in photographs or video sequences. Its primary application is in the field of face detection. This method focuses specifically on the identification of human faces by leveraging trained data to analyse crucial facial attributes such as the distance between the eyes and the ratio of forehead-to-nose. Through a process of autonomous learning, the system acquires the ability to distinguish normal human faces from other objects. These identified facial characteristics are then utilized to detect human faces captured by the camera [12].

The Haar Cascade technique operates by training a classifier using a collection of positive and negative images. Positive images contain the object of interest, in this case, human faces, while negative images do not. The classifier is trained to discern patterns in the positive images that differentiate them from the negative images [7]. This enables the algorithm to effectively detect and locate the presence of human faces in images or videos, contributing to its widespread use in various applications related to face detection and recognition. The Haar Cascade technique employs a cascading approach, wherein a classifier is applied in a sequential manner through multiple stages. Each stage comprises a series of elementary classifiers, referred to as features [11].

These features are derived from a set of Haar-like features, which exploit intensity differentials between neighbouring rectangular regions within the image. The detection process begins by applying the initial set of classifiers to the complete image. Upon detecting an object, the algorithm progresses to subsequent stages, where increasingly complex classifiers are applied to smaller regions of interest surrounding the identified object [16]. This iterative procedure continues until the object is accurately detected or until the classifier fails to detect it. The Haar Cascade technique exhibits notable speed and efficiency, rendering it very suitable for real-time applications [20].

2. Methodology

The proposed methodology involves using PyCharm and Python programming language, along with the OpenCV library. The system utilizes a web camera to fetch students' faces, which are pre-processed through resizing, grayscale transformation, and conversion to arrays. The LBPH algorithm is then employed to recognize patterns in the faces. Training is conducted using the Haar Cascade Classifier and LBPH as the recognizer. During testing, the model compares the faces on the webcam with the dataset, automatically updating attendance if a match is found, or displaying 'Unknown' otherwise.

2.1 Experimental Setup

The proposed implementation involves employing PyCharm as the integrated development environment, utilizing Python programming language, and leveraging the OpenCV library. Essential packages, such as Openpyxl, NumPy, and OpenCV-python, are installed within the PyCharm environment. For training and assessing the facial recognition model, a Kaggle dataset of 5 Celebrity Faces is utilized as the training and testing data source (Becker 2017). The experimental procedure includes the following steps:

i. Create a Python file to fetch the students' faces using a web camera.
ii. Pre-process the photos including scaling, grayscale image processing, and image to array conversion. The photographs of the students uploaded into a folder with their associated names.
iii. Apply LBPH to recognize the patterns in the students’ faces.
iv. Train the model using Haar Cascade Classifier and LBPH as the recognizer.
v. Test the model with the images in the dataset, and then compare the students' faces from the webcam. If the system recognizes the person, his or her name shows on the screen, continuing with their attendance immediately changing in the CSV file and the number of students attending being added. Otherwise, if it is not matched, the system shows 'Unknown' on the student's face, as his or her photos are not in the collection. Hence, their attendance is not being taken.

Figure 1 explains the technique utilizing LBPH. As the device starts to take images, the algorithm splits facial images into blocks. Then, histograms for each block are generated and aggregated into a single histogram. After the facial image is analysed, the recognition result will be shown.

2.2 Data Description

In this project, the training of the facial recognition model is conducted using the 5 Celebrity Faces Dataset obtained from the Kaggle Datasets Repository [9]. The dataset encompasses a collection of images stored in distinct folders, with file formats varying between 'jpg' and 'png'. Specifically, the training directory contains 14-20 images per celebrity, while the validation directory comprises 5 photographs per celebrity.

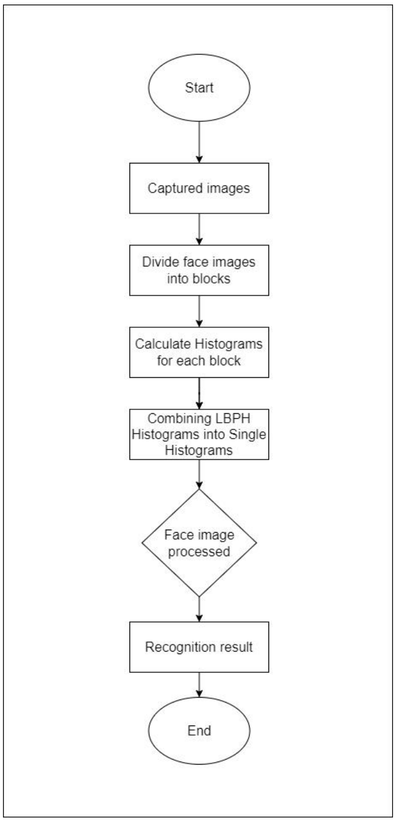

Fig. 1. Flowchart for LBPH Model

2.3 Datasets Pre-Processing

OpenCV is extensively utilized in industry, research, and education for various applications including image/video processing, object detection, and machine learning, particularly in domains such as robotics, surveillance, and driver assistance systems.

