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# Enhancing Face Recognition Robustness with Haar-Gabor Fusion and Dynamic Pan-Tilt Tracking

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## Abstract

Security system technology with identity recognition has grown significantly due to the increasing demand for accurate face detection and recognition. The widely used Haar Cascade method, however, provides suboptimal recognition and often requires image enhancement. This study aims to improve facial recognition accuracy by combining the Haar Cascade method with the Gabor Filter for image enhancement. The research was conducted in two stages: dataset training and input data testing, including experiments with variations in distance, occlusions, and camera angles. The combined method achieved optimal face detection and recognition up to 200 cm, compared to 100 cm when using Haar Cascade alone. The system successfully recognized faces partially blocked by masks, hats, goggles, or hands. Incorporating a Pan-Tilt camera further enhanced performance, achieving 99.8% accuracy at 88° pan and 84° tilt. The integration of Haar Cascade and Gabor Filter significantly improves facial recognition robustness, extending detection range, handling occlusions, and maintaining high accuracy across varying camera angles, making it suitable for advanced security applications.

## Keywords

Face Detection, Face Recognition, Gabor Filter, Haar Cascade, Image Enhancement, Pan-Tilt Camera.

## 1. Introduction

Along with the advancement of electronic technology, the current security system has also evolved (Çıtak, 2024). Examples include transitioning traditional locks to digital ones and using biometric identification technologies like fingerprint, retinal, and facial recognition (Al Fatta, 2009; Burrueal et al., 2024; Abdul et al., 2024). The ability of image processing is still only capable of recognizing a small number of conditions that are still challenging to identify as technology advances. It is related to the poor image. The two main categories of facial image recognition systems are feature-based and image-based. The first system used features extracted from the facial features (such as the eyes, nose, mouth, and so on) before modeling the relationship between these features geometrically. The second system uses raw data from image pixels that are then represented using a specific technique and used for image identity classification simultaneously (Al-Aidid & Pamungkas, 2018; Elngar et al., 2021). One of the visual tasks that humans can almost effortlessly complete is facial recognition, which is a difficult task for computers to complete (Alexander & Sentinuwo, 2017; O'Toole & Castillo, 2021; Adyapady & Annappa, 2023; Karnnati et al., 2023). As a result, numerous techniques are still being developed to satisfy the accuracy requirements.

Numerous studies have been created, among them to determine the speed of facial detection using four different methods: specifically, on Dlib, the algorithm to be examined is CNN and HoG, and from OpenCV is DNN and Haar Cascades. This study evaluated the speed and accuracy of these four algorithms and found that Haar has the highest speed level (Syarif & Wijanarto, 2015; Suwarno & Kevin, 2020; Siddiqua & Saher, 2024). Face detection is performed by Santoso and Kristianto (2020) using the Local Binary Pattern Histogram Algorithm and the Haar Cascade Classifier method, with an ideal range of up to 150 cm, and the inability to detect faces if there is an obstruction in the face. The current application system can detect multiple face objects in one frame. In the study by Gunawan et al. (2021), a facial recognition system with trials on nine facial images and other Haar Cascade techniques achieved a percentage of success in the overall detection trial of 100% but could not recognize faces when wearing facial equipment like masks.

One of the methods used in image recognition is the Gabor Filter (Khairunnisa et al., 2018). In this research, a combination of the Skin Color Model and Gabor Filter was analyzed by carrying out the process of identifying facial identity in digital images. The Skin Color Model method in this research is used to separate the facial area from the facial image based on the skin color value in the facial image. Then, the facial area is extracted using the Gabor Filter. This research resulted in the highest accuracy, 93.6349%. Moreover, the lowest accuracy was 82.45%. The Skin Colour Model and the Gabor Filter are alternative methods of recognizing faces in digital images. Another innovation by Pandya et al. (2021) created an intruder face detection system using the Gabor Filter, and the study's findings confirmed the effectiveness of the suggested system. The system's accuracy has increased from 85%, 64.13%, 56.70%, and 44.01% to 97.01%, 84.13%, 78.19%, and 66.5% when the intruder does not hide his face, partially conceals it, completely conceals it, or is detected in the dark. Facial recognition needs can be developed as part of an intelligent system. Researchers by Babu et al. (2020) created a system that mimics camera operators in, detecting people or objects and shifting the camera accordingly to follow and record them without knowing who the object is.






