

Principal Component Analysis Algorithm For Face Recognition in Kindergarten Students

*Ahmad Abul Khair¹, Muhammad Ibnu Sa'ad²

¹Teknik Informatika, STMIK Widya Cipta Dharma

² Teknik Informatika, STMIK Widya Cipta Dharma

Jl. M. Yamin No. 25, Samarinda, Kalimantan Timur

Email: ¹abul@wicida.ac.id, ² saad@wicida.ac.id

ABSTRACT

In kindergarten, understanding each student's activities is crucial for evaluating their learning and adaptation to the school environment. However, manually tracking individual student activities during class is challenging for kindergarten teachers. This paper proposes using face recognition for kindergarten students as a preliminary step to monitor and record their activities. The process involves converting video footage of students into digital images. Faces are detected using the Viola-Jones method, and feature extraction on the images is performed using the Principal Component Analysis (PCA) method. Euclidean Distance is then applied to recognize the students' faces. Our experiments utilize 70 images for training data, consisting of 5 different images from each of the 14 students. The experimental results demonstrate an accuracy of 91.42% when testing 14 new images of the students.

Keyword: Face Detection, Viola-Jones, Face Recognition, Principle Component Analysis (PCA), Euclidean Distance.

1. INTRODUCTION

Face recognition is a technology that identifies individuals using their facial features in digital images, employing specific parameters for recognition. This advancement in image processing technology also enhances facial features. Various algorithms support and detect faces, with the eigenface algorithm being commonly used due to its easily implementable

formulas and fast execution times. Early Childhood Education (PAUD) serves children from birth to six years old, preparing them for formal, non-formal, and informal education through developmental stimuli.

The human face is a major research focus due to its critical applications in areas like security, entertainment, and surveillance. Among many face detection methods, the Viola-Jones method is highly regarded for its

real-time performance and processing speed. In 2018, Fachrurrozi et al. developed a real-time face recognition system capable of detecting and recognizing multiple faces using Local Binary Pattern (LBP), Agglomerative Hierarchical Clustering (AHC), and Euclidean Distance methods, achieving an accuracy of 61.64%.

Previous face recognition research utilized various techniques and applications. In 2012, Dabhade et al. used Haar-Cascade Classifier and PCA methods with natural lighting and 25 training images per person, achieving an 88% accuracy rate. In 2015, Abdu et al. compared the PCA method with the Hidden Markov Model (HMM) approach for face identification, finding PCA had an 86.6% accuracy while HMM had 77.7%. In 2016, Sri Vignesh et al. developed a class attendance system using RFID and the FANNC method, achieving a 98% accuracy rate for frontal faces.

In 2017, Lukas et al. conducted research on face recognition prototypes using PCA and Euclidean Distance, resulting in an 83.36% accuracy rate. In 2009, Korrani et al. automated meeting

attendance in academic institutions using a fingerprint sensor system. In 2018, Teddy et al. explored multi-face recognition using a hybrid Haar-Cascade and Eigenface method, detecting 55 faces with a 91.67% accuracy rate. Jacky et al. in 2017 developed an attendance system application using the Viola-Jones algorithm for face detection and Eigenface for recognition, achieving 90% accuracy with specific lighting and webcam settings.

Unlike previous research, this study focuses on identifying children's faces in real-time using a webcam indoors. It employs the Eigenface PCA method tailored to children's unique facial characteristics. A 640x480 pixel resolution webcam identifies students' faces during the teaching and learning process. Early childhood education emphasizes holistic development, accommodating all aspects of growth in an engaging and stimulating environment.

2. PROPOSED METHOD

In this paper, the authors propose a face-based attendance system utilizing the Viola-Jones and Principal

Component Analysis (PCA) methods. The Viola-Jones method, known for its real-time detection capabilities, speed, efficiency, and high accuracy, is employed for face detection. It combines four key components: Haar-Like Features, Integral Image, AdaBoost Learning, and Cascade Classifier. For face identification, the Eigenface algorithm is used, applying PCA to the detected face images. During the training phase, face images of the students are collected. The face identification process involves capturing indoor video data at a resolution of 640x480 pixels, which is then processed through digital image processing, face detection, feature extraction, and face recognition. This study uses the Python programming language and the OpenCV library. The system design comprises four main components, as illustrated in Figure 1:

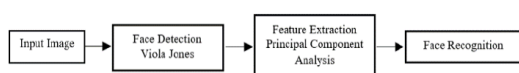


Figure.1. General System Design

1. Input Image

Face images are introduced to the system via media input. The face identification process starts by capturing indoor video

footage at a resolution of 640x480 pixels.