It is an open-source computer vision and machine learning library, initially developed by Intel and later supported by Willow Garage and Itseez. It offers a wide array of tools for image and video processing, encompassing feature identification, object recognition, and machine learning [9]. Although primarily implemented in C++, OpenCV also provides interfaces for programming languages such as Python, Java, and MATLAB, facilitating its adoption across various programming environments.

To load an image, the imread() method from OpenCV is employed, with the file's path provided as input. Subsequently, an iteration is performed over each of the five celebrity folders. To visualize the loaded images, the imshow() function is utilized, followed by the plt.show() function to display them. Using matplotlib, the BGR photos are converted to grayscale images in order to eliminate distractions when identifying facial photographs. Figure 2 displays a sample image that has undergone modification.

Fig. 2. Image transformation example

To avoid running out of resources during the model's training, the loaded images are resized to a smaller dimension. The presence of multiple image datasets with varying sizes poses a challenge, as all images must have the same dimensions to form a coherent array for model processing. Thus, the OpenCV resize function is applied to uniformly scale the photos to 47 x 62. The original image size is 320 x 240, and Figure 3 exemplifies an image that has undergone the resizing process.

Fig. 3. Image scaling example

The final images after pre-processing are shown in Figure 4.

Fig. 4. Pre-processing test images and labels

2.4 Live Implementation Tests

Experimental trials were conducted using live images. Upon system initiation, the webcam was utilized to capture the facial appearances of two students. In the event of successful face detection, a rectangular boundary was drawn around the detected face. To enhance the performance of the model, a substantial image dataset was required. Consequently, each student's face was meticulously captured from diverse angles and motions, resulting in a collection of 1000 images per student. Subsequently, these images, initially in BGR format, were transformed into grayscale using the OpenCV module.

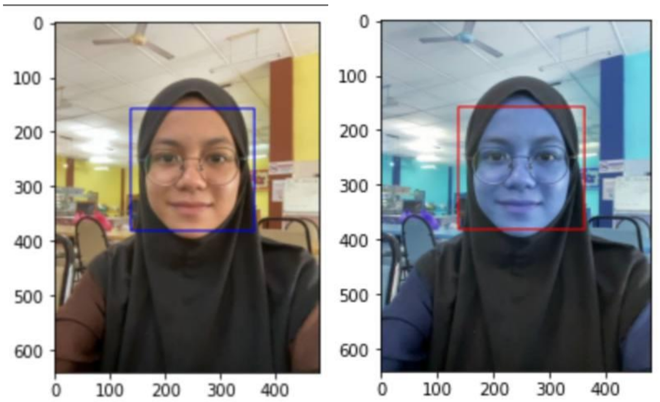

Fig. 5. Data transformation of a student with a rectangle around the face

The images associated with each subfolder name were meticulously stored in the designated directory named "FaceData." For example, within a specific folder named "annesa_maisarah," a collection of 1000 images depicting the respective individual was stored. Subsequently, face detection will be conducted utilizing the Haar-Cascade Classifier from the OpenCV library. Prior to face identification, feature extraction will be performed to enable the recognition of human faces by training the Haar Cascade algorithm. This process will involve employing an XML file containing the trained data for the Haar Cascade frontal face classifier, commonly referred to as the "Haar cascade frontal face default."

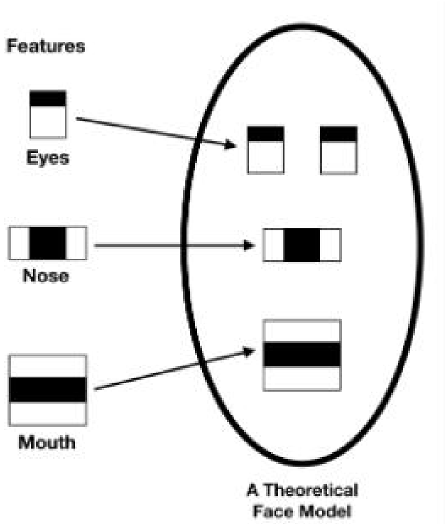

Fig. 6. Feature extraction in the Haar classifier

In this study, the images present in the dataset will serve as the training data. Each image will be assigned a numerical label indicating the corresponding student to whom it belongs. The LBPH algorithm will be employed as a face recognizer for these images. During the recognition process, the histogram of the face to be identified will be generated, and a comparison will be made against pre-computed histograms to determine the best-match label representing the corresponding student.