In this research, the Haar Cascade and Gabor Filter methods were used to create a facial recognition system. In this research, a facial recognition system is proposed that can track the position of the face in addition to the facial detection and recognition process. In this developed tracking system, the use of the camera can be more optimal in recognizing faces, because it can track the position of the face

dynamically if the face position changes. However, existing studies still show clear limitations, such as reduced accuracy at longer distances, failure to recognize faces under partial occlusions, and the absence of dynamic tracking that adapts to user movement. These gaps indicate the need for a more robust and adaptive method. This study focuses on examining how the combination of the Haar Cascade method and the Gabor Filter can improve facial detection and recognition accuracy compared to using a single method, as well as evaluating how effectively the integrated system performs at different distances and under partial facial occlusions. This study aims to improve facial recognition accuracy by combining the Haar Cascade method with the Gabor Filter for image enhancement, and to develop a system capable of dynamically tracking face positions to maintain recognition performance under varying distances, occlusions, and changes in face orientation.

## 2. Methods

The stages of this study started with gathering facial datasets for input data. Following data collection, training is conducted to serve as a guide for processing the facial recognition test. One user's user-face ID was photographed from various angles, and up to 100 face samples were used to collect facial data. Up to five user IDs used the data, which was then given a name label based on facial identity. The facial image capture results that will be used as a dataset are shown in Figure 1, and the five face data samples that will be used are listed in Table 1. The selection of sample numbers and variations in shooting angles was carried out to ensure that the model remained stable and could be replicated by other researchers under similar testing conditions.

Table 1. Face and User-ID Sample Data

Image	User-ID	Name
	1	ANNISA
	2	WISNU
	3	MARSHA
	4	GITA
	5	AMALIA

Training on the data in the database is required in order to determine data compatibility. Thus, when the system is given input data, it will be read based on the data that has been trained (Fadel, 2019). The Local Binary Pattern Histogram (LBPH) algorithm and Haar Cascade were then used to store the face data training process in the database (Simaremare, 2018). LBPH was chosen for its robustness in representing local texture features, which complements Haar Cascade's ability to detect facial structures efficiently. The recognition process also compares the threshold value of the stored dataset with the input face value captured in real-time using the camera to match the face based on the histogram value approach after using Haar Cascade with the Local Binary Pattern Histogram algorithm. This result is then used as a predictive value to identify the face's owner. This combined approach ensures that the system not only detects faces but also reliably identifies them under

varying conditions by leveraging both structural and textural information. The equation for estimating the histogram value is given below:

$$D = \sqrt{\sum_{i=1}^n (\text{hist}1_i - \text{hist}2_i)^2} \quad (1)$$

The face in the database and the face detected by the camera are compared using the value of D. Feature extraction is a technique for facial recognition that involves looking directly at the image for features unique to the human face (Agrawal & Samson, 2016). The Gabor filter is an orientation-sensitive filter used for texture analysis (Gabor, 2000; Jurniawan et al., 2015). Its ability to capture details at multiple frequencies and orientations makes it particularly effective for analyzing the complex textures present in facial images, such as skin pores, wrinkles, and edges of facial components. The Gabor Filter, a linear filter that can remove variability brought on by contrast illumination, slight image shift, and deformation, is used to extract facial features as a feature detector; for facial recognition, the Gabor Filter output has been used successfully. In this study, the Gabor Filter is applied to pre-process facial images, enhancing their textural features before the recognition step to improve discrimination between individuals, especially under suboptimal conditions like poor lighting or partial occlusions. According to Hammouda and Jernigan (2000), the formula used in the Gabor Filter is:

$$G(x, y, \theta, \mu, \sigma) = \frac{1}{2\pi\sigma^2} - \exp\left\{-\frac{x^2-y^2}{2\sigma^2}\right\} \exp\{2\pi \cdot i(\mu \cdot x \cdot \cos\theta + \mu \cdot y \cdot \sin\theta)\} \quad (2)$$

with:

- $i^2 = -1$
- $\mu =$  The frequency of the sinusoidal wave controls the orientation of the Gabor function.
- $\sigma =$  standard deviation Gaussian Envelope
- $x, y =$  The coordinates of the Gabor Filter

The equation for the Gabor Filter 2-D above is formed from two components: a Gaussian envelope and Sinusoidal waves in complex form. The Gaussian envelope of the above equation is:

$$g(x, y) = \frac{1}{2\pi\sigma^2} - \exp\left\{-\frac{x^2+y^2}{2\sigma^2}\right\} \quad (3)$$

