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Comparative Analysis of Haar Cascade Classifier, Dlib, and Mediapipe for Face Recognition

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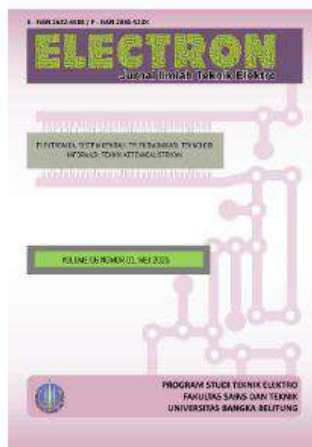
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DOI: <https://doi.org/10.33019/electron.v6i1.240>

Keywords: Face Recognition, Face Detection, Haar Cascade Classifier, Dlib, Mediapipe

Abstract

Technological developments are having considerable effects on a lot of industries, particularly in the security sector. One of the important technologies in security sector is face recognition. Face recognition is a technology that verify and identify individual identity using face. There are many processes that involved in face recognition technology such as face detection methods, Face



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ISSN ELECTRON

E-ISSN 2622-6588

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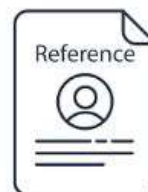
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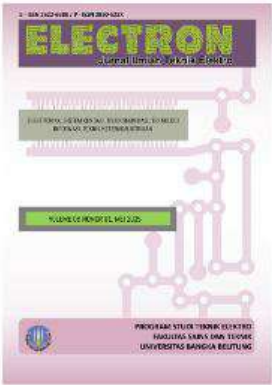
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DOI: <https://doi.org/10.33019/electron.v6i1>

Published: 2025-05-31

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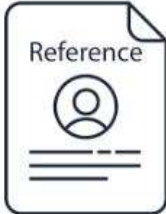
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Comparative Analysis of Haar Cascade Classifier, Dlib, and Mediapipe for Face Recognition

Analisis Perbandingan Haar Cascade Classifier, Dlib, dan Mediapipe untuk Pengenalan Wajah

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[Received: 3 October 2024, Revised: 21 May 2025, Accepted: 26 May 2025]

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ABSTRACT — Technological developments are having considerable effects on a lot of industries, particularly in the security sector. One of the important technologies in security sector is face recognition. Face recognition is a technology that verify and identify individual identity using face. There are many processes that involved in face recognition technology such as face detection methods. Face detection is a process of searching for faces in images. Each face detection method has different way to searching the face in image. It can affect the performance of face recognition technology itself. In this study, an analysis comparison between different face detection methods for face recognition was carried out. Face detection methods that used in this study was haar cascade classifier, dlib, and mediapipe. Technology that used to identify faces was Convolutional Neural Network (CNN). CNN model was trained with different face detection methods. Then it was used to carry out a simulation in identifying faces. The result of the comparison was shown in the form of performance metrics. The performance metrics include confusion matrix, accuracy, precision, recall, and f1-score. Based on the simulation that has been carried out, CNN model with haar cascade classifier face detection method generated the highest accuracy value of 98%, precision value of 98.08%, recall value of 98%, and f1-score of 97.99%.

KEYWORDS — Face Recognition, Face Detection, Haar Cascade Classifier, Dlib, Mediapipe

