An Enhancement of Haar Cascade Algorithm Applied to Face Recognition for Gate Pass Security

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Abstract

This study is focused on enhancing the Haar Cascade algorithm to decrease the false positive and false negative rate of face recognition in images with variations in lighting, facial expressions, and occlusions to increase accuracy. The face recognition library was applied with Haar Cascade where 128-dimensional vectors representing the unique features of a face were encoded. The Enhanced Haar Cascade Algorithm produced a 98.39% accuracy rate, in comparison, the Haar Cascade Algorithm achieved a 46.70% - 77.00% accuracy rate. Both algorithms used the Confusion Matrix Test with 301,950 comparisons using the same dataset of 550 images. The 98.39% accuracy rate shows a significant decrease in false positive and false negative rates in facial recognition in images with complex conditions

1. Introduction

Facial recognition is increasingly common in various applications ranging from security systems to social media platforms. The effectiveness of such systems hinges upon the robustness of the underlying algorithms employed for facial recognition. Haar Cascade algorithms have been widely utilized in this domain due to their computational efficiency and satisfactory accuracy. Haar Cascade algorithm is a type of machine learning wherein a classifier is used from a great deal of positive and negative photos. Haar feature-based cascade classifiers are utilized for object detection purposes. This classifier employs a machine learning technique where a cascade operation is applied to images to detect objects in subsequent images. (Shetty et. al., 2021).

However, challenges persist in achieving reliable facial recognition under various conditions such as changes in lighting, facial expressions, and occlusions. Typical facial recognition doesn't go into the depth of the image, it just checks for the relevant similarities. This can sometimes become a vulnerability to bypass this kind of system (Minu, et. al, 2020). Before the introduction of the Haar Cascade algorithm in 2001, several object recognition applications were developed. Additional principal component analysis (PCA) was utilized to reduce the complexity of face images, decrease data size, and eliminate noise. PCA was also integrated with neural networks for face recognition and sex determination. However, these earlier algorithms exhibited certain drawbacks, such as a low classification percentage (ranging from 31.48% to 94.5%) and high mean square error (ranging from 0.02 to 0.12).

A refinement of the Haar cascade algorithm was proposed by (Cuimei et al., 2017), which combined three different classifiers: color HSV, histogram matching, and eyes/mouth detection. This enhanced algorithm was subsequently utilized by Arreola et al. in 2018, who applied it to a quad-rotor Unmanned Aerial Vehicle (UAV) for face recognition purposes. In addition to the Haar cascade algorithm, other approaches can be applied to real-time tracking tasks, including local binary patterns (LBPs) or histogram of oriented gradients (HOG). A comparative study involving three algorithms—Haar cascade, LBP, and HOG—was conducted for object detection using UAVs. The results indicated that the Haar-like cascade outperformed LBP in accuracy rate and was faster than HOG (Phuc et. al., 2019)

In this study, we will implement a combination of a Haar cascade algorithm and the face recognition model from OpenCV. The outcome of this implementation will be an enhanced facial recognition system, titled " An Enhancement of Haar Cascade Algorithm Applied to Face Recognition for Gate Pass Security" which will significantly improve security by providing accurate and efficient identification of individuals, thereby preventing unauthorized access and ensuring the safety of individuals.

1.1 Haar Cascade Algorithm Pseudocode

STEP 1:

1.1 Load images using OpenCV's imread function.

STEP 2:

2.1 Convert image to grayscale.

2.2 Detect faces using Haar cascade classifier in grayscale images. (scaleFactor, minNeighbors, and minSize are used for face detection.)

2.3 Put boxes in the detected faces

STEP 3:

3.1 Convert faces to LBPH.

3.2 Extract the face region from the grayscale image using the detected face coordinates.

3.3 Apply the Local Binary Pattern (LBP) transformation to the face region.

3.4 Compute a normalized histogram of the LBP values.

STEP 4:

4.1 Convert each faces region to an LBP histogram.

4.2 Compute the Euclidean distance between the two LBP histograms.

4.3 Convert the distance to a similar percentage

STEP 5:

5.1 Show images and their similarity percentage

1.2 Literature Review

The Haar Cascade Algorithm, developed by Paul Viola and Michael Jones, are well-known for their significant contribution to object detection. Their innovative approach has greatly influenced subsequent research in the field, including the work described in the paper "Rapid object detection using a boosted cascade of simple features". By introducing efficient methods for feature computation, such as the "integral image" representation, and utilizing learning algorithms like AdaBoost (Viola & Jones, 2001).