The frequencies used in this study were five, namely ( $u = 0, 1, 2, 3, 4$ ), and 8 orientation angles, namely ( $\theta = 0, 1, 2, 3, 4, 5, 6, 7$ ), resulting in 40 Gabor Responses (Magnitude Responses). This specific configuration of five scales and eight orientations is a common and effective setting in face recognition literature, as it densely covers the spatial-frequency domain to capture a wide range of facial structures, from coarse to fine details. The conversion result is used to get the magnitude value as the core of the Gabor Filter process. The magnitude value utilizes the image's frequency and orientation (Lussiana et al., 2011). The determination of frequency and orientation was chosen because it was considered optimal in balancing facial texture detail and computational efficiency, and so that the procedure could be replicated in subsequent studies. Empirically, this parameter set provided a sufficient representation of facial features without overburdening the processing pipeline, which is crucial for real-time applications such as the system developed in this work. The training process is illustrated in Figure 1.



Figure 1. Training Dataset Flowchart

Based on Figure 1, once a face is detected and recorded, it becomes stored data. Additionally, the dataset folder's data serves as the system's training data to more precisely identify the faces that have been stored in the file (trainer.yml) based on the ID that has been stored. Each user ID is associated with a unique label, ensuring that the model learns discriminative features corresponding to individual identities. This structured labeling is essential for supervised learning, as it allows the system to map extracted facial features directly to specific persons during recognition.

Figure 2 illustrates the facial recognition process, where a system module named "face\_recognition" loads the trained model from the file (trainer.yml). The Haar Cascade algorithm performs initial face detection, after which the camera feed is activated. Subsequently, the local binary pattern histogram (LBPH) and Gabor filter algorithms work in tandem to identify a face by matching it against the enrolled dataset; upon a successful match, the system displays the recognized name along with a confidence percentage. This multi-stage approach ensures robustness by combining fast detection (Haar) with accurate, texture-based recognition (LBPH and Gabor). If the face moves, the pan-tilt mechanism dynamically adjusts the camera to keep the face within the frame. However, if the face is not recognized, the system re-initializes the detection cycle and re-attempts identification using the LBPH algorithm for comparison (Wijaya et al., 2017). This fallback procedure enhances reliability in challenging scenarios, such as partial occlusions or suboptimal lighting, by allowing repeated attempts at verification.

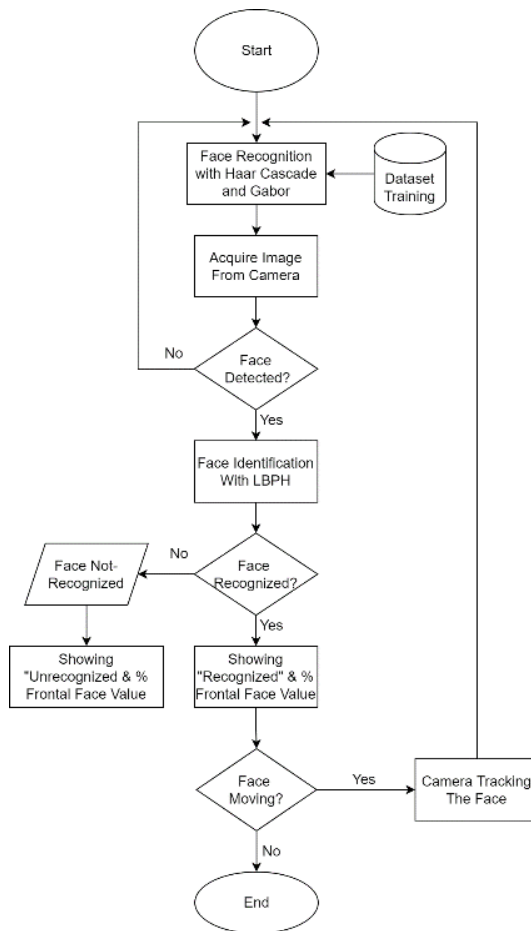


Figure 2. Face Recognition and Tracking Process Flowchart

This tracking process is essential in facial recognition security systems because it improves the image quality of the detected face and enables tracking of both known and unknown objects. Two supporting servos that track faces vertically and horizontally support this tracking capability as part of an intelligent system, as illustrated in Figure 3. Here is an image of the series: a non-profit foundation, the Raspberry Pi Foundation, developed the Raspberry Pi (Kharisma et al., 2021). The programming language of Python can be used for various software development purposes and runs on various operating system platforms (Riyanto, 2019).