The system will commence by prompting the students to input their names and matriculation numbers. Subsequently, the webcam will automatically capture their facial images until a total of 1000 sample images are obtained. These pre-processed images will then be stored in the designated training images folder. Following this, the captured data from the students will be utilized in both the training and testing phases. The resulting model will be saved as "trainz.yml" and subsequently deployed in the face attendance system.

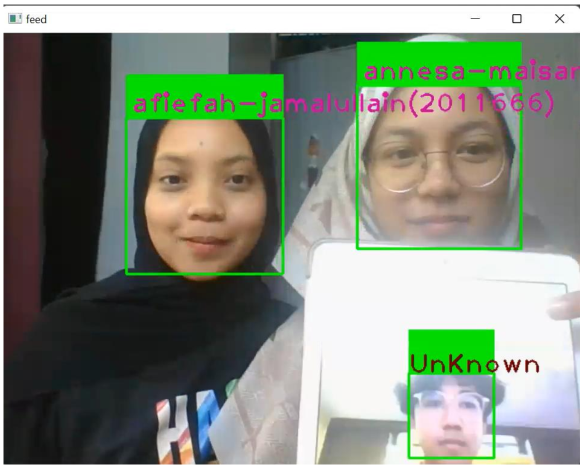

Fig. 7. Students Face Recognition and ‘Unknown’

To verify the attendance of students, the system will compare the faces of individuals captured by the webcam with those present in the dataset. Upon successful recognition, the system will display the student's name and matriculation number, automatically updating the attendance file accordingly. Conversely, if the system is unable to recognize a student, their status will be marked as ‘Unknown’, and their attendance will not be recorded in the attendance file. This in the form of an excel sheet as shown in Figure 8.

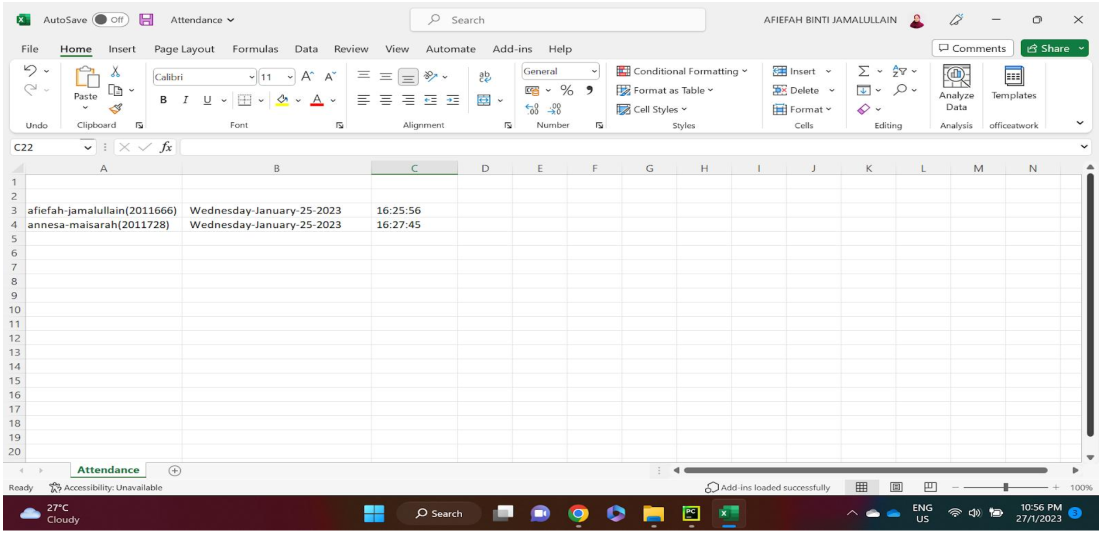

Fig. 8. Example Recorded Attendance in an Excel Sheet

3. Results

After training the model, the test data was used to evaluate the model's performance by comparing the predicted labels to the true labels. It also shows the images in the test set and their predicted labels, highlighting any labels that were predicted incorrectly in red. Figure 9 shows an example of correctly labelled images in black and incorrectly labelled images in red.