INTISARI — Perkembangan teknologi mempunyai dampak yang besar terhadap banyak industri, terutama di sektor keamanan. Salah satu teknologi penting dalam bidang keamanan adalah pengenalan wajah. Pengenalan wajah adalah sebuah teknologi yang berfungsi untuk memverifikasi dan mengidentifikasi identitas individu menggunakan wajah. Terdapat banyak proses yang terlibat dalam teknologi pengenalan wajah salah satunya adalah pendeteksian wajah. Pendeteksian wajah merupakan proses pencarian wajah dalam sebuah gambar. Setiap metode untuk pendeteksian wajah memiliki cara yang berbeda-beda dalam mencari wajah pada gambar. Hal ini dapat mempengaruhi kinerja teknologi pengenalan wajah itu sendiri. Dalam penelitian ini, dilakukan analisis perbandingan antara berbagai jenis metode deteksi wajah untuk pengenalan wajah. Metode deteksi wajah yang digunakan dalam penelitian ini adalah haar cascade classifier, dlib, dan mediapipe. Teknologi yang digunakan untuk mengidentifikasi wajah adalah Convolutional Neural Network (CNN). Model CNN dilatih dengan metode deteksi wajah yang berbeda kemudian digunakan untuk melakukan simulasi dengan tujuan berupa mengidentifikasi wajah pada gambar. Hasil perbandingan tersebut ditampilkan dalam bentuk metrik kinerja. Metrik kinerja mencakup matriks kebingungan dan beberapa nilai berupa akurasi, presisi, penarikan kembali dan skor f1. Berdasarkan simulasi yang telah dilakukan, model CNN dengan metode deteksi wajah haar cascade classifier menghasilkan nilai akurasi tertinggi sebesar 98%, nilai presisi sebesar 98,08%, nilai penarikan kembali sebesar 98%, dan skor f1 sebesar 97,99%.

KATAKUNCI — Pengenalan Wajah, Pendeteksian Wajah, Haar Cascade Classifier, Dlib, Mediapipe

I. INTRODUCTION

Technology is developing quickly and widely as time goes by. Developments in technology are one of the things that drive people's lives to change. Technology advancements have led to the development of several industries, particularly in the security industry. Face recognition is an example of a technology that continues to develop in the security sector.

Face recognition is a method with facial recognition properties that is applied to existing systems or technology [1]. Face recognition identifies a person by using their facial features. This technology recognizes a person's face using artificial intelligence and image processing techniques. Face recognition is frequently used in security systems, such as for criminal identification and facility access. There are various processes that involved in face recognition. Face detection is one of the important processes in face recognition. Face detection is the process of searching for faces in the received image. There are several methods that can be used for face detection such as haar cascade classifier, dlib, and mediapipe. Every face detection technique uses a distinct way to determine the bounding box that contain face location. Bounding box is a technique that is able to mark faces on images in the form of images and frames [2]. The portion of the face that is used for recognition may not be the best if the bounding box is incorrect. For instance, it may be too big, too small, or it may not fit in the middle of the face. This could reduce the accuracy and have an impact on face recognition technology.

Different types of face detection methods affect the accuracy of face recognition technology. It is necessary to conduct a study on the comparison of face detection methods to find the most appropriate approach for face recognition. Comparison of face detection methods is quite important to provide overview and suggestion for such approaches [3].

In this study, a comparative analysis of face detection methods in face recognition is conducted. Face detection methods that used in this study are haar cascade classifier, dlib, and mediapipe. Convolutional neural network (CNN) model is used to identify faces. The parameter used for this comparison are performance metrics include confusion matrix, accuracy, precision, recall, and f1-score. This study aims to compare and identify the most accurate face detection method for face recognition by convolutional neural network from these 3 approaches.

II. METHODOLOGY

This study focused on comparing the 3 CNN model that has been trained using haar cascade classifier, dlib, and media pipe face detection methods. This study was started by preparing dataset. Dataset that was used are face image of several subject. After obtaining dataset, the next step is device preparation and creating the CNN model. Then followed by training the CNN model with each face detection methods. After that, simulation was carried out to identify face in image. After simulation is done, it provides performance metrics including confusion matrix, accuracy, precision, recall, and f1-score for the comparison. The study stages flow is shown in Figure 1 below.