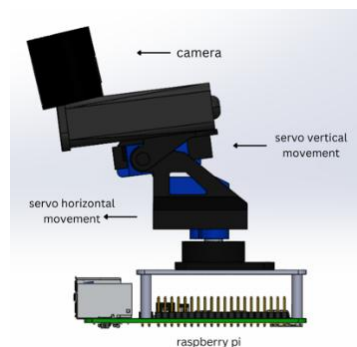
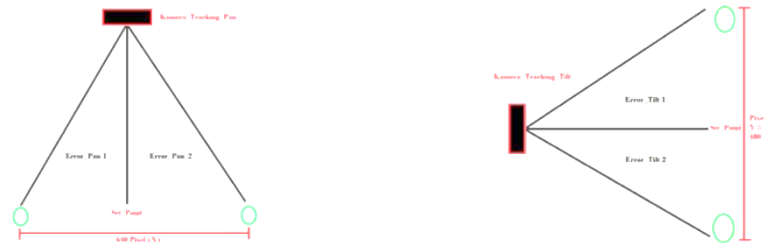


Figure 3. Servo Position and Camera

The tracking algorithm first looks for the midpoint, width, and length position and then limits the area (Wang et al., 2023). The CamShift calculation will consider

the combination's outcomes to determine the new search window's midpoint, width, and length (Endriansyah et al., 2024). This process is ongoing as long as a pan-tilt camera captures the object. Figure 4 is the limit of the area of reach of the face object that can be done by the pan-tilt camera using horizontal direction servos and vertical direction servos.



**Figure 4.** Horizontal & Vertical Area Range of Pan-Tilt Camera

The methods used in this research combine the Haar Cascade and Gabor Filter techniques to build a more accurate facial recognition system. Haar Cascade serves as the primary method for face detection by classifying features extracted from facial images and identifying objects based on contrasts in pixel intensity. Meanwhile, the Gabor Filter is applied to enhance image quality prior to recognition; its sensitivity to orientation and frequency makes it highly effective for texture analysis, allowing the system to capture facial features more precisely, even under poor lighting or minor distortions. The overall process consists of two main stages: dataset training and testing.

During the training stage, face images collected from various angles are used to form a dataset that teaches the system to recognize users based on their IDs. In the testing stage, new facial inputs are matched against the trained dataset using the Local Binary Pattern Histogram (LBPH) algorithm, strengthened by the combined Haar Cascade and Gabor Filter processing. Furthermore, the system integrates a face-tracking mechanism using a Pan-Tilt camera, enabling dynamic tracking of facial movement to maintain the face within the camera's field of view and improve recognition accuracy, especially when the user's position shifts. The study combines image processing and dynamic tracking techniques to create a face recognition system that can identify and track faces more accurately, even under poor lighting conditions or when the face is partially obscured by objects such as masks, hats, or glasses. A detailed explanation of the parameter setting, the number of datasets, and the reasons for selection are provided so that the research process can be replicated consistently and provide a stronger methodological basis.

### 3. Results

The face detection system was tested using a scenario that began with registering facial data through the creation of a facial dataset. Five frontal face samples were used, each consisting of 100 image poses that included variations in frontal conditions and the presence of facial barrier attributes. Before registration, the user is required to input the face ID. The system applies a minimum similarity threshold of 50%; if the detected face score is below this value, it is classified as "Unrecognized." The system successfully demonstrates its ability to detect full facial features as well as specific regions of the face, including the eyes and lips.

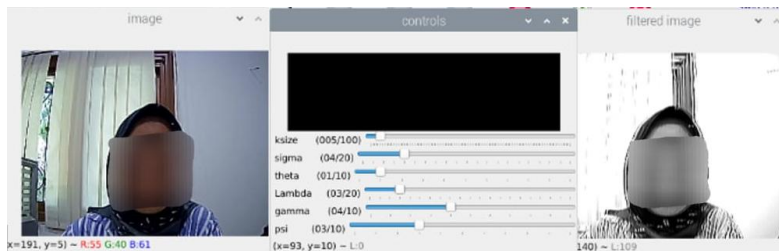


Figure 5. Test Process of Gabor Filter Parameters

Figure 5 shows that the facial image becomes more apparent after providing Gabor Filter parameters. Furthermore, testing suitable Gabor Filter parameters for facial recognition on datasets created using ksize, sigma, theta, lambda, gamma, and psi are 5/100, 4/20, 1/10, and 3/20, 4/10, and 3/10, respectively.

