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The Effect of Dataset Count on Facial Recognition Accuracy Using Haar Cascade Classifier

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Abstract

This study examines the difference in the number of facial image datasets and whether it affects the accuracy value of facial recognition with the Haar Cascade Classifier method. The difference in the number of datasets is set with variations of 150 pieces, 100 pieces, and 50 pieces of facial images. Facial images were taken in the same situation, conditions, and places using the Raspberry Pi Camera v1.3. Collecting and creating datasets, training dataset images, and facial recognition are processed using a Single Board Computer (SBC), Raspberry Pi 4. Lighting conditions are not a factor affecting the study's results. The facial image dataset was trained with a Local Binary Pattern Histogram (LBPH) recogniser and Haar Cascade Classifier detector. Face recognition was performed using a facial image dataset that was taught twice. Face recognition was tested with distance variations of 25cm, 50cm, 75cm, 100cm, 125cm, and 150cm from the Raspberry Pi Camera v1.3. The results showed that the face recognition system using the Haar Cascade Classifier method had the best recognition accuracy value of 98%, with an optimal distance of 75cm from the camera and a total dataset of 150 facial images. The weakest distance of face recognition is at a distance of 125cm and 150cm with a variety of datasets totalling 150 pieces, 100 pieces, or 50 pieces of facial images that produce a recognition accuracy of 0%. This shows that the greater the number of facial images used, the more the accuracy value of facial recognition will increase. Further studies are recommended for testing facial recognition systems with this Haar Cascade Classifier method.

Keywords: Dataset; Facial Recognition; Haar Cascade Classifier; LBPH; Raspberry Pi.

1. Introduction

Every human doesn't have an identical body shapes; there must be differences. These differences can be seen in the face, hairstyle, hands, fingerprints, foot shape, eyes, voice, and other limbs. With these differences, humans can distinguish between one person and another. These differences also make it easier for everyone to get to know each other. More about human body shape recognition, referred to as biometrics. Biometrics are measurements that use the physical characteristics of a person's identity to determine or reveal their identity. [1]. This recognition of identity disclosure is no longer limited to people. Previously, people only recognised others by human senses; now, devices such as cameras, fingerprint scanners, microphones, and so on can be used to identify them. [2].

Nowadays, facial recognition is one of the most popular forms of recognition. [3]. Face recognition is personal identification using a person's facial characteristics. This characteristic can be seen from facial expressions, face shape, and additional components listed on the face, such as the shape of the nose, mouth, eyebrows, cheeks, and eyelids. The recognition system will find and match facial identities with a reference database that has recorded the registration process (dataset) [4]. Face recognition is high-level recognition that maintains exclusivity (security matters). Facial recognition is also easy to create and run. Face recognition is applied in various fields, especially in security. [5]. Some of its applications include Smartphones, Laptops, and Personal Computers (PCS). Face recognition uses the camera to recognise the face. [6]. Of course, facial recognition through the camera can't work without a series of programs and compiled method steps. The program is created and run on a computer to process captures from the camera as input data. [7].

Face recognition has become one of the most active areas of cognitive pattern research. [8]. The most common matching method of face recognition can be easily classified into three categories based on comprehensive features, local features, and multiple matching methods. [9]. In the comprehensive feature-based matching method, the entire face region is used as the raw input to the detection system; in the matching process, local features, such as eyes, nose, and mouth, are extracted first. Then, their location and spatial statistics (geometrically or appearance-wise) are entered into the structural classifier. A hybrid scheme of facial recognition features by merging global and local features was first proposed in 2002 [10]. Face recognition programs run the steps of a compiled method, an algorithm. Experts have developed several methods or algorithms for face recognition. [11]. One of the several methods developed is the Haar Cascade Classifier. Haar Cascade Classifier, also known as Haar-like Feature, recognises objects based on simple values of features, but not values of the object's image. This algorithm has the advantage of high-speed computation because it only depends on the number of pixels in a square, not every pixel value of an image. [12].

This paper presents a prototype face recognition system based on the test data with single-face objects. This prototype system implements an LBPH algorithm to generate a model for face recognition purposes. The Haar cascade method generated the training data, which detects specific objects based on a model loaded in the program. The LBPHS were utilised to extract features from the training and testing datasets, and the Euclidean Distance between image histograms to indicate accuracy. [13]. In this study, the focus is to examine whether there are differences in facial recognition accuracy values based on variations in the number of face datasets collected for the face recognition process, along with variations in face recognition distance from the camera. [14].