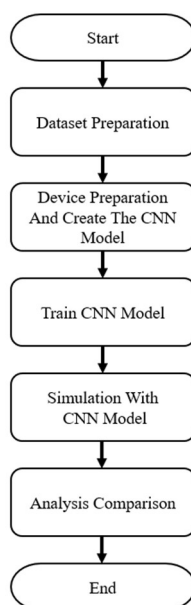


Figure 1. Study Stages Flow

A. DATASET PREPARATION

This phase involves the preparation of dataset that used in this research. The dataset that used are face images. The dataset used in this study contain 10000 images. This dataset includes facial images of 10 different subjects. Each subject has 1000 image consisting of 600 training images, 200 validation images, and 200 testing images for simulation.

B. DEVICE PREPARATION AND CREATE THE CNN MODEL

This phase involves the preparation of devices and creating the CNN model to support the implementation in comparative analysis of face detection method for face recognition. For device preparation, there are 2 categories of tools that are used. They are hardware and software. The hardware devices used in this study include a laptop with windows operating system. The hardware used in this study is a laptop with a windows operating system. The laptop that used in this study is asus X409FJ with Intel Core i7 8565U 1.8 GHz processor and 8.00 GB RAM. The software that used in this study are the visual studio code version 1.92.1. The desktop view of visual studio code is shown in Figure 2 below.

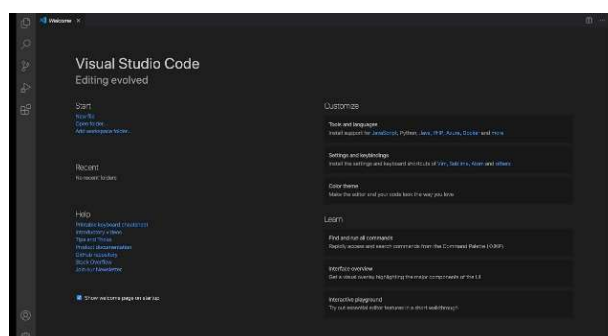


Figure 2. Visual Studio Code Desktop View

Convolutional Neural Network (CNN) is a development of multilayer perceptron which is designed to process two dimensional data [4]. CNN can be used to process and analyze image. CNN are generally used to categorize images. In order to process data, CNN requires an architecture.

In general, CNN architecture consists of convolution, pooling, flatten and fully connected layer. Convolution layer is a layer that used to extract features from the image [5]. Pooling layer is a layer for reducing the size of image data with the aims to increase invariance position of features [5]. Flatten layer is a layer that convert the 2 dimensional data into 1 dimensional vector [6]. Fully connected layer is a layer that usually used to process the converted data so that it can be classified [5].

CNN also using activation function for feature extraction and classification. Activation function is a function that determines the output of a neuron either is linear or nonlinear [7]. Activation function is used in the end of each layer inside the sneural network. Activation function that used in this CNN architecture are Rectified Linear Unit (ReLU) and Softmax. An example of CNN architecture is shown in Figure 3 below.

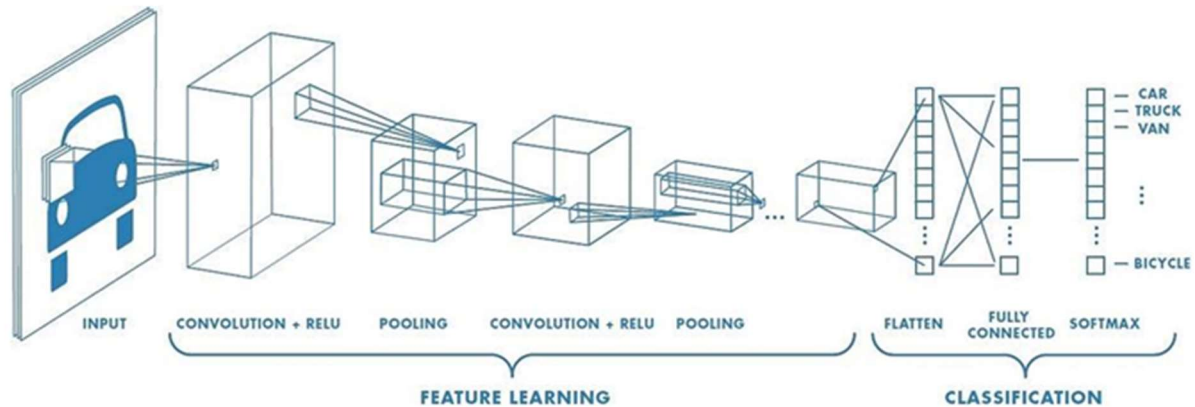


Figure 3. An Example of CNN Architecture [8]