According to the study "Use of Haar Cascade Classifier for Face Tracking System in Real Time Video." (Wanjale et al., 2013) introduced a comprehensive face detection and tracking system designed for real-time video inputs, emphasizing its application in security contexts. Incorporating the Haar-Cascade method and OpenCV libraries, the system's initial phase encompasses face recognition and detection. Subsequently, face tracking is performed using a Face clustering algorithm. The system primarily targets security purposes, operating on video recordings from public areas to identify and track individuals or suspicious activities.

The paper "A Novel Real-Time Face Detection System Using Modified Affine Transformation and Haar Cascades" addresses the challenges posed by tilted, occlusion, and varying illumination in computer vision (Sharma et al. 2018). Their approach employed a Haar-cascade classifier enhanced with Modified Census Transform features, traditionally inadequate for detecting faces under such conditions.

In the study “Analyzing of Different Features Using Haar Cascade Classifier” conducted by (Yustiawati et al., 2018) discusses the utilization of face recognition for enhancing security measures focusing on the application of a Haar cascade classifier. Their research aims to investigate the effectiveness of using the Haar cascade classifier for analyzing different features, particularly in the context of identifying and matching faces for access control purposes. Through experimental testing, the study demonstrates the efficacy of the proposed method in accurately processing the features of objects, particularly in the context of facial recognition for room security applications.

Another study named “Multi-Faces Recognition Process Using Haar Cascades and Eigenface Methods” reveals how traditional face recognition suffers from processing time and accuracy (Mantoro et al., 2018). To overcome these problems, the study proposes an accelerated approach. By combining Haar Cascades and Eigenface methods, they achieved remarkable results, detecting multiple faces with 91.67% accuracy. By Utilizing OpenCV, specifically designed for Haar-cascade classifiers, the system meticulously examines images, categorizing them as "face" or "not face." Operating within a fixed scale, the classifier continuously analyzes until a face is detected, using data from an XML file for classification decisions.

In “Face Detection Using Haar Cascade in Difference Illumination” (Hapsari et al., 2018) conducted a study exploring the dynamic nature of facial features and their importance across various applications in computer image processing. The research highlighted the challenges in face detection due to the dynamic characteristics of facial features, emphasizing the pivotal role of object detection techniques, particularly in identifying faces within images or video frames. Haar cascade features were specifically noted for their effectiveness in enriching simple features and their efficient processing capabilities. The findings underscored the promising potential of Haar cascade features, particularly in addressing face detection challenges posed by varying illumination conditions.

“Face detection using Haar cascade classifier” proposed by (Pandey et al., 2019) explores the efficacy of the Haar cascade classifier as one of the best techniques for object detection, including face detection. Leveraging predefined datasets stored in XML format, the classifier operates by converting real-time face RGB colors into grayscale, facilitating comparison with the dataset to detect faces accurately. This workflow underscores the effectiveness of the Haar cascade classifier in the domain of face detection.

(Gangopadhyay et al., 2019) proposed a process for face detection and expression recognition, presenting a comprehensive approach to recognizing eight expressions: happy, angry, surprise, contempt, disgust, fear, surprise, and neutral. The face detection process utilizes the Haar classifier, known for its robustness and accuracy in detecting facial features.

In the paper “Automatic Face Recognition and Detection Using OpenCV, Haar Cascade and Recognizer for Frontal Face “(Arya & Tiwari, 2020) investigated real-time facial recognition across varying angles and lighting conditions. Employing recognizers such as Eigenface, Fisherface, and LBPH in conjunction with Haar cascade, the algorithms were initially trained with a database of images before testing with real-time captures.