2. Methods

Haar Cascade Classifier is a mathematical function (Haar Wavelet) in a box shape. Image processing began by looking at the RGB value of each pixel, but it turned out that this method was ineffective. Then, Viola and Jones developed a way to manage images and formed the Haar-like feature. [15]. The Haar-like feature will process images in boxes with several pixels in each box. Each box will then be processed to generate a difference of values indicating the dark and bright areas. These are the values that will form the basis for image processing. Haar system detects faces using statistical techniques. [16]. For this procedure, sample hair-like features are used. The fixed-size picture used by this classifier is typically 24 by 24. A 24x24 sliding window approach is applied to the image to identify faces in a photo to determine whether any area resembles a face. In addition, Haar can scale, allowing it to identify faces bigger or smaller than the classifier's picture. Every characteristic of a haar-like feature, including its size and location, is determined by the form of the feature. [17].

Counting Haar Feature values frequently and repeatedly is a step toward achieving more accurate results using the Cascade Classifier. Figure 1 shows the Cascade Classifier procedure. Each sub-image in the stage 1 classification will be assigned a single feature; if the classification does not match the predetermined criteria, the result is rejected. Every subimage will be reclassified in step 2. Proceed to the next filter stage (stage 3 classification) if the necessary threshold value is attained, and continue until the passing sub-images are reduced to a size that is similar to the picture on the sample [18].

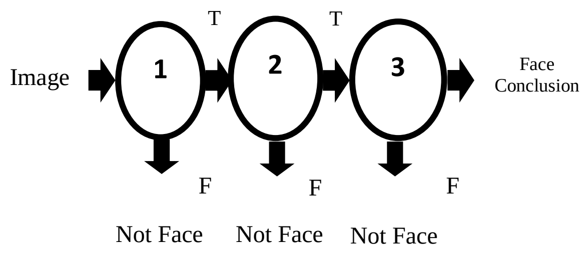

Figure 1. Haar Cascade Classifier method workflow

The Wavelet Haar serves as the foundation for the Haar Feature [19]. Haar is a single square wave for two dimensions—one light and one dark—with one high and one low interval. A mixture of boxes is then utilized to improve visual object detection.

Integral images effectively identify whether hundreds of Haar features are present on a picture at various scales. [20]. Such integration typically entails the simultaneous addition of smaller units. The values of pixels are the little units in this instance. The total of all the pixels from top to bottom is the integral value for every pixel. [21]. Multiple integer operations per pixel can sum up the entire image, starting from the top left and working down to the bottom right. For instance, a pixel (a, b) has a cumulative value for all pixels (x, y). x ≤ a and y ≤ b in this case, as shown in (1) to (3) and (3) below.

$$ii(x,y) = \sum_{x' \le x, y' \le y} i(x', y') \tag{1}$$

Where ii(x, y) is the integral image and i(x, y) is the original image. Using the following pair of recurrences:

$$s(x,y) = s(x, y-1) + i(x,y) \tag{2}$$
$$ii(x,y) = ii(x-1, y) + s(x,y) \tag{3}$$

Where s(x, y) is the cumulative row sum, s(x, -1) = 0, and ii(-1, y) = 0), the integral image can be computed in one pass over the original image.

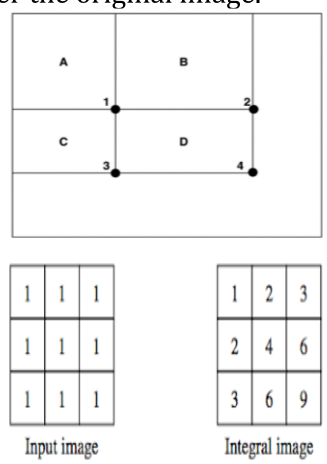

Figure 2. Integral image

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A cascade classifier is a series of stage classifiers; each used to determine if an object of interest is present in the picture subwindow. [22]. The adaptive-boost algorithm (AdaBoost) is used to construct the stage classifier. The method aggregates several weak classifiers' output to create a robust classifier. The haar-like feature's value serves as the weak classifier in this instance. AdaBoost of the Gentle variety is being used. [23].

