ISSN:2302-8149
e-ISSN:2540-9719

Face Recognition for Personal Data Collection using Eigenface, Support Vector Machine, and Viola Jones Method

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(***received*** **:** 30 October 2024, ***revised*** **:** 20 November 2024, ***accepted*** **:** 9 January 2025)

Abstract

Personal data recording through facial recognition is a modern solution for individual identification; however, the main challenge lies in the accuracy and reliability of the system under various conditions. This study examines the implementation of machine learning as a solution, utilizing video and photo data for face detection and recognition. The study's goal is to evaluate the effectiveness of facial image recognition by combining several methods, aiming for practical application across diverse settings, such as offices and schools. The methodology includes segmentation testing for edge detection, feature extraction, and real-time recognition. The system was developed using Eigenface, Support Vector Machine, and Viola-Jones methods, trained over 20 sessions. The results indicate that the system can recognize faces under both daytime and nighttime conditions, achieving 87% accuracy during the day and 81% at night. These findings make a significant contribution to the development of security systems based on facial recognition and emphasize the potential of this technology to enhance personal data security across various contexts

Keywords: eigenface, facial recognition, image processing, machine learning, support vector machine, viola jones

1 Introduction

The rapid advancement of technology has spurred various innovations in self-identification or biometric systems, particularly facial recognition, which has gained significant attention in recent years for its potential across multiple applications. The use of facial recognition in surveillance and security, digital libraries, and human-computer interaction demonstrates the considerable benefits of this technology [1]. In facial recognition processes, the system identifies or verifies a face image by matching the recorded image with stored facial data in a database. However, challenges in accuracy and identification speed, especially under varying lighting conditions or facial angles, remain primary obstacles to the optimal implementation of this technology.

Previous studies have showcased various efforts to advance facial recognition technology. For example, identify faces using the Local Binary Pattern (LBP) and Support Vector Machine (SVM) methods [2], [3], while the Principal Component Analysis (PCA) and Eigenface methods developed for facial recognition in online attendance applications [4]–[6]. Additionally, combined SVM with Sobel Edge Detection to enhance image quality based on luminance and object distance parameters [7]. Other studies apply Two-Dimensional Linear Discriminant Analysis (TDLDA) and SVM on datasets such as ORL and YALE to improve accuracy [8], [9]. Another study used the Viola Jones

 ISSN:2302-8149
e-ISSN:2540-9719

and Eigenface methods for facial recognition through video with a dataset of 500 images, successfully enhancing face detection performance through deep learning [10]–[14]. Other studies also show the reliability of the Haar Cascade method in detecting other objects such as cars. The results of the study showed that the accuracy obtained was very good, even though it was applied during day and night detection times [15]–[18].

This research is unique in combining multiple methods to improve accuracy and efficiency in real-time facial recognition using a laptop camera. Unlike previous studies, this study will also test accuracy levels by integrating different methods to determine the most optimal approach under varied conditions. Through a comparative analysis, this research aims to provide a novel and more effective approach in developing a non-contact, automatic, and timely facial identification system, contributing significantly to facial biometric technology.

2 Literature Review

In this study, we propose a facial recognition system for personal data recording, building on several machine learning methods that have been tested in previous research. The first study applied the Local Binary Pattern (LBP) and Support Vector Machine (SVM) methods to design a webcam-based facial recognition system. In that research, LBP was used to extract features from facial images, while SVM served as the classification model. This approach showed that the combination of LBP and SVM could create an efficient facial identification model, especially for systems based on simple camera setups such as webcams. This study provided a strong foundation for the use of LBP and SVM in static data-based facial recognition systems, which can be quickly deployed on a small scale [2], [3].

In addition, other research utilized PCA and Eigenface methods for facial recognition in online attendance applications. With this method, PCA was employed to reduce data dimensions and optimize processing time, while Eigenface was applied to detect facial features for identification purposes. This approach demonstrated good accuracy for facial recognition in environments with varying lighting conditions, making it suitable for web-based attendance or remote applications [4]–[6]. On the other hand, the application of SVM combined with Sobel Edge Detection in a facial detection system aimed to enhance image quality. This method used parameters such as luminance and distance to improve facial image results and considered the dataset size. The application produced better image quality and accurate facial classification in large datasets [7]. The TDLDA and SVM methods were also implemented in a facial recognition application tested on ORL, YALE, and BERN datasets. In this study, the TDLDA and SVM combination yielded high accuracy across variations in expression and lighting, making it a reliable choice for developing facial recognition systems with improved precision in response to visual condition changes. This method shows development potential in systems that require real-time adaptation, especially in controlled environments [8], [9].