2. Face Detection

Face detection is employed to ascertain the presence or absence of a face in an image, serving as the initial and crucial step in the identification process.

3. Feature Extraction

The image size is resized to 200x200 pixels for face recognition. Afterward, RGB color images are converted to grayscale to reduce color depth. The original image will be transformed to grayscale, and contrast adjustments will be applied using the Histogram Equalization method on the face images.

4. Face Recognition

The introduction process is the most crucial stage of the face recognition system, as it determines the system's accuracy. During this stage, input images are recognized and classified by comparing them with images in the database.

A. Algorithm Viola-Jones

The face detection algorithm developed by Viola and Jones is used to identify faces in the input image. This

algorithm scans the entire image for specific features, known as Haar features, associated with a human face. When a Haar feature is detected, the identified face candidate is passed to the next detection level. The face candidate is a rectangular portion of the original image, called a sub-window. These sub-windows are typically of a fixed size but are often scaled to detect faces of varying sizes. The Viola-Jones face detection algorithm initially converts the input image into an integral image, where each pixel's value is the sum of all pixels above and to the left of the pixel in question. The algorithm relies on four key concepts for face detection:

1. Haar-like features.
2. Integral image
3. Adaptive Boosting
4. Cascade of Classifier

B. Principal Component Analysis (PCA)

Principal Component Analysis (PCA) is a dimensional reduction technique that is commonly used in image processing applications. The basic principle of the PCA algorithm is to maintain and determine the components of a set of images that have the maximum

distribution. PCA is used to obtain vectors or also called the principal component which can provide information about the maximum variance of the face database. Each principal component is a representation of a linear combination of all training face images that have been reduced by the mean image. This combination of face images is called eigenface. Eigenface is a feature of a face image that will be recognized. What is done in the PCA Technique is to arrange the training image into a matrix. By first defining a face-sized image ($N_x \times N_y$) converted into a one column matrix (T) with the size ($N \times 1$) where is the size $N = (N_x \times N_y)$ which is then arranged into a sized training set ($N \times P$). P is the amount of training images.

1) Steps in training

a). Face database creation: Each face image is represented as a matrix that has m rows and n columns, where at each pixel (x, y) x_{em} , y shows the direction of the image and the location of pixels. To make it easier for each face image to be converted into a column vector, if we have q images then the size of the face database size will be $mn \times q$.

Let the face database be (Face_Data)
 mn*q.

b). *Mean Calculation:* Calculate the average in the image, here the vector will have dimensions mn * 1.

$$M = \sum_{i=1}^{mn} \sum_{j=1}^q \text{Face_Data}(i,j) \quad (1)$$

$$M = \sum_{i=1}^{mn} \sum_{j=1}^q = 1$$

c). *Subtract mean:* The average face is subtracted from each face image, let the normalized face become Δ,

$$(\Delta(i))_{mn \times q} = (\text{Face_Data}(i))_{mn \times q} - (M)_{mn \times 1} \quad (2)$$

Where $i \in 1, 2, 3, \dots, q$.

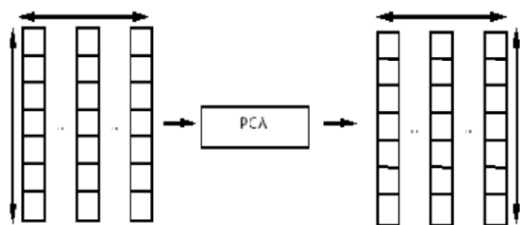


Figure. 2. Eigenface generation process

In this section Eigenface generation process shown in the Figure 2 is Eigenface data extraction from the input vector image is normalized so that get the weight value from the model needed for the matching process.