Local binary pattern (LBP) is one of the best-known object recognition methods. In this case, the method is to distinguish objects from the background [24]. Local Binary Pattern Histogram (LBPH) is an algorithm combination between LBP and Histogram of Oriented Gradients (HOG) [25]. Facial recognition is an advanced stage in facial recognition, and face recognition can use template matching using LBPH. The face image taken in real-time using the camera will be compared and matched using the extracted histogram with the face image in the database. The pixel's value in the center determines the threshold of the other eight pixels. In such a matrix, the binary value in the center will be compared to its surrounding values. If the value on the middle matrix is more than the value surrounding it, the value of its surrounding matrix will be "1"; conversely, if the value on the middle matrix is less than that surrounding it, the value will be '0'. The histogram is then generated to compare and match the faces captured by the camera. The histogram values are then generated to compare and match the faces captured by the camera to those in the database [26]. The equation used is Euclidean Distance (ED). Using two histograms, the Euclidean Distance (ED) method measures the straight-line distance between two places. This method calculates the distance between images based on their histograms. Using the ED method, the distance value can indicate the amount of confidence in facial recognition accuracy. Equation 4 below is to calculate the histographic values.

$$D = \sqrt{\sum\nolimits_{i=1}^{n} = \ (hist\ 1_i - hist\ 2_i)^2} \tag{4}$$

Where D is the ED value, hist1 and hist2 compare the camera's and the database's facial image, and n is the histogram length (255 for gray-level images).

In this paper, we will test the accuracy of the facial recognition system with the variation of the face recognition distance with the camera and the variability of the number of datasets of facial images collected and stored in the database. The tests are done in the exact location and conditions and do not take into the light intensity values (the lighting conditions are the same for each test). The number of face image datasets stored in the database is varied by 50 datasets, 100 datasets, and 150 datasets. Face recognition distances with cameras vary by 25cm, 50cm, 75cm, 100cm, 125cm, and 150cm.

3. Results and discussion

The results of the distance variation test on the accuracy of facial recognition with dataset quantities ranging from 50 to 150 facial images are presented in sections (1) to (3) below

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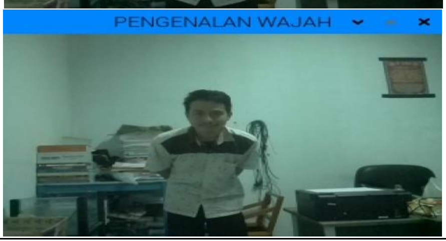
Table 1. Results of the distance variation against the accuracy of face recognition (50 datasets)

Distance Variation (cm)	Face Detection Results (Detected or Undetected)	Face Recognition Accuracy (%)	Validation
25	Undetected	-	
50	Detected	82	
75	Undetected	-	
100	Undetected	-	
125	Undetected	-	
150	Undetected	-	

Based on a distance variation test against the accuracy of facial recognition with a dataset of 50 facial images according to (1), it was found that faces were only detected and recognized at a distance of 50cm with an accuracy of 82%. Equation 5 is used to determine the success of facial detection, as follows.

With x = 1 (number of successful detections) and n = 6 (number of distance variations), the result is:
Face Detection Success = (1/6) × 100% = 16.67%

$$Face\ detection\ success = \frac{x}{n} \times 100\% \tag{5}$$

Where the face detection success is in percent (%), x is the number of results "detected," and n is the number of distance variations (6). From the equation above, the result:

$$Face\ detection\ success: \frac{1}{6} \times 100\% = 16{,}67\%$$

To determine the total accuracy of facial recognition, use a distance variation test with a dataset of 50 facial images and then count with Equation 6 as follows.

$$Accuracy = \frac{y}{n} \times 100\% \tag{6}$$

Where the accuracy is in percent (%), y is the total accuracy value, and n is several distance variations (6). From the equation above, the result:

$$Accuracy = \frac{82}{6} \times 100\% = 13{,}6\%$$

From the above equation, a face detection success score of 16,67% and an accuracy of 13,6% were obtained. Figure 4 shows the accuracy of facial recognition at each test distance below.