Another method, such as Viola Jones or the Haar Cascade Classifier, was combined with Eigenface for video-based facial recognition. Viola Jones was used for facial detection, while Eigenface was applied in the recognition stage using a dataset of 500 images. This approach demonstrated good effectiveness for facial recognition in moving video contexts, making it highly relevant for surveillance or real-time monitoring applications [10]–[14]. Other studies have also demonstrated the reliability of the Haar Cascade method in detecting non-facial objects, specifically vehicles. The results indicated that the application of Haar Cascade in vehicle detection using the Region of Interest (ROI) detection concept achieved up to 90% accuracy, 86% precision, and 92% sensitivity. This result highlights the flexibility of the Haar Cascade method for detecting objects beyond faces, such as vehicle recognition [15]–[18].

Based on this literature review, it is evident that previous research has successfully improved the accuracy and efficiency of facial recognition using various machine learning methods. The system

ISSN:2302-8149
e-ISSN:2540-9719

proposed in our study aims to integrate these proven effective methods to achieve optimal facial recognition for personal data recording, while enabling stable performance under various lighting conditions and facial variations.

3 Research methods

Based on the discussion in the previous chapter, the methodology used in writing and completing this research adopts the stages of system development from the waterfall model.

3.1. Research Stages

This research is conducted using several methods aimed at providing a foundational guide for the development process of the facial recognition system. The methods employed include Eigenface, Support Vector Machine (SVM), and the Viola-Jones algorithm. The Eigenface method is used for face pattern recognition, SVM for classification, and Viola-Jones for face detection. The stages of the research are illustrated in the block diagram in Figure 1.

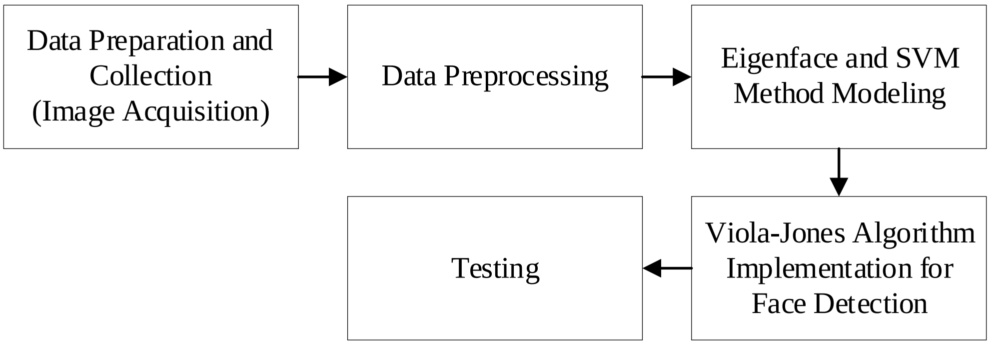

Figure 1. Block diagram of research stages

3.2. Data Preparation and Collection Stage

In this stage, the preparation of the facial dataset to be used in the training and testing processes is conducted. Facial data is collected from users who will be recognized, and this data will be processed and stored in a database.

3.2.1. Data Preprocessing Stage

Preprocessing aims to prepare the data for use in the face detection and recognition algorithms. The preprocessing steps include normalization, resizing, and converting images to grayscale to facilitate face detection and recognition.

3.2.2. Modeling Stage with Eigenface Method and SVM

After the data is processed, the Eigenface method is used to extract facial features, while SVM is employed to classify the results of this feature extraction. These two methods work together to support the face recognition process.

3.2.3. Implementation Stage of the Viola-Jones Algorithm for Face Detection

The Viola-Jones algorithm is used in this stage to detect faces in images in real-time. This algorithm identifies whether a face is present in an image, allowing facial features to be extracted and classified further.

3.2.4. Testing Stage

Testing is performed to measure the performance of the facial recognition system in terms of accuracy, detection precision, and computation time. The testing is conducted under two conditions: during the day and at night, to assess the system's stability.