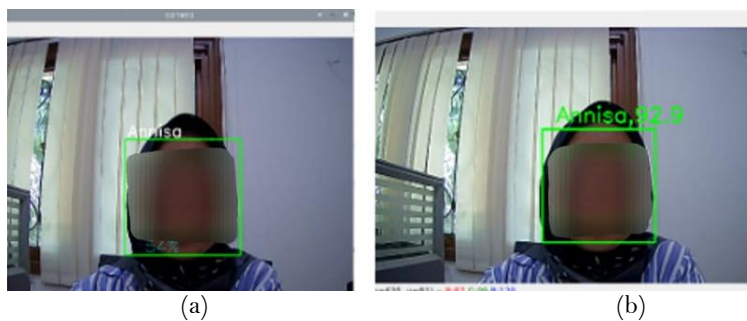


Figure 6. (a) Detection of the Haar Method (b) Combination of Haar & Gabor Filter Method

Figure 6 contrasts the performance of the Haar Cascade method by itself with that of the combined Haar Cascade and Gabor Filter method. In Figure 6(a), the Haar Cascade detects the facial area but shows limitations in identifying finer facial details, especially under variations in lighting or texture. Meanwhile, Figure 6(b) demonstrates how the integration of the Gabor Filter enhances feature extraction, producing clearer and more stable detection results. This improvement is visible in the sharper contour recognition and higher consistency in identifying facial components, indicating that the combined method offers superior accuracy and robustness compared to using Haar Cascade alone. The results of testing the camera's ability to detect and recognize faces can be seen in Figure 7. As seen in the image, the system can identify Annisa's User ID from faces with green square marks on the face area with a percentage of facial detection accuracy of 91.6%.

Table 2. Results of the Face-Distance Test of ID 1

Methods	Distance (cm)				
	50	80	100	120	200
Haar Cascade (%)	57	55	55	0	0
Haar Cascade and Gabor Filter (%)	100	100	100	100	96

Table 2 shows the facial recognition test results data for User ID 1 with varying facial distances. Table 2 shows User ID 1 facial recognition results using the Haar Cascade (HC) method versus the Haar Cascade and Gabor Filter (HCG) combination method. The test results showed a difference in the ability to recognize better in the combination method (HCG) compared to the Haar Cascade method (HC). The combination method (HCG) can still recognize faces up to 200 cm away, while the Haar Cascade method can no longer detect faces starting from a distance of 120 cm.

Furthermore, Table 3 presents the results of trials for different identities, namely ID-2, ID-3, ID-4, and ID-5. The test results are not significantly different from the test on ID-1, where the combination method (hCG) performs better because it can identify faces up to 200 cm away.

**Table 3.** Results of the Face-Distance Test of ID 2 to ID 5

ID	Methods	50cm	80cm	100cm	120cm	200cm
2	HC	59	55	55	0	0
	HCG	100	100	100	98	97
3	HC	57	55	51	0	0
	HCG	100	100	100	98	96
4	HC	55	55	54	0	0
	HCG	100	100	100	98	95
5	HC	54	52	53	0	0
	HCG	100	100	98	96	96

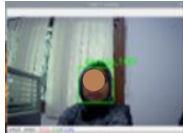
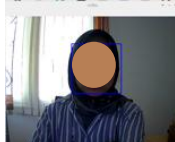
Based on Table 3, an analysis of test results, using a Gabor filter can improve facial recognition because it improves the quality of separating the identified facial object from the surrounding area at a specific frequency of the image based on spatial locality, edge orientation, and contour, sharpening the edges of facial features. Haar Cascade can detect and recognize faces up to 200 cm from the face, unlike combination methods, which lose their effectiveness as the distance from the face increases. Each identity's (ID) facial recognition accuracy is measured to calculate the average accuracy. Here is the accuracy of facial recognition based on distance with the following formula:

$$\% \text{ Face Detected} = \frac{\Sigma \text{Data detected}}{\Sigma \text{Total input data}} \times 100\% \tag{4}$$

$$\frac{\text{Haar Cascade's Accuracy}}{15 \text{ Face Detected}} \times 100\% = 60\%$$

$$\frac{\text{Combination Accuracy}}{25 \text{ Face Detected}} \times 100\% = 100\%$$

**Table 4.** Lighting Conditions Test Results for ID-1

Image	User-ID	Condition	Description
	Annisa	Light	Detected
		Dark	Detected

The next test was facial recognition with lighting conditions in both light and dark conditions. As shown in Table 4, the system was able to detect the face of ID-1 (Annisa) in both scenarios, indicating that the combination of Haar Cascade and Gabor Filter provides stable detection performance even when illumination changes

significantly. This result demonstrates that the enhanced feature extraction process helps maintain recognition accuracy despite reduced lighting quality, which is essential for real-world security applications where lighting is often inconsistent.