The study “Face Recognition based Attendance System using Haar Cascade and Local Binary Pattern Histogram Algorithm” They developed a robust attendance system based on face recognition to track student attendance accurately (Chinimilli et al., 2020). In their study, they addressed some of the false positives by incorporating a strong threshold based on Euclidean distance values during the detection of unknown individuals. Comparative analysis revealed the superiority of the Haar cascade algorithm with Local Binary Pattern Histogram (LBPH) algorithm over other Euclidean distance-based algorithms like Eigenfaces and Fisherfaces. The Haar cascade was chosen for face detection due to its robustness, while the LBPH algorithm was employed for face recognition, renowned for its robustness against monotonic grayscale transformations. The system achieved a student face recognition rate of 77% with a false positive rate of 28%. Even in scenarios where students wore glasses or had facial hair, the system exhibited remarkable performance. Additionally, the recognition rate for unknown individuals reached nearly 60%, with false positive rates of 14% and 30% with and without applying a threshold, respectively. This highlights the significance of Haar cascade in developing efficient face recognition-based attendance systems.

According to the study "Localizing Face Recognition with Haar-Cascade Classifier and LBPH using Python" (Legaspi, 2023) employ the integration of the Haar-Cascade Classifier and Local Binary Pattern Histogram (LBPH) in developing a Face Recognition System using Python. With a dataset consisting of 1000 photos per individual gathered through Python scripting, the model underwent training, identification, and recognition processes. Achieving an overall efficiency rating of 84%, this study presents a practical recommendation for the utilization of the combined approach. The findings contribute as a valuable reference for further advancements in face recognition systems, particularly in conjunction with other image classification algorithms

2. Research Methods

In this section, the researcher will outline the design and methodology of the study, detailing both the framework and approach used to achieve the research objectives. The design includes an explanation of the Enhanced Haar Cascade Algorithm, which is used for face recognition, and the system architecture, illustrating how the system will be structured and developed. The methodology covers the data gathering procedure for the dataset, the analysis of this data, and the solutions proposed to address the identified problem. Together, these elements provide a comprehensive guide to the structure and execution of the research process.

2.1 Enhanced Haar Cascade Algorithm Pseudocode

STEP 1:

1.1 Load images using OpenCV's imread function.

STEP 2:

2.1 Convert image to grayscale.

2.2 Detect faces using Haar cascade classifier in grayscale images. (scaleFactor, minNeighbors, and minSize are used for face detection.)

2.3 Initialize scaleFactor to 1.1 and minNeighbors to 10, then loop until scaleFactor = 1.01 and minNeighbors = 1.

2.4 Select the largest detected face that is close to the center of the image.

2.5 Put boxes in the detected faces

STEP 3:

3.1 Convert the detected faces from grayscale to RGB

3.2 Extract the face encodings of each face using face_recognition and face_encoding

STEP 4:

4.1 Compute the Euclidean distance between the two extracted encodings.

4.2 Convert the distance to a similarity percentage

STEP 5:

5.1 Show images and their similarity percentage

The Enhanced Haar Cascade Algorithm combines the strengths of the Haar Cascade Algorithm and the face_recognition library to perform a comprehensive analysis of facial features in two distinct images. This process is initiated by the ingestion of the images, followed by a conversion to the RGB format necessary for the operations of the face_recognition library. The core of this process uses the Haar Cascade classifier, a machine learning tool for detecting faces. It looks for facial features like eyes, nose, and mouth by recognizing their spatial arrangement. The classifier works on grayscale images and uses the detectMultiScale function to find possible faces. Instead of manually adjusting the parameters (scaleFactor, minNeighbors, minSize) for each image, we automated the process. The logic iterates through different parameter values and selects the best setting based on filtering. Since faces are usually larger than non-face objects, we choose the largest detected face that is closest to the center of the image as the real face. Once the facial regions are successfully identified, the methodology proceeds with converting these grayscale regions back to RGB format, the RGB image will be processed by face_recognition library. This library utilizes advanced deep learning models to generate numerical 128- dimension encodings that encapsulate the unique features of the detected faces. These encodings from face_encoding, derived from both images, are then subjected to a comparative analysis to determine the degree of similarity between the faces. The comparative analysis hinges on calculating a similarity percentage based on the distance between the facial encodings. A critical element in this process is the establishment of a similarity threshold. This threshold, which can be adjusted to meet specific requirements, plays a pivotal role in classifying pairs of faces as either matching or non-matching. The flexibility of this threshold allows for the modulation of the sensitivity of the facial matching process, making it adaptable to different application contexts. In essence, this process synergistically combines the Haar Cascade's facial detection capabilities with the deep learning-driven encoding and comparison functions of the face_recognition library.

