Implementation of Face Recognition for Patient Identification Using the Transfer Learning Method

Stephanie Pamela Adithama [1], Martinus Maslim [1], Rio Gunawan [1]

[1] *Universitas Atma Jaya Yogyakarta, Babarsari Street No. 43, Yogyakarta, Indonesia*

Abstract **– The hospital's status as a health center requires it to ensure patient safety, decrease incidents and treat patients. Identification of the patient is the primary source of patient safety difficulties. In addition to the patient's name and number, further patient-identifying components are needed to reduce this neglect. This work provides a solution in the form of biometric authentication, namely, face recognition. The convolutional neural network (CNN) approach can enable machine facial recognition. CNN is one of the deep learning techniques used to detect and identify picture objects. In this study, facial recognition was carried out using the transfer learning technique, VGGFace2 model pretraining, and SENet 50 model architecture. The dataset was collected via one-shot learning or a single sample per individual sampling. Applying the CNN model to the patient identification system yields two distinct outcomes: patient registration and verification. Registration utilizes a minimum distance of 0.35 and matches data with the complete database, whereas patient verification has a minimum distance of 0.28 and matches only the face in question. At the time of patient registration, the accuracy was between 90% and 100%. However, at the time of patient verification, the accuracy was 100%.**

Keywords **– patient identification, face recognition, convolutional neural network (CNN), SENet 50, VGGFace2.**

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Corresponding author: Martinus Maslim ,
Universitas Atma Jaya Yogyakarta, Babarsari Street No. 43, Yogyakarta, Indonesia.
Email: martinus.maslim@uajy.ac.id

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1. Introduction

Hospitals play a crucial role in the community. They offer and supply services with numerous highly complicated components and, if not handled properly, might lead to errors in providing services to patients, endangering patient safety [1]. Healthcare institutions face a variety of safety issues on a worldwide scale [2]. As a provider of healing (curative) and recovery (rehabilitative) health services, the hospital has a huge commitment to offer outstanding care to its patients; in addition to treating patients, the hospital must emphasize patient safety to reduce patient incidents. Patient identification is the primary cause of patient safety issues [3]. The "five rights (right patient, right medicine, right dose, right route, and right time)" are particularly crucial in patient identification [4]. Correct patient identification is key to the success of all treatments and operations in medical facilities [2], [5]. Necessary identification steps include patient movement, transfer, handoff, preparation and diagnosis, medication administration, management (including prescription, medication, and transfusion management (including infusion venipunctures)), and receiving medical treatment, including surgical procedures, devices, and implants [6].

Errors in patient identification are a common problem that regularly occurs in medical facilities. The most common areas for patient misidentification are medicine delivery, phlebotomy, blood transfusions, and surgical procedures [7],[8],[9]. Patient misidentification can result in inaccurate diagnoses, inappropriate treatment (including surgical procedures on the wrong patients), medication administration, and mislabeling pathology specimens [6]. Misidentification of a patient can result in severe suffering, psychological harm, and even death [5]. In addition to causing damage to patients, medical errors and incorrect identification can increase healthcare expenses for patients and healthcare professionals [9].

There have been numerous cases of inaccurate patient identification throughout the world.

An estimated yearly average of 400,000 deaths in the United States are related to medical errors [10]. The United Kingdom National Patient Safety Agency documented 236 cases of patient misidentification between November 2003 and July 2005 [8]. Each year, approximately 850 individuals in the United States receive blood transfusions intended for someone else, and at least 20 die as a result [11]. Kenyatta National Hospital 2018, located in Kenya; Sushrut Trauma Center in 2018, located in India; and Siloam Hospital 2015, located in Indonesia, are among the hospitals that failed to implement patient safety procedures in this instance, identifying patients who made surgical errors. Due to improper patient labeling, Kenyatta National Hospital performed cranial surgery on the incorrect patient [12]. Due to the similarity between the names Vijendra and Virendra, the Sushrut Trauma Center Hospital amputated the wrong patient's leg [13]. In addition, neglect of patient safety has occurred in Indonesia, specifically at the Siloam Karawaci Hospital. In contrast to the previous two hospitals, Siloam Hospital was negligent in its surgical treatment of patients, culminating in the death of two Siloam Hospital patients due to an anesthetic overdose [14]. This news highlights the significance of hospital patient safety rules in preventing life-threatening incidents.