d). *Co-Variance Calculation:* In general, the covariance of data is calculated by:

$$C = \sum_{i=1}^n (X - X')((Y - Y')^t) \quad (3)$$

Where, X', Y' are the mean of Xi and Yi and C is the covariance matrix. If we follow the same convention on face data that we get is:

$$C(mn, mn) = \sum_{z=1}^m \sum_{y=1}^n (\Delta(z, i) - m_z) * (\Delta(z, i) - m_z)^t \quad (4)$$

Here we get mn directions, which is very hard to process count and store. A new way suggested by Turk and Pentland [11]. to calculate the covariance matrix that is:

$$C(q, q) = \sum_{z=1}^m \sum_{y=1}^n \sum_{i=1}^q (\Delta(z, i) - m_z) * (\Delta(z, i) - m_z)^t \quad (5)$$

Hence here get only q * q dimension, which directions shows maximum variance, and rest of the directions have eigenvalues equal to zero.

e). *Do eigenvalue and eigenvector decomposition:* Now we have covariance matrix (C)_{q*q}, find out the eigenvectors and eigenvalues. For any image A, The eigenvalue is:

$$A.v = \lambda.V \quad (6)$$

Where λ is static. The value of (λ) q*q that gives a solution for the equation (9) is called the eigen value of A and eigen vector is the value that match up with the vector (V) q*q,

$$A.v-\lambda.I.v=0 \quad (7)$$

$$(A-\lambda.I).v=0 \quad (8)$$

Finding the root of $|A-\lambda.I|$ will give the eigenvalues

f). *Feature vector generation:* Now select the best direction from q directions, for this sort the eigenvalues in the ascending order and choose the best k eigen values. On the basis of k eigen value we can generate the Feature vector $(\Psi) q \times k$.

g). *Generating Eigenfaces:* For generating the eigenfaces (ϕ) each will point to the face towards the resulting feature vector.

$$(\phi) k \times nm = (\Psi) q \times k \times (\Delta) k \times nm \quad (9)$$



Figure. 3. Eigenface generation

h). *Generate weight of each face:* For generating weight of each face (w) , project each mean aligned face to the eigenfaces.

$$(w) k \times nm = (\Psi) k \times nm \times (\Delta) nm \times i \quad (10)$$

Where $I \in 1,2,3, \dots, q$. hence 'w' will have the size $k \times q$.

2). Steps in Testing

a). For testing, consider an image (I) , make it as a column vector $(I) nm \times 1$

b). subtracting mean face (M) to this test face $(I \text{ new})$.

$$(I \text{ new}) nm \times 1 = (I) nm \times 1 - (M) nm \times 1 \quad (11)$$

c). project this mean aligned faces $(I \text{ new})$ to eigenface (Φ) , we get the projected test face (Ω) .

$$(\Omega) k \times nm = (\Phi) k \times nm \times (I \text{ new}) nm \times 1 \quad (12)$$

d). Now we have projected test face Ω and signature of each face Φ , calculate the *Euclidean distance* between Ω and each column of Φ .

3. RESULT AND DISCUSSION

A. Data Acquisition

Data Acquisition uses video data for data input. In the initial stage, it is necessary to prepare video data taken using a digital camera with 1.3 MegaPixel HD 720P resolution. The size of video data per frame is processed with a resolution of 680x480 pixels. Video data about detecting children's faces are taken directly in the room in Melati Early Childhood Education (PAUD) in Makassar city, South Sulawesi,

Indonesia. Position the camera must as high as 2 meters from the direction of the class entrance as shows in the figure 4.



Figure. 4. Pole and Camera Position

B. Pre-processing

In the Pre-processing process, images are obtained from a webcam sensor, Figure 5 shows the input in the form of the original image is changed color from the RGB image to be converted into a grey model (greyscale) to facilitate the subsequent color reduction process of depth. The purpose of this conversion process is to make pixel values into only one component so that it is easy to process or manipulate pixels.



Figure. 5. Image origin before Pre-processing

RGB color images are converted into grayscale images to reduce color depth, The original image will experience Grayscale changes like Figure 6.



Figure. 6. Image of Pre-processing results

Figure 7 shows from the grayscale image will be done face detection process from image data acquisition using the AdaBoost method.