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e-ISSN:2540-9719

3.2.5. Results Analysis Stage

The results obtained from the testing will be analyzed to determine the system's accuracy. The use of a confusion matrix will aid in evaluating the model's performance in terms of correct and incorrect classifications.

3.3. Use Case Diagram for Facial Recognition

The Use Case diagram is used to understand the interaction between the user (admin) and the developed facial recognition system. This diagram defines the functions available in the system and the user access rights, as shown in Figure 2.

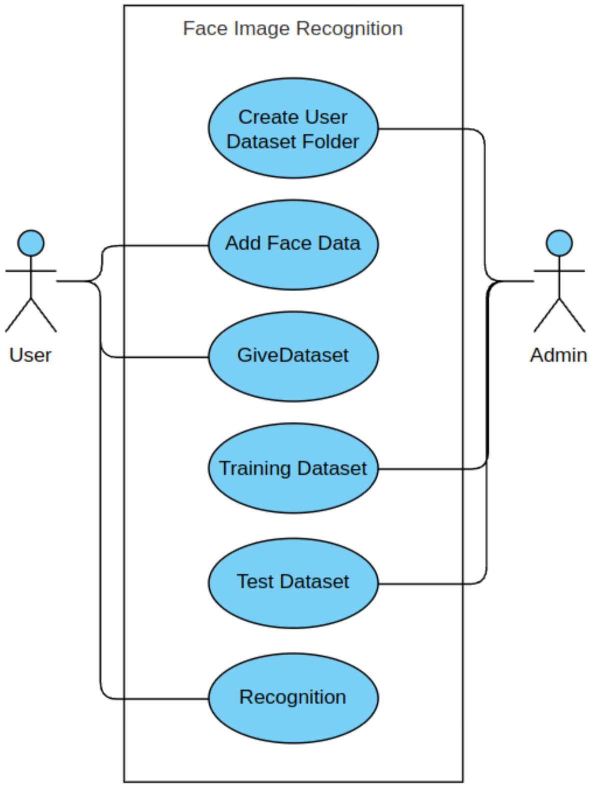

Figure 2. Use case diagram for facial recognition

In this use case, it is explained that the admin is responsible for:

a. Adding user names and creating folders for the dataset.
b. Collecting facial data from users and saving it to the database.
c. Dividing the facial data into two parts: training data and testing data.
d. Performing facial recognition based on the registered names.
e. The user only has the function of providing the facial data to be recognized.

3.3. Confusion Matrix

Testing using the confusion matrix is conducted to evaluate the classification results of the system. The confusion matrix presents a comparison between the predictions made by the model and the actual known results. The confusion matrix is a table that displays four categories: True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN). This matrix will help measure other evaluation metrics, such as precision, recall, and F1-score [1].

3.4. Accuracy Test

The accuracy test is conducted to determine the model's prediction accuracy in recognizing faces. Testing is performed under two lighting conditions: during the day and at night, to assess the system's stability in different conditions. Accuracy is calculated based on the comparison between the number

ISSN:2302-8149
e-ISSN:2540-9719

of correct predictions and the total predictions made. Previous research results indicated a relatively high level of accuracy for the facial recognition system under both conditions [6].

4. Results and Discussion

In this section, we present and analyze the outcomes of the conducted experiments, focusing on the performance of the developed facial recognition system. The results are assessed based on various testing conditions, such as dataset size, facial positions, lighting conditions, and distance from the camera. Additionally, the system's accuracy is measured through different evaluation metrics, including classification reports, and Confusion Matrix. The following sub-sections provide a detailed account of the training process.

4.1. Training Data Testing

This testing is conducted to determine the accuracy level of the developed program and to evaluate the resulting SVM model using a test dataset. Additionally, it aims to calculate the Classification Report, providing results for Accuracy, Precision, Recall, and F1 Score.

```
Predicting people's names on the test set
0.8840579710144928
done in 0.001s

Classification Report :
                      precision    recall  f1-score   support

                Dafa       1.00      0.83      0.91         6
               Didik       0.89      0.89      0.89         9
             Giovani       0.73      0.80      0.76        10
Megawati_Sukarnoputri       0.88      0.78      0.82         9
          Tony_Blair       0.92      0.94      0.93        35

            accuracy                           0.88        69
           macro avg       0.88      0.85      0.86        69
        weighted avg       0.89      0.88      0.88        69
```

Figure 3. Classification report result

4.2. Data Testing

Testing is conducted to determine the prediction results from several images in the test dataset folder. The results show some incorrect predictions in certain facial images, likely due to an accuracy level reaching only 60%.