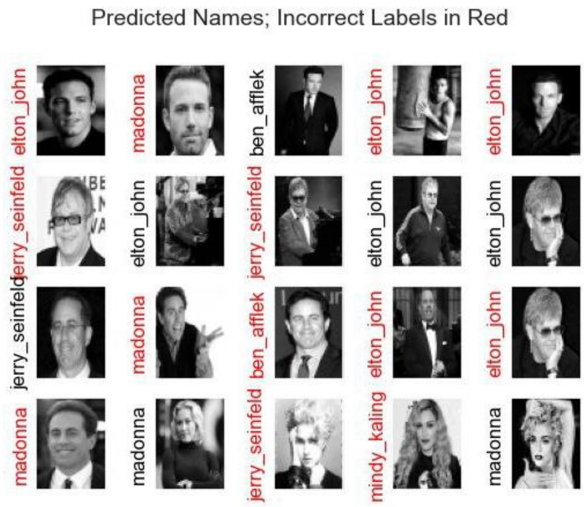

Fig. 9. Example Classifications by the Model

These findings were derived from a series of experiments conducted using multiple datasets consisting of varying numbers of images. The purpose of these experiments was to evaluate the performance accuracy of the facial recognition system. Initially, different dataset sizes were considered, but based on the obtained results, it was determined that utilizing 500 datasets for each individual yielded optimal outcome.

Table 1 presents the accuracy results, revealing a consistent enhancement in performance as the quantity of datasets increases. The accuracy of the face recognition system was assessed by comparing the predicted labels with the true labels of the test data, utilizing metrics such as average precision and recall. Multiple datasets were employed, varying in the number of images, to evaluate the system's performance. The findings revealed a positive relationship between dataset size and recognition accuracy, with larger datasets providing a more comprehensive understanding of facial patterns and features, leading to improved performance.

Table 1
Accuracy Achieved for Each Dataset Sizes

Number of Datasets per Individual	Average Precision	Average Recall	Accuracy
1	0.72	0.67	78.0%
10	0.85	0.89	81.0%
50	0.96	0.98	97.1%
100	0.95	0.97	93.8%
500	0.99	0.99	99.0%
1000	0.99	0.99	99.0%

Notably, a significant milestone was reached when utilizing datasets with 500 images, achieving an impressive accuracy rate of 99.0%. This noteworthy achievement indicates that a dataset comprising 500 images per individual offers substantial information, facilitating effective face recognition capabilities. Based on this remarkable accuracy result, it was decided to use a dataset of 500 photos for each person in the subsequent investigations.

These results emphasize the significance of accumulating sufficiently large datasets to ensure robust facial recognition outcomes. The study's insights contribute to optimizing facial recognition attendance systems through data augmentation and expansion, offering valuable guidance to researchers and practitioners in the field. It guarantees good accuracy while minimizing the computational burden related to increasing dataset sizes.

4. Conclusion and Future Work

The findings from the experiments demonstrate a positive correlation between the number of datasets per person and the accuracy of the face recognition system. Specifically, a larger dataset size provides more comprehensive information about facial patterns and features, resulting in improved recognition performance. Notably, a substantial increase in accuracy is observed when utilising 50 datasets per participant compared to smaller dataset sizes, achieving an accuracy of 97.1%. This suggests that even with a relatively modest dataset size, a significant portion of the necessary data for effective face recognition has already been captured.

Furthermore, the most noteworthy accuracy rates of 99.0% are achieved when employing dataset sizes of 500 and 1000 datasets per person. These outcomes highlight that larger dataset sizes offer a more detailed representation of facial traits, leading to highly accurate facial feature identification. Hence, it is recommended to focus on collecting and utilising a dataset consisting of 500 datasets per individual, striking a balance between computational complexity and resource requirements while achieving remarkable accuracy in the face recognition system.

Investigating advanced methods, especially those based on deep learning like Convolutional Neural Networks (CNNs), will allow for future improvements in facial recognition systems. These algorithms are promising for further development because they have shown notable accuracy gains. Additionally, as position and illumination fluctuations might affect recognition accuracy, it is essential to design techniques that can resolutely address these problems. The inclusion of the Canny filter in our facial recognition system is not directly relevant to the Haar Cascade and Local Binary Pattern Histogram algorithms used for detection. However, similar to the research on using Canny filters to improve steganography, exploring pre-processing techniques to enhance facial features in various lighting conditions could be beneficial for improving the accuracy of our attendance system [1].

Implementing privacy and security safeguards is a critical component to take into account for future advancements. Data protection must be ensured by implementing secure storage and communication mechanisms. Additionally, ethical aspects should be given full consideration, including gaining informed consent, maintaining transparency, and abiding by pertinent laws. Face recognition systems can improve their ethical standards, accuracy, and dependability by taking into account these factors, ensuring a harmony between technology progress and moral considerations.

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