ReLU is an activation function that converts linear values to nonlinear by activating and deactivating neurons [8]. ReLU change all the negative value to 0. If the value is positive, ReLU will maintain it. The equation for ReLU activation function is shown in (1) below.

$$f(x) = \max(0, x) \quad (1)$$

Based on equation (1), x is the input value [8]. ReLU usually used in convolutional layer for feature extraction. This function allows CNN to study more complex pattern. Softmax is an activation function that used to obtain output which are probability or classification values [8]. Softmax uses a set of values to determine a probability for every class so that the sum of all probabilities equals to 1. Softmax activation function usually used in the final layer with fully connected layer. The equation for softmax activation function is shown in (2) below.

$$f_i(\vec{v}) = \frac{e^{x^1}}{\sum_{j=1}^n e^{x^j}} \quad (2)$$

Based on equation (2.2), $f_i(\vec{v})$ is the probability of each class. e is the euler value equal to 2,71828183. v is the vector value for all class. n is the length of v . i is the position of the class value [8]. The CNN architecture in this study used 64 and 128 filter because it can capture simple and complex features for faces without taking long time to train the model. The CNN architecture that used in this study is shown in Table I.

TABLE I
CNN MODEL ARCHITECTURE

Layer	Layer Configuration
Convolution	64 filter, 3×3 kernel, and ReLU
Convolution	64 filter, 3×3 kernel, and ReLU
Pooling	2×2 kernel
Convolution	128 filter, 3×3 kernel, and ReLU
Convolution	128 filter, 3×3 kernel, and ReLU
Pooling	2×2 kernel
Flatten	10368 neuron
Fully Connected	128 neuron and ReLU
Fully Connected	64 neuron and ReLU
Fully Connected	10 neuron and Softmax

C. TRAIN CNN MODEL

After the CNN model was created, it will be trained using dataset and face detection methods. Dataset that used in this study for training the CNN model include 10000 images with 10 subjects. The CNN model will be trained using 3 different face detection methods, namely haar cascade classifier, dlib, and mediapipe.

Haar cascade classifier is a machine learning algorithm for object detection. Haar cascade classifier uses a filter called haar features [9] [10]. Haar features has a similar concept to the convolutional kernel [9]. It extracts features from images for object detection. There are several features that are extracted with this filter such as edge, line, and four rectangle features that are shown in Figure 4.

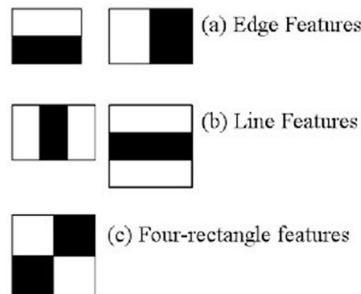


Figure 4. Features that Extracted with Haar Feature [9]

This filter will check one section at a time. For each section, the sum of the pixel intensities for the white and black section will be obtained. Then the difference between the sum of the 2 sections will be calculated. The difference value is the extracted feature value. Then there will be multilevel classification to determine the section that has the part of object or not. Workflow of the multilevel classification is shown in Figure 5 below.