There are several reasons why patient identification mistakes arise. Most occurrences are due to human error. Before administration, many nurses need to verify that the correct drug and dosage have been administered. Common causes include excessive workload, workplace distractions, and work-related burnout [4], [6]. In addition to human mistakes, hospital regulations are also a contributing factor, even though the World Health Organization (WHO) has established patient safety regulations. In addition, many nations, such as Indonesia, have adopted legislation on this subject (Minister of Health Regulation Number 11 of 2017). The creation of patient safety goals utilizes the World Health Organization's (WHO) Nine Life-Saving Patient Safety Solutions, which are also used by the Hospital Accreditation Commission and Joint Commissions International (JCI) [3]. Despite the evident importance, many hospitals frequently lack explicit patient safety regulations. Several measures can be utilized to aid in the reduction of patient identification mistakes. Strategies include the following: 1) every patient is uniquely and unambiguously identified; 2) identification is maintained consistently throughout the care period; 3) every procedure, treatment, or medication is uniquely and unambiguously identified; and 4) patient identification is explicitly linked to all requests, medications, procedures, and devices that are applied. In addition, it was suggested that healthcare facilities evaluate the feasibility of implementing technology methods to reduce identification errors [6].

Most research on patient administration systems focuses on "human error" elimination [15]. The growing use of technology has improved the safety of medication administration, the deployment of checklists has led to a fall in surgical errors, and the implementation of safety protocols has decreased the frequency of hospital-acquired infections [16]. If the patient actively participates in the process, hospitals can provide flexibility and responsiveness in such a technology-enabled environment to satisfy the patient's needs [17]. Numerous studies examine the technology that healthcare institutions may employ, including barcode medication administration [7], [18], [19], Internet of Things [17], mobile application [20], radio frequency identification (RFID) [9], [21], and biometric authentication such as fingerprints [10], [11]. In addition to conventional identification, biometric identification is now being explored. The fundamental idea of biometric authentication is that individuals are unique and may be identified based on their inherent physical or behavioral characteristics [10]. The utilization of biometric identification with the aid of the most recent computing technology can be more effective in identifying patients because biometrics measures the characteristics of each patient, whereas conventional identification requires a remembered marker that can be exchanged or authorized to other individuals, such as the use of cards, usernames and passwords, wristbands, etc., so identification can be incorrect if the markers are exchanged. In addition to fingerprints, face recognition can be used for biometric patient identification.

Face recognition is a computer technology that uses specific algorithms to detect human faces in digital images and photographs. One approach that can be utilized to conduct face recognition is the convolutional neural network (CNN). CNN is a deep learning method that can reduce the number of independent factors and manage picture deformations such as translation, rotation, and scaling. This capacity makes the CNN algorithm widely employed to distinguish objects in digital photos. From the existing challenges, this study aims to leverage existing technologies to construct a facial recognition system to aid in identifying patients. The face recognition process uses the CNN transfer learning method to achieve a high accuracy percentage. It is believed that errors in patient identification can be decreased or eliminated using face recognition technologies.