2.2 System Architecture

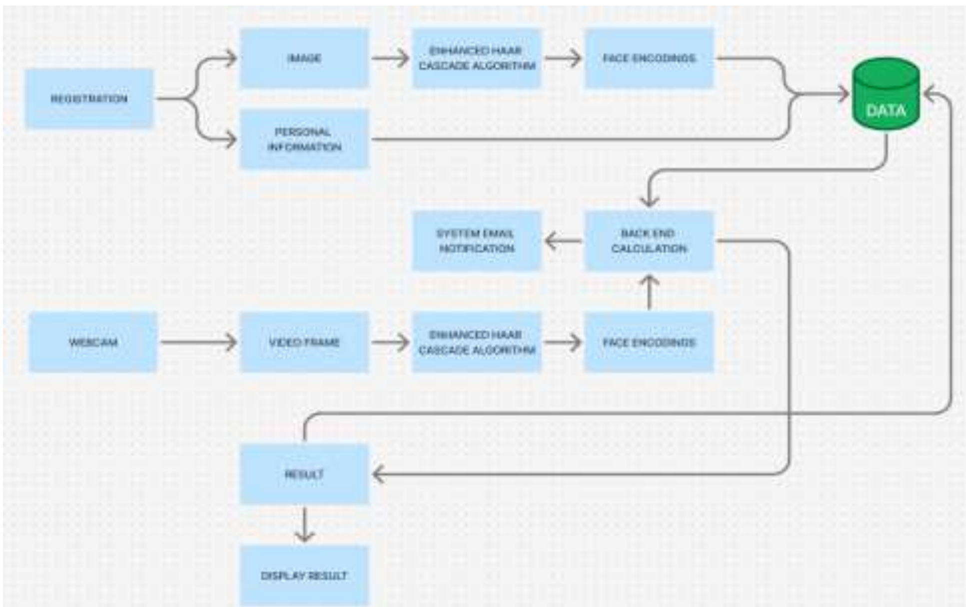


Fig. 1 System Architecture of the Face Recognition System with Enhanced Haar Cascade Algorithm

Figure 1 illustrates the system architecture of the facial recognition system, which utilizes the enhanced Haar Cascade algorithm. The process begins at the registration stage, where each person's image and personal information are collected and submitted. Each image is processed by the enhanced Haar Cascade algorithm to generate encodings, which are then stored in the database along with the individual's information. In real-time recognition, the system captures live video from a webcam. Each video frame is processed by the Haar Cascade algorithm, generating an encoding that is compared to the stored encodings in the database. If a match is found, the system displays the persons "recognized id" alongside their stored information. If no match is found, the individual is classified as "unknown," and the system sends an alert notification to the appropriate authority. This process ensures real-time identification and alerts for unregistered individuals.

2.3 Data Gathering Procedures and Data Analysis Method

The researchers will employ a systematic approach to collect a comprehensive dataset of facial images, ensuring a diverse range of conditions and characteristics to robustly test the enhanced facial recognition algorithm and compare it side by side with the Haar Cascade Algorithm with LBPH. The procedure is as follows:

1. **Selection of images:**
    a. A total of 263 well-known individuals will be chosen to provide facial images. These participants will represent a diverse range of facial features and demographics, including various ages, genders, and ethnicities. Additionally, 12 non-face images will be included.
2. **Environmental Variations:**

a. To ensure the dataset encompasses various real-world scenarios, images will be captured under different environmental conditions. This includes settings with complex backgrounds, dynamic lighting (such as varying light intensities and angles), and additional elements like glasses and varying hairstyles.