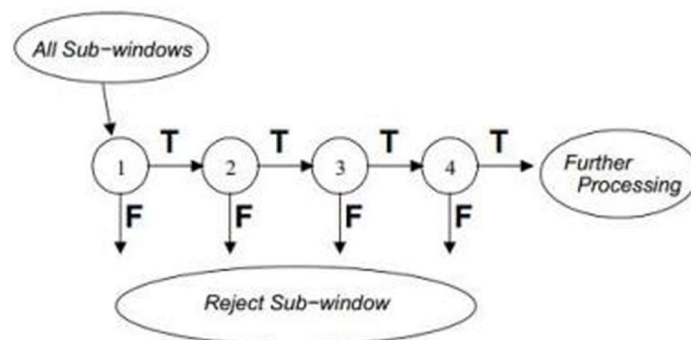


Figure 5. Workflow of Multilevel Classification [11]

In the initial level of classification, one characteristic will be used to classify each section. For example, when a section fulfills the criteria for haar features it is classified as True (T) else False (F). As the level of classification rise, more specific requirements are needed for categorization. Haar cascade classifier can be used to detect various type of object including human faces.

Dlib is an open source library that offers a C++ development environment [12]. Dlib can be used for detect face in image. Dlib using Histogram of Oriented Gradients (HOG) with Support Vector Machine (SVM) algorithm for face detection [12]. HOG is used for extract features from images. Then SVM will determine parts that contain face and non-face.

HOG extract features on image by converting image in color format Red, Green, and Blue (RGB) into grayscale then calculate the gradient value of each pixel in the image. Each image has unique characteristic. This can be seen in the gradient distribution that is produced by splitting the image into tiny sections know as HOG cell [12]. Each HOG cell contain histogram of a gradient that represent an object [12]. HOG will produce a vector array from pixel that has a histogram. Image transformation using HOG is shown in Figure 6 below.

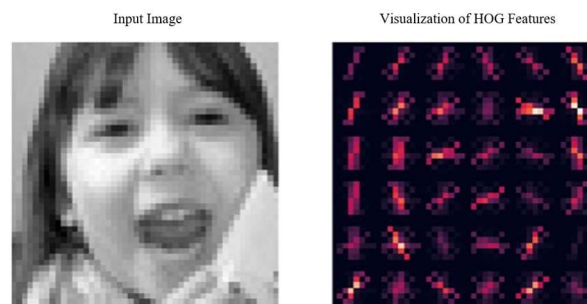


Figure 6. Image Transformation using HOG [13]

The vector array from HOG will be used for SVM for classify part that has face and not. The vector array will be inputed into SVM. SVM will use hyperlane for classify the input data [14]. It will separate the value with face part and without it.

Mediapipe is an open source machine learning framework that can used on various programming languages and platform [15]. This framework simplifies the process of implementing complex machine learning models. Mediapipe uses blazeface algorithm to detect human face in image. Blazeface is an algorithm that used to identify the center of face with concentrating on mouth center, eye center, ear lobe, and tip of the nose [15]. Blazeface can be used for various task related to face classification, segmentation, facial features, and expressions. Blazeface uses 468 face landmark for various task related to face including detection [15] [16]. Face landmark that detected with blazeface is shown in Figure 7.

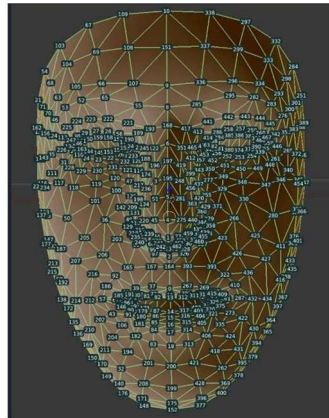


Figure 7. 468 Face Landmark Point with Blazeface Mediapipe [15]

D. SIMULATION WITH CNN MODEL

When the CNN model training was done, it is used for face identification simulation. Dataset that are used for this simulation are 2000 images consisting of 10 subjects. Each model with different face detection method will perform the simulation. The result of simulation is shown in the form of performance metrics. Block diagram for this simulation is shown in Figure 8.



Figure 8. Block Diagram for Simulation

E. ANALYSIS COMPARISON

Analysis comparison is carried out after each CNN model has finished identifying the given data. The performance metric produced by each model are used to compare and identify the most accurate face detection method for face recognition. Performance metrics include several things, namely the confusion matrix, accuracy, precision, recall, and f1-score. Confusion matrix is a table that states the quantity of data from correct and incorrect test [17]. There are four terms as a representation of the classification results in confusion matrix. The four terms are True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) that can be viewed in Figure 9.