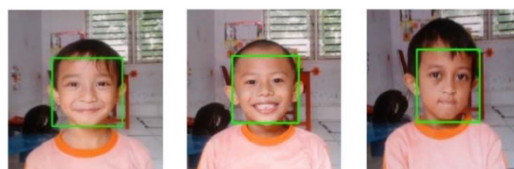


Figure. 7. Face detection using the Viola-Jones Method

The Viola-Jones process has several step-by-step procedures that can perform face detection. Before the Viola-Jones process, the matrix of face images is calculated by the integral image method. An integral image is a representation of a new model, where the pixel value of a pixel is on the left and above that point. Integral imagery is beneficial in calculating Viola-Jones. By

using integral imagery, calculation of Viola-Jones features can be done very quickly. After the process of calculating the integral image process, face classification will be carried out using the Haar-Cascade Classifier. The results of face image segmentation will be extracted from each feature with the PCA method so that PCA values will be obtained from each face image and stored in the database as a result of training data.

C. Feature Extraction

The following are step by step feature extraction stages on faces images and the application of Principal Component Analysis: Face image to – I, shown in Figure 8.

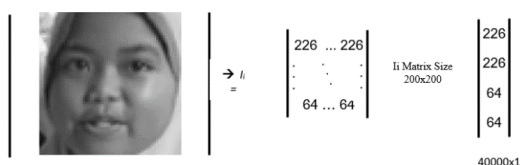


Figure. 8. The process of transforming face images into column vectors.

Table I. Process Feature Extraction

No	Image Test	Face Image	Image Resolution → M x N	Normalization	Vector image of training	Average training vector
1	ifa_1		200 x 200	[[255 255 255 ... 255 255 255]]	[226 226 226 ... 218 218 218] [64 64 64 ... 205 205 205]	208.392
2	ifa_2		200 x 200	[[255 0 255 ... 255 255 255]]	[226 226 226 ... 218 218 218] [64 64 64 ... 205 205 205]	208.443
3	ifa_3		200 x 200	[[255 255 255 ... 255 0 255]]	[226 226 226 ... 218 218 218] [64 64 64 ... 205 205 205]	204.975
4	ifa_4		200 x 200	[[255 255 255 ... 255 255 255]]	[226 226 226 ... 218 218 218] [64 64 64 ... 205 205 205]	205.185
5	ifa_5		200 x 200	[[255 255 255 ... 255 255 255]]	[226 226 226 ... 218 218 218] [64 64 64 ... 205 205 205]	204.567

Table II. Process Eigenfaces

No	Eigenfaces	Eigenfaces Value	Eigenvectors	Eigenface average
1		[[[234.6] [234.8] [234.6] ... [217.6] [218] [217.4]]]	[[6.746- 8.907- ... 5.601- ... 1.500- 1.601- 1.580-]]	228.664

Principal Component Analysis (PCA) is a mathematical tool for extracting distinctive features called eigenface from original image data. Each principal component is a representation of a linear combination of all training face images that have been reduced by the average model. This combination of Face images is called eigenface. PCA value is the value between one face and another person's face. PCA reduces the facial characteristics of facial processes in the training process, the results of the method obtained on the front are shown in Figure 9.



Figure. 9. Results of *Eigenface* Process

Each prepared training data is carried out by feature extraction from each face using PCA so that the value of feature extraction obtained from each sample of the person is obtained. The PCA value is stored as a database for later face processes.

D. Feature Selection

Introduction to *Euclidean Distance* in the figure shows a diagram of facial recognition themes. This is illustrated as a follow-up in Table III: Testing Data, and Table IV: Training Data. Described as follow.

Table III. Process Testing Data

No	Image test	RGB	Image resolution	Grayscale
1	Test_1		200 x 200	
(Test Image) Blur & Treshold		Matrix	Vector Image Test	Test Vector Average
		[255 255 255 ... 255 255 255]	[[255 255 255 ... 255 255 255]]	207.621

Table IV. Process Training Data

No	Test Image	Eigenface Grayscale	Eigenface Image Resolution
1	Test_lfa		200 x 200
(Test Image) Eigenface Blur & Treshold		Eigenface Vector	Average Eigenfaces
		[[[225.825] [225.925] [225.95] ...[217.575] [217.975] [217.775]]]	228.664