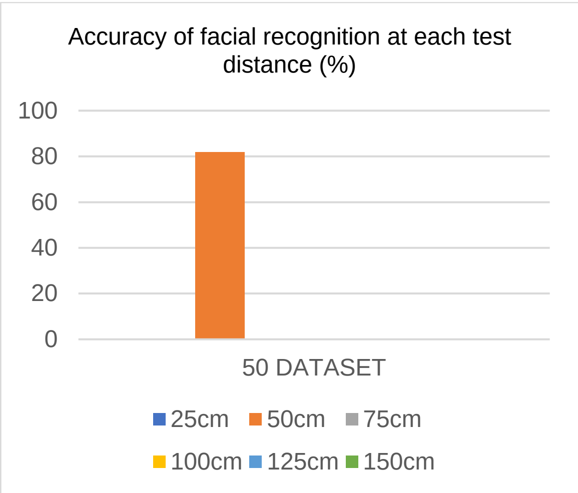


Figure 4. Accuracy of facial recognition at each test distance 50 datasets (%)

Table 2. Results of the distance variation against the accuracy of face recognition (100 datasets)

Distance Variation (cm)	Face Detection Results (Detected or Undetected)	Face Recognition Accuracy (%)	Validation
25	Undetected	-	
50	Detected	82	
75	Detected	Unrecognized (below 0%)	
100	Undetected	-	
125	Undetected	-	
150	Undetected	-	

Based on a distance variation test against the accuracy of facial recognition with a dataset of 100 facial images according to (2), it was found that faces were detected at distances 50cm and 75cm. At a distance of 50cm, faces are recognized with an identification accuracy of 82%, whereas at a distance of 75cm, unrecognized faces with an accuracy ≤ 0%. To determine the success of facial detection, count with (5), as previously shown above.

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Face detection success :

$$\frac{2}{6} \times 100\% = 33\%$$

To determine the total accuracy of facial recognition on a distance variation test with a dataset of 100 facial images, then count with (6) as previously shown above.

$$Accuracy = \frac{82}{6} \times 100\% = 13{,}6\%$$

From the above equation, a face detection success score of 33% and an accuracy of 13.6% were obtained. Figure 5 shows the accuracy of facial recognition at each test distance below.

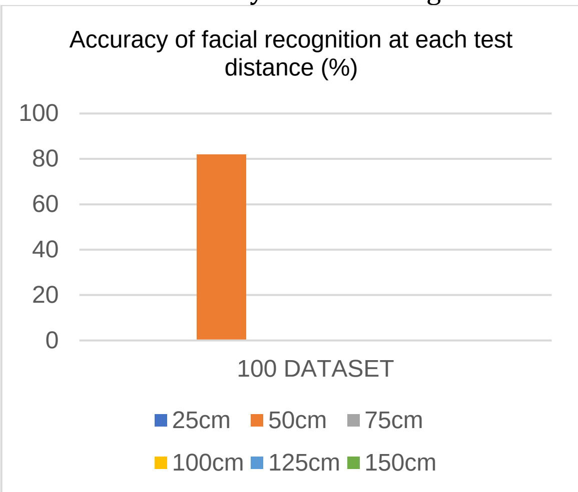

Figure 5. Accuracy of facial recognition at each test distance 100 datasets (%)

Table 3. Results of the distance variation against the accuracy of face recognition (150 datasets)

Distance Variation (cm)	Face Detection Results (Detected or Undetected)	Face Recognition Accuracy (%)	Validation
25	Detected	77	
50	Detected	92	

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75	Detected	98	
100	Detected	95	
125	Undetected	-	
150	Undetected	-	

Based on a distance variation test against the accuracy of facial recognition with a dataset of 150 facial images according to (3), it was found that faces were detected at distances 25cm, 50cm, 75cm, and 100cm. At a distance of 25cm, faces are recognized with a recognition accuracy of 77%; at a distance of 50cm, face recognition with an identification accuracy of 92%; at a distance of 75cm, facial recognition is recognized at a recognition accurate of 98%, and 100cm faces recognition at 95%. To find out the success of facial detection then count with (5) as previously shown above as follows

$$Face\ detection\ success : \frac{4}{6} \times 100\% = 67\%$$

To determine the total accuracy of facial recognition on a distance variation test with a dataset of 150 facial images, then count with (6) as previously shown above as follows.

$$Accuracy = \frac{362}{6} \times 100\% = 60{,}33\%$$

The above equation obtained a face detection success score of 67% and an accuracy of 60,33%. Figure 6 shows the accuracy of facial recognition at each test distance below.