4.3. Testing on a Single Person within the Dataset

This test is performed using a computer/laptop camera with varying facial positions at slight angles. Table 1 shows recognition test results based on facial positions in the dataset..

Table 1. Facial position testing within the dataset

No	Face Position and Condition	Recognition Result
1	Facing the Camera	Recognized
2	Facing Right	Recognized
3	Facing Left	Recognized
4	Facing Up	Recognized
5	Facing Down	Recognized
6	Eyes Closed	Recognized
	Recognition Accuracy Level	**100%**

4.4. Testing on a Person Outside the Dataset

This test is conducted similarly, but the user's facial data is not registered in the dataset. Table 2 shows recognition test results based on facial positions without a dataset

ISSN:2302-8149
e-ISSN:2540-9719

Table 2. Facial position testing without a dataset

No	Face Position and Condition	Recognition Result
1	Facing the Camera	Not Recognized
2	Facing Right	Not Recognized
3	Facing Left	Not Recognized
4	Facing Up	Not Recognized
5	Facing Down	Not Recognized
6	Eyes Closed	Not Recognized
Recognition Accuracy Level		**100%**

4.5. Dataset Quantity Testing

This test measures the system's accuracy using dataset counts of 25, 50, and 100 entries, as shown in Table 3.

Table 3 Dataset Quantity Testing

No	Dataset Name	Dataset Count	Result
1	Giovani	25	Success
2	Ghali		Success
3	Dafa		Failure
4	Didik		Failure
5	Giovani	50	Failure
6	Ghali		Success
7	Dafa		Failure
8	Didik		Success
9	Giovani	100	Success
10	Ghali		Failure
11	Dafa		Success
12	Didik		Success

4.6. Testing at Specific Distances in Daytime Conditions

Testing is done with a computer/laptop camera at varying face distances and brightness levels during the day, as shown in Table 4.

Table 4 Distance Testing in Daytime Conditions

No	Dataset Name	Distance (cm)				Result	
		50	100	150	200	Success	Failure
1	Giovani	1	1	1	1	4	0
2	Dafa	1	1	1	0	3	1
3	Didik	1	1	1	1	4	0
4	Ghali	1	1	0	1	3	1
Total Samples						16	
Correctly Identified						14	
Not Identified						2	

$$Accuracy = \frac{Correct\ Trials}{Total\ Trials} x100\%$$

$$Accuracy = \frac{14}{16} x100\%$$

$$Accuracy = 87\%$$

4.7. Testing at Specific Distances in Nightime Conditions

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e-ISSN:2540-9719

This test is conducted similarly but during the night, as shown in Table 5.

Table 5. Distance testing in nightime conditions

No	Dataset Name	Distance (cm)				Result	
		50	100	150	200	Success	Failure
1	Giovani	1	1	1	1	4	0
2	Dafa	1	1	0	1	3	1
3	Didik	1	0	1	0	2	2
4	Ghali	1	1	1	0	3	1
Total Samples						16	
Correctly Identified						13	
Not Identified						3	

$$Accuracy = \frac{Correct\ Trials}{Total\ Trials} x100\%$$

$$Accuracy = \frac{13}{16} x100\%$$

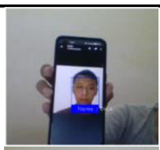
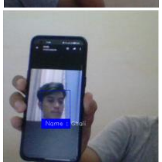
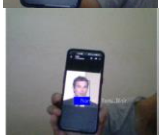
$$Accuracy = 81\%$$

4.8. Additional Testing with 2D Face Data

This test assesses if the system can recognize 2D facial images, such as smartphone photos. Figure 3 shows sample face data in the dataset, and test results are shown in Table 6.