The next process is a test image of a known person. As in the training phase, a feature vector is calculated using PCA, then calculate the similarities between feature vectors in the training data. Each training data prepared as performed by feature extraction from each face using PCA so that the feature extraction value was obtained from each sample of the person received. The PCA value is stored as a database for the next face process. Use *Euclidean Distance* to find r_i the smallest difference between eigenfaces training image in the database with faces testing image r_{new} in the database with eigenface test face. In the example of the count of facial recognition processes carried out by the

authors obtained calculations. described as follow.

$$Euclidean\ Distance : \sqrt{\sum (X - Y)^2}$$

\sum = Summation

X = Result Testing Data

Y = Result Training Data

TABLE V. Process Euclidean Distance

No	Pointer Pixel	1	2	3	4	5
1	X Value	255	255	255	255	255
2	Y Value	255	0	255	255	255
3	(X-Y) Value	0	255	0	0	0
4	(X-Y) ² Value	0	65025	0	0	0
5	$\sum((x-y)^2)$ Value	5,419				
6	$(\sum((x-y)^2))$ Sqrt Value	73,61				

.....	39996	39997	39998	39999	40000
.....	255	255	255	255	255
.....	255	255	255	255	255
.....	0	0	0	0	0
.....	0	0	0	0	0



No	Name Image	Test Image		No	Name Image	Result Recognition
1.	Test_1		➔	30.	Ifa_5	

Table VI. All Training Results Data

No	Name Eigenfaces	Euclidean Distance	No	Name Eigenfaces	Euclidean Distance
1.	Abdi 1	100.458	36.	Ijat 1	110.267
2.	Abdi 2	98.427	37.	Ijat 2	102.985
3.	Abdi 3	98.716	38.	Ijat 3	100.563
4.	Abdi 4	97.185	39.	Ijat 4	102.073
5.	Abdi 5	98.792	40.	Ijat 5	101.705
6.	Arsan 1	99.819	41.	Ikram 1	99.126
7.	Arsan 2	95.739	42.	Ikram 2	101.459
8.	Arsan 3	102.068	43.	Ikram 3	99.589
9.	Arsan 4	101.744	44.	Ikram 4	98.193
10.	Arsan 5	98.442	45.	Ikram 5	98.994
11.	Diman 1	104.952	46.	Ira 1	104.052
12.	Diman 2	104.110	47.	Ira 2	110.995
13.	Diman 3	106.979	48.	Ira 3	103.662
14.	Diman 4	104.556	49.	Ira 4	108.843
15.	Diman 5	109.549	50.	Ira 5	106.943
16.	Furqon 1	100.692	51.	Lely 1	92.330
17.	Furqon 2	100.359	52.	Lely 2	93.674
18.	Furqon 3	100.856	53.	Lely 3	92.347
19.	Furqon 4	99.554	54.	Lely 4	93.722
20.	Furqon 5	100.866	55.	Lely 5	94.079
21.	Hikma 1	102.127	56.	Taufik 1	101.769
22.	Hikma 2	95.775	57.	Taufik 2	100.309
23.	Hikma 3	95.498	58.	Taufik 3	100.950
24.	Hikma 4	99.025	59.	Taufik 4	102.765
25.	Hikma 5	99.959	60.	Taufik 5	100.533
26.	Ifa 1	99.704	61.	Tyfa 1	105.640
27.	Ifa 2	97.790	62.	Tyfa 2	103.942
28.	Ifa 3	89.927	63.	Tyfa 3	102.883
29.	Ifa 4	92.401	64.	Tyfa 4	102.127
30.	Ifa 5	73.627	65.	Tyfa 5	102.093
31.	Iin 1	98.096	66.	Vesty 1	100.772
32.	Iin 2	96.659	67.	Vesty 2	100.424
33.	Iin 3	91.815	68.	Vesty 3	105.867
34.	Iin 4	93.770	69.	Vesty 4	96.984
35.	Iin 5	93.241	70.	Vesty 5	96.994

The test results concluded that the face test was more similar to the Ifa_5 image no 30 than all training images stored in the database. With the following explanation, Min Distance: 73.627 and recognizable faces are: Ifa_5 and the accuracy of each training image is as follows: Average Test/Training Average*100, 207.621/228.664*100= 90.79%. The similarities between feature vectors were compued using the *Euclidean Distance*.