3. **Image Collection:**
    a. Each selected famous personalities and non-face images will have a pair of different images taken from the internet. (Google, Facebook, Instagram, etc.) resulting in a total of 550 images. The dual-image approach per individual aims to capture slight variations in expression, angle, or lighting to test the algorithm's robustness and consistency

The researchers will carry out a comprehensive testing phase to evaluate the performance of the enhanced Haar Cascade Algorithm and the integrated face recognition model. The primary metrics for evaluation will include Confusion Matrix, which has Accuracy, Precision, Recall, and F1 Score. The testing process will be automated to ensure efficiency and reproducibility. The detailed procedures are as follows:

Automated Testing Process:

- An automated testing script will be developed to handle the pairwise comparison of images. This script will ensure that each image is compared to every other image in the dataset.
- The script will iterate through the dataset, comparing each image (denoted as <image name>1 or <image name>2) to all other images except for the same file name. This will be repeated for every image in the dataset.
- A total of 301,950 comparison will be made, considering the 549 x 550 computation.

Confusion Matrix Values

There will be two types of testing, one for face detection and one for face matching, the following are the set conditions:

- **Face Detection**
    - (TP): There's 1 face in the image.
    - (FP): There is more than 1 face in the image.
    - (TN): There's no face in the image.
    - (FN): There's 1 face in the image but it wasn't detected.
- **Face Matching**
    - (TP): Both faces are perfectly matched.
    - (FP): Different face but resulted to match or there’s a face but not detected
    - (TN): Different face and returned as not match.
    - (FN): Same face but resulted as not match.

2.4 Solution

To address the inaccuracy of the Haar Cascade Algorithm particularly in scenarios with variations in lighting, facial expressions, and occlusions that result in False Positive or False Negative. The researchers propose the modification in Haar Cascade Algorithm by implementing open-source face_recognition library. The face_recognition library is a popular Python package used for recognizing, and analyzing faces in images it computes face encodings, which are 128-dimensional vectors representing the unique features of a face. Similarity is based on the Euclidean distance between these feature vectors.

1. Calculate the Euclidean distance of face encoding. Each image has their own unique 128 face encoding
2. Given two face encodings:
    - Face encoding 1: $E_1 = \left[E_{1,1},\ E_{1,2}, \ldots, E_{1,128}\right]$
    - Face encoding 2: $E_2 = \left[E_{2,1},\ E_{2,2}, \ldots, E_{2,128}\right]$
3. For two face encodings, E_1 and E_2, the Euclidean distance d_{face} is:

$$d_{face} = \sqrt{\sum_{i=1}^{128} \left(E_{1,i} - E_{2,i}\right)^2}$$

- d_{face} = is the distance of the two face encodings
- $\sum_{i=1}^{128} \left(E_{1,i} - E_{2,i}\right)^2$ = summation of the 128 face encodings from the images

4. The similarity percentage can be calculated as:

$$Similarity\ Percentage = \left(1 - \frac{d_{face}}{d_{max}}\right) \times 100 + 25$$

Where:

- If d_face = 0, it indicates a perfect match, resulting in 100% similarity
- If d_face = d_max, it indicates a not match, resulting in 0% similarity
- d_max = 1.0, is the assumed maximum distance

5. With this calculation, we can assume the similarity percentage of the two images, if the similarity percentage is ≥ 75% then the images is taken as match, if not then it's not match

3. Results and Discussion

After applying the solutions from section 2.4, the researchers will conduct testing and a comparison between the Haar Cascade Algorithm and Enhanced Haar Cascade Algorithm

Table 1 shows the comparison between the Haar Cascade algorithm and Enhanced Haar Cascade algorithm, without the enhancement, the similarity percentage of the two different image is 92.02% which indicates that the images are similar or "match" even that they are different person, this result is considered as a type of False Positive. After the enhancement, the same image was tested and the result return a similarity percentage of 70.40% which is not match, considering the acceptance threshold of 75%. This implies that the images are classified as "not matched" and is a True Negative since the images contain two different persons.