Figure 7. The Camera Does the Tracking Results When the Face is Moved in Position

Based on the forward-facing face’s movement, the left side’s direction, and the right side’s direction, the tracking of the position of the face (CamShift) is performed. Figure 7 shows how the visible position of the camera against the face shifts from a left-facing position to a right-facing position in response to the movement of the right-facing face and the degree of change in the camera servo position visible on the system display. Table 5 provides specifics regarding the movement modifications put to the test.

Table 5. Result of ID 1 Data from Face Tracking Position Testing

No.	Pan Servo (°)	Tilt Servo (°)	Accuracy (%)	Description
1	87	90	95.8	Detected
2	88	84	99.8	Detected
3	85	84	92.4	Detected
4	89	90	97.6	Detected
5	86	86	96.9	Detected
6	86	86	98.1	Detected
7	88	86	97.4	Detected
8	86	88	96.9	Detected
9	85	86	98.1	Detected
10	83	86	97.4	Detected

The pan servo angle of 88° and tilt servo of 84° is the ideal angles in the face tracking position test, with an accuracy of 99.8%. This test involves putting facial recognition skills to the test under unique circumstances, such as masks, hats, goggles, and partial face coverings. As shown in Figure 8 from the test results, the system can still detect and recognize faces.

Figure 8 shows the system’s performance when tested under several particular conditions, including (a) wearing a mask, (b) wearing goggles, (c) wearing a hat, and (d) using both goggles and a hat, as well as partially covering the face with a hand. These test scenarios represent common real-world obstacles that often reduce the accuracy of traditional face recognition systems.



**Figure 8.** (a) Wearing a Mask, (b) Face with Goggles, (c) Wearing a Hat, (d) The Face Uses Goggles and a Hat, and the Face Uses the Hands to Cover Part of the Face

As illustrated in Figure 8, the developed system is still capable of identifying facial objects even when a significant portion of the face is obstructed. This capability is achieved through the integration of the Haar Cascade method and the Gabor Filter, which strengthens feature extraction by emphasizing texture and orientation information that remains detectable despite occlusion. Moreover, the system not only detects faces but can also dynamically track facial movement. This means that when the face shifts positions, whether due to head movements or attempts to partially hide behind an object, the Pan Tilt camera automatically adjusts its angle to keep the face centered within the frame. These results indicate that the facial detection and tracking system performs robustly under various obstructed conditions, demonstrating its potential effectiveness for security and monitoring applications where users may wear accessories or unintentionally cover parts of their faces.

#### 4. Conclusion

This research produces a facial recognition and tracking system by displaying the name of the facial identity and the level of accuracy of facial detection. Test results, at a distance of the camera and face up to 200 cm, the use of the Haar Cascade and Gabor Filter methods can increase face detection accuracy by up to 100%. Face tracking can be done using a pan-tilt servo application with an accuracy rate of 99.8%. The system created can also recognize faces even if the face is covered by an object (for example, a mask, glasses, hat, or part of the hand covering part of the face). These contributions demonstrate improvements in detection robustness, wider operating range, and enhanced adaptability to real-world occlusion scenarios, making the system suitable for security, surveillance, and smart monitoring applications.

Despite these strengths, the system still has limitations, particularly in handling extreme lighting conditions, high-speed facial movement, and long-range detection beyond 200 cm, which may reduce recognition reliability. Further research can be

carried out by improving the camera function which can have zoom in and zoom out functions, so that faces can be recognized in more detail. Future work may also explore integrating deep learning-based detectors, optimizing computational efficiency, and expanding the dataset to increase generalizability across diverse user profiles.

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### ***Ethical Approval and Originality Statement***

Ethical approval was obtained for this study. The manuscript represents original work and has not been previously published, nor is it under consideration by another journal.

### ***Data Disclosure Statement***

The data that support the findings of this study are available from the corresponding author upon reasonable request.



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