On the other hand, recognition is done by projecting a new image into a

subspace that is stretched by eigenface and then classifying faces by comparing positions in face space. With known individual locations. Calculation of the distance is carried out by *Euclidean Distance*. Distance weight values are representations of image training that are similar to image test. The process of face detection and identification testing is carried out in the room when the children are present. Children only have to see the camera provided, and then the system will identify the face of the test image by comparing the face database obtained in the training process with the *Euclidean distance* method shown in Figure 10.

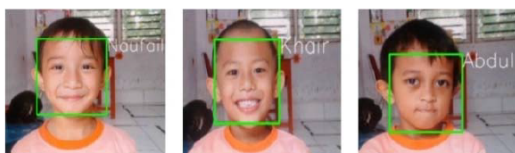


Figure. 10. Test the identification of one face in class

In addition to identifying faces using one face, the testing process is also done with multifaceted or more than one look shown in Figure 11.



Figure. 11. Identifying many faces outside the classroom

From the results of the detection process, of the fourteen children who were in front of the camera, all faces were detected by the presence of their faces, with the same lighttaking conditions namely, daytime when indoors and also outside the room before the learning process. After the successful identification process, all images that have PCA values and stored in the database will look for similarities with face images in the testing process using *Euclidean Distance* to calculate the proximity distance between learning pictures and objects to be classified. Thus, it can be concluded that *Euclidean Distance* calculates the minimum

distance between the images to be tested with the recognizable image from the database. If the distance is small, a comparable image can be determined, which can be determined which model is most similar to the database.

4. CONCLUSION

1. This Study uses real-time data from the classroom, which aims to identify the faces of children in the room using a webcam, using the Principal Component Analysis algorithm.
2. The Video data used in the training process is that of the total 70 training data that have PCA values stored in a database, The correct amount of data is 64, and 6 training data are not identified because they have nothing in common.
3. There is no similarity with the image in the testing process using *Euclidean Distance*. From the result of testing 14 test data and 70 training data, the percentage of the succes of the face recognition process with an accuracy rate reached 91.42%.

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REFERENCES

- [1] “Early Childhood Education Curriculum (PAUD).,” 04-Apr-2012.
- [2] P. Viola and M. J. Jones, “Robust Real-Time Face Detection,” *Int. J. Comput. Vis.*, vol. 57, no. 2, pp. 137–154, May 2004.
- [3] M. Fachrurrozi *et al.*, “Real-time Multi-object Face Recognition Using Content Based Image Retrieval (CBIR),” *Int. J. Electr. Comput. Eng. IJECE*, vol. 8, no. 5, p. 2812, Oct. 2018.
- [4] M. S. Bewoor, “Real Time Face Detection and Recognition using Haar-Based Cascade Classifier and Principal Component Analysis,” 2012.
- [5] A. R. Syakhala, D. Puspitaningrum, and E. P. Purwandari, “Comparison of Principal Component Analysis (PCA) methods with the Hidden Markov Model (HMM) method in the introduction of a person’s identity through the face,” vol. 3, p. 14, 2015.

[6] S. Pss and M. Bhaskar, "RFID and pose invariant face verification based automated classroom attendance system," in *2016 International Conference on Microelectronics, Computing and Communications (MicroCom)*, Durgapur, India, 2016, pp. 1–6.

[7] L. Tommy and Y. Setiawan, "Face recognition prototype using Principal Component Analysis and Euclidean Distance," p. 6, 2017.

[8] A. Korrani, "Development of Academic Attendance Monitoring System Using Fingerprint Identification," *Int. J. Comput. Sci. Netw. Secur.*, vol. 9, p. 5, May 2009.

[9] T. Mantoro, M. A. Ayu, and Suhendi, "Multi-Faces Recognition Process Using Haar Cascades and Eigenface Methods," in *2018 6th International Conference on Multimedia Computing and Systems (ICMCS)*, Rabat, 2018, pp. 1–5.

[10] J. Efendi, M. I. Zul, and W. Yunanto, "Real Time Face Recognition using Eigenface and Viola-Jones Face Detector," *JOIV Int. J. Inform. Vis.*, vol. 1, no. 1, pp. 16–22, Mar. 2017.

[11] E. Lawson, "Summary: "Eigenfaces for Recognition" (M. Turk, A. Pentland)," *J. Cogn. Neurosci.*, vol. 3, pp. 71–86, 1991.