Table 1. Comparison between Haar Cascade and Enhanced Haar Cascade Algorithm

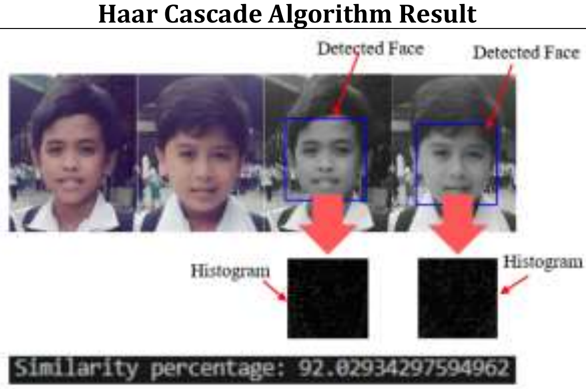
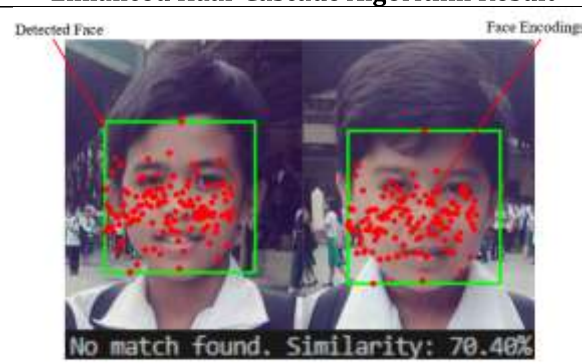
Haar Cascade Algorithm Result	**Enhanced Haar Cascade Algorithm Result**
	

Table 2 shows the result of the 301,950 comparisons, it clearly indicates that the enhanced Haar Cascade algorithm significantly outperforms the standard version across all metrics except recall, where it maintains comparable performance. The stark improvement in accuracy and precision suggests that the modifications have effectively reduced the number of false positives, leading to a more trustworthy face detection system. The high recall values in both algorithms imply that the detection coverage is comprehensive, ensuring that most faces are captured. The enhancement in the F1 Score for the enhanced algorithm underscores the balanced improvement across both precision and recall, making it a more robust and reliable option for practical applications.

Table 2. Confusion Matrix Result of Haar Cascade and Enhanced Haar Cascade Algorithm

	Haar Cascade Algorithm			
	True Positive	**False Positive**	**True Negative**	**False Negative**
Face Matching	504	265234	12504	14
Face Detection	250500	33810	17424	216
	Accuracy	**Precision**	**Recall**	**F1 Score**
Face Matching	4.674832	0.18966	97.2973	0.378583
Face Detection	88.73125	88.10805	99.91385	93.64031
	Accuracy	**Precision**	**Recall**	**F1 Score**
TOTAL SCORE	**46.70%**	**44.15%**	**98.61%**	**47.01%**
	Enhanced Haar Cascade Algorithm			
	True Positive	**False Positive**	**True Negative**	**False Negative**
Face Matching	512	1186	282906	18
Face Detection	276150	8472	17328	0
	Accuracy	**Precision**	**Recall**	**F1 Score**
Face Matching	99.57698	30.15312	96.60377	45.9605
Face Detection	97.19424	97.02342	100	98.48923
	Accuracy	**Precision**	**Recall**	**F1 Score**
TOTAL SCORE	**98.39%**	**63.59%**	**98.30%**	**72.23%**
	Accuracy	**Precision**	**Recall**	**F1 Score**
Haar Cascade Algorithm	46.70%	44.15%	98.61%	47.01%
Enhanced Haar Cascade Algorithm	**98.39%**	**63.59%**	**98.30%**	**72.23%**

4. Conclusions

The researchers discovered that incorporating the face recognition library into the Haar Cascade algorithm significantly improved image comparison accuracy, even under challenging conditions. The enhancement achieved a remarkable 98.39% accuracy, a substantial improvement of 21.39% from the baseline accuracy rate of 77.00%, up from 46.70%. The original Haar Cascade results showed a precision of 44.15%, recall of 98.61%, and an F1 score of 47.01%. In contrast, the enhanced Haar Cascade results demonstrated a precision of 63.59%, recall of 98.30%, and an F1 score of 72.23%. This substantial improvement in precision and F1 score underscores the effectiveness of integrating advanced face recognition techniques with traditional algorithms, leading to more reliable and accurate image comparisons. This enhancement not only boosts overall performance but also makes the system more robust in diverse and challenging conditions.

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