Figure 3. Sample facial data contained in the dataset

Table 6 2D Face Data Testing Results

No	Name	Dataset	Result
1	**Didik**		Success
2	**Dafa**		Failure
3	**Ghali**		Success
4	**Tony blair**		Success

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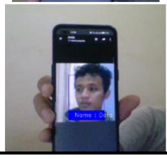
5	**Megawati**		Success
6	**Dafa**		Success

4.9. Analysis and Accuracy Calculation from Test Data

Based on training and testing results, a statistical approach was used to assess overall system performance by comparing test variables. Table 7 presents the test data results.

Table 7. Test data sample results

No	Face Sample	Test Data Samples	Identification Result	
			Recognize	Unrecognized
1		4	3	1
2		4	4	0
3		4	4	0
4		4	2	0
5		4	4	0
6		4	3	1
7		4	4	0
Total Test Data Samples			28	
Correctly Identified			24	
Not Identified			4	

$$\boldsymbol{Accuracy} = \frac{24}{28} x\ 100\%$$

$$\boldsymbol{Accuracy} = 85\%$$

4.10. Testing Using Confusion Matrix Algorithm

ISSN:2302-8149
e-ISSN:2540-9719

To determine overall system accuracy, a Confusion Matrix was employed, providing four test variables shown in Table 8.

Table 8. Confusion matrix testing

Actual Data		Identification Result	
Known (In Dataset)	**Unknown (Not in Dataset)**	**The system is successful in recognizing**	**The system fails to recognize**
True Positif (TP)	*True Negatif* (TN)	*True Positif* (TP)	*False Negatif* (FP)
False Positif (FP)	*False Negatif* (FN)	*True Negatif* (TN)	*False Negatif* (FN)

$$Akurasi = \frac{TP + TN}{TP + FP + TN + FP} x\ 100\%$$

Explanation:

- **True Positive (TP)** : Recognized faces in the dataset are correctly identified.
- **False Positive (FP)** : Recognized faces in the dataset are incorrectly identified.
- **True Negative (TN)** : Unregistered faces are correctly identified as unknown.
- **False Negative (FN)** : Unregistered faces are incorrectly identified as known.

Table 9. Confusion matrix testing results

No	Face Sample	Distance (cm)	Test Data Samples	Identification Result			
				TP	TN	FP	FN
1		20-200	4	4	0	0	0
2		20-200	4	3	0	1	0
3		20-200	4	4	0	0	0
4		20-200	4	1	1	2	0
5		20-200	4	3	0	1	0
6		20-200	4	4	0	0	0

ISSN:2302-8149
e-ISSN:2540-9719

No	Face Sample	Distance (cm)	Test Data Samples	Identification Result			
				TP	TN	FP	FN
7		20-200	4	4	0	0	0
8		20-200	4	2	0	0	2
Total Test Data Samples				32			
Successfully Identified				16			
Failed to Identify				16			

From Table 9, the following test variable values are obtained:

- TP (True Positives) = 25
- FP (False Positives) = 4
- TN (True Negatives) = 0
- FN (False Negatives) = 3

To calculate overall accuracy, based on the test data sample, the Confusion Matrix formula can be used:

$$Accuracy = \frac{25 + 0}{25 + 4 + 0 + 3} x100\%$$

$$Accuracy = \frac{25}{32} x100\%$$

$$Accuracy = 78\ \%$$

Based on testing conducted with a sample of 32 test data points, the system achieved an accuracy rate of 78% in facial identification.

5. Conclusion

This study shows that the facial recognition system developed using the Eigenface, SVM, and Viola-Jones methods has successfully completed 20 training experiments, resulting in a validation accuracy of 71% and a loss of 29%. Testing was conducted under two lighting conditions: during the day, the system achieved an accuracy of 87%, while at night it reached 81%. The testing process included two stages: first, face recognition, which demonstrated an accuracy of 90% as assessed through the Confusion Matrix; second, face recognition using two-dimensional data from a smartphone, achieving an accuracy of 50%. For future research, it is recommended to use a high-quality external webcam to improve facial recognition results, as well as to consider adding new methods to enhance accuracy. Additionally, the use of multiple higher-resolution cameras could aid in recognizing faces from a greater distance.

Acknowledgement

Thank you to Bumigora University for its support for this research.

ISSN:2302-8149
e-ISSN:2540-9719

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ISSN:2302-8149
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