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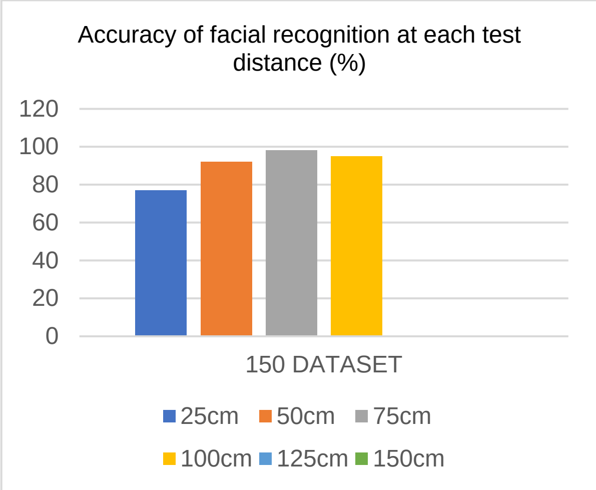

Figure 6. Accuracy of facial recognition at each test distance 150 datasets (%)

Comparisons between successful facial detection and facial recognition accuracy tests of 50, 100, and 150 facial image datasets are shown in (7) below.

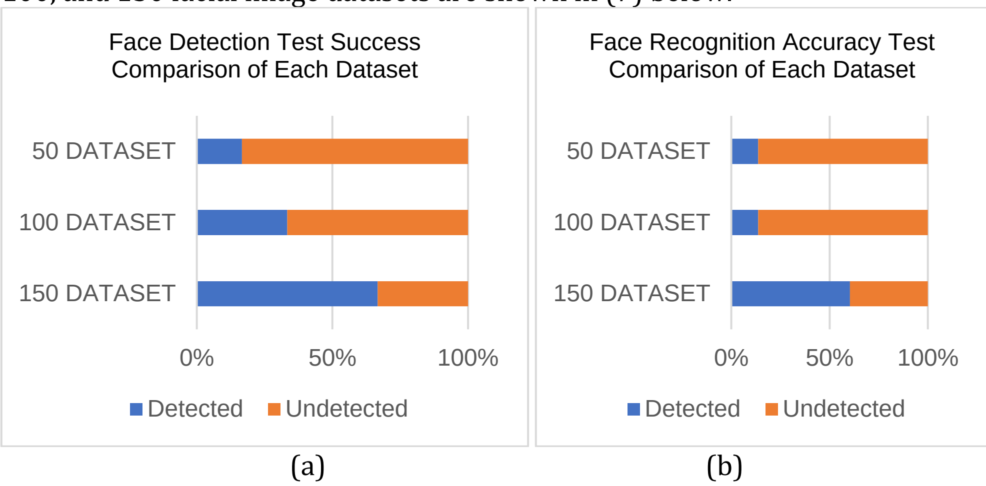

Figure 7. (a) Face detection test success comparison of each dataset and (b) Face recognition accuracy test comparison of each dataset

Fig. 7 Shows an optimal facial recognition distance of 75cm and a facial accuracy of 98% on a dataset of 150 facial images.

Comparison with Previous Studies

The findings of this study are consistent with the research conducted [27], which stated that increasing the number of facial images per individual significantly improves the accuracy of face recognition systems. They used the Haar Cascade method for face detection and Local Binary Pattern (LBP) for facial recognition. Their study concluded that a large volume of training data allows the system to better recognize facial pattern variations in real-world conditions.

However, unlike this study which explicitly evaluated distance variation as a test variable, their research focused more on variations in lighting and facial expressions. Nevertheless, they also emphasized that parameters such as face distance and orientation have a major influence on the performance of face recognition systems and must be controlled during testing procedures [27].

4. Conclusion

Based on the tests that have been done, the overall success of the face detection system from the number of datasets from 50 facial images to 150 facial images has increased the success ratio initially of 17% on 50 datasets, then increased by 16% to 33% on 100 datasets, and increased by 34% to 67% on 150 datasets. The overall accuracy of the facial recognition system has also increased with an initial accurate value of 13.67% on 50 datasets, then remains (as before) on 100 datasets and increased by 46.66% to 60.33% on 150 datasets. This indicates that the more datasets used, the higher the success of facial detection and facial recognition accuracy. Face recognition is an active research area with numerous challenges and opportunities. Advances in technology, such as deep learning and optimization algorithms, have significantly improved face recognition accuracy. However, challenges, such as the curse of dimensionality, remain. Future research needs to focus on developing efficient and reliable methods for feature extraction and selection, dataset reduction to minimize database requirements, and improving face recognition systems' robustness to real-world conditions.

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