		TRUE VALUES	
		TRUE	FALSE
PREDICTION	TRUE	TP <i>Correct Result</i>	FP <i>Unexpected Result</i>
	FALSE	FN <i>Missing Result</i>	TN <i>Correct absence of result</i>

Figure 9. True Positive, True Negative, False Positive, and False Negative in Confusion Matrix [18]

True Positive is a positive value that is detected correctly. True Negative (TN) is the number of negative data that is detected correctly. False Positive (FP) is negative data but detected positively and False Negative (FN) is negative data detected as negative data [18]. These 4 values also used to generated accuracy, precision, recall, and f1-score. Accuracy is the ratio of correctly predicted observations to all observations [19]. Precision is the ratio of correctly predicted positive observations to the all positive observations [19]. Recall is the ratio of correctly predicted positive observations to all observations in actual class [19]. F1-score is the average value of precision and recall [19]. The performance metrics can be generated by using formula that was shown in Table II.

Metrics	Formula
Accuracy	$\frac{TP + TN}{TP + TN + FP + FN}$
Precision	$\frac{TP}{TP + FN}$
Recall	$\frac{TP}{TP + FP}$
F1-Score	$2 \times \frac{Recall \times Precision}{Recall + Precision}$

The results of simulation are discussed in this section. The simulation is carried out with 3 CNN model with different face detection method. The results of simulation are shown in the form of performance metrics including confusion matrix, accuracy, precision, recall, and f1-score. Confusion matrix is a method that is usually used to calculate accuracy. The confusion matrix also displays the number of correctly and incorrectly identified face in image for each subject. The confusion matrix for each model is shown in Figure 10.

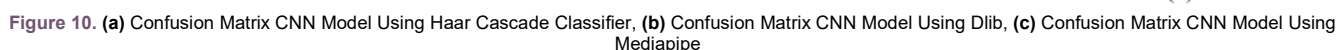


TABLE III
ACCURACY VALUE WITH HAAR CASCADE CLASSIFIER, DLIB, AND MEDIAPIPE FACE DETECTION METHOD

Face Detection Method	Accuracy Value
Haar Cascade Classifier	98%
Dlib	88.05%
Mediapipe	93.19%

Face Detection Method	Precision Value
Haar Cascade Classifier	98.08%
Dlib	89.44%
Medianipe	93.83%

TABLE V
RECALL VALUE WITH HAAR CASCADE CLASSIFIER, DLIB, AND MEDIAPIPE FACE DETECTION METHOD

Face Detection Method	Recall Value
Haar Cascade Classifier	98%
Dlib	88.05%
Mediapipe	93.2%

TABLE VI
F1-SCORE VALUE WITH HAAR CASCADE CLASSIFIER, DLIB, AND MEDIAPIPE FACE DETECTION METHOD

Face Detection Method	F1-Score Value
Haar Cascade Classifier	97.99%
Dlib	87.61%
Mediapipe	92.93%

IV. CONCLUSION

Based on the results of the simulation that has been carried out, it can be concluded that face recognition technology is influenced by the face detection method that being used. The CNN model using haar cascade classifier face detection method has the highest accuracy value of 98%, precision value of 98.08%, recall value of 98%, and f1-score of 97.99%. Haar cascade classifier has the highest value possibly because it tends to produce more consistent bounding boxes that dlib and mediapipe, which tend to focus on facial landmarks. Haar cascade classifier can be developed through real-time application and using databases for large amounts of subject data.

CONFLICT OF INTEREST

The authors state that no potential conflict of interest exists related to this article.

ACKNOWLEDGMENT

The authors would like to thank Lembaga Penelitian dan Pengabdian Kepada Masyarakat (LPPM) Universitas Tarumanagara for the support given.

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