2. Related Work

Face recognition involves recognizing a person's face, either manually or with computer software. Computer-assisted facial recognition is utilized as a security system, surveillance tool, and for intelligent human-computer interaction [22]. In general, facial recognition systems can be classified as either feature-based or image-based. A feature-based recognition system is a system that performs feature extraction before performing facial recognition, such as mapping the components of the eyes, nose, and mouth [23]. The traits in the human facial area are distinct, allowing the computer to identify individuals with similar features. Some research discusses face recognition. The first study shows a new method to determine the human face. The research compared multiple facial recognition techniques to CNN. Eigenfaces with principal component analysis (PCA), local binary pattern histogram (LBPH), and k-nearest neighbor (kNN) are the approaches compared. The researcher uses seven layers that he created for its application. The test images originate from The ORL Database of Faces, which contains 40 categories with ten unique photographs per category. The researcher utilised the Euclidean distance to establish the similarity between the test and training data, although the minimum threshold for testing similarity was not specified. Based on his investigation, the researcher found that CNN is more accurate than the other three approaches. This CNN method has the disadvantage of requiring significant training data to provide more accurate results. The more important the amount of data, the greater the computational strain and memory consumption [24].

Another study analyzed the benefits and drawbacks of deep learning for face recognition against picture deterioration. Several architectural models are utilized in this study, including AlexNet, VGGFace, Google Net, and Squeeze Net. Google Net uses Inception Version 3, while VGGFace uses the VGG 16 architecture (V3). Tests were conducted using the cosine distance assessment model and the VGGFace dataset. The collection contains approximately 2.6 x 106 photos organized into 2622 categories or about 1000 images per category. However, only 1.8 x 106 pictures were utilized in the study. According to the findings of the conducted tests, there is no architecture capable of recognizing all the conditions of the quality change. VGGFace can identify visual noise but performs poorly when tested with lower image brightness, whereas GoogleNet performs the opposite [25].

Some researchers have reviewed the use of transfer learning in health domain research.

One study discusses transfer learning in medical image analyses. In that study, there are four broad information transfer categories: instance-based transfer learning, feature-based transfer learning, parameter-based transfer learning, and relation-based transfer learning. Methods for instance-based transfer learning are implemented primarily through an instance weighting mechanism. By changing the original features, feature-based approaches generate new feature representations, which can be further separated into asymmetric and symmetric feature-based methods. Asymmetric techniques alter the source characteristics such that they fit the goal characteristics. On the other hand, symmetric approaches seek to identify the shared feature spaces where both source and destination characteristics can be mapped. In parameter-based methods, information is transmitted at the parameter level, where source domain model parameters have been adapted to the destination domain. The challenges in the relational area are resolved by transfer learning techniques based on relations. The logical relationships or rules learned in the source domain are transferred in relation-based transfer learning approaches. Transfer learning approaches for medical image analysis are primarily parameter-based deep learning models either employed as feature extractors or modified for analysis [26]. Another study shows that transfer learning helps handle the difficulty of transferring information from a source task to a target task when both activities have weak labels. Following the discussion of the objective model for multiple instances of transfer learning with weak labels, an iterative framework is provided to solve the model [27].

3. Methodology

3.1. Convolutional Neural Network (CNN)

A convolutional neural network (CNN) is a deep artificial neural network and the most used machine learning tool [28]. A CNN is a variant of a multilayer perceptron or a multilayered human artificial neural network. CNN's training method uses multiple layers to perform filtering operations, including the convolution layer, the pooling layer, and the fully connected layer [29]. The structure of the CNN is shown in Figure 1. CNN’s filters for filtering include the following: (1) The convolution layer applies a convolution operation to the previous layer's output value. At this point, all the entered data will generate an activation map or 2D feature map. The activation map or feature map results from the convolution layer's filter. The convolution layer contains three optimization parameters: depth, stride, and zero padding settings [30].

Figure 2 depicts the process that occurs in the convolution layer. (2) The pooling layer is a filter with a particular size and stride. The filter generates a matrix dependent on the method of pooling employed. The most prevalent pooling strategies are maximum pooling and average pooling. Both techniques will utilize the previously set value of the pooling layer size. The distinction resides in how the activation map values generated by the convolution layer are retrieved. If the size of the pooling layer is 2x2 and the stride is 2, then when max pooling is applied, each filter shift will pick the greatest value in the 2x2 area, whereas average pooling will take the area's mean value [30]. (3) Fully Connected Layer. Before approaching the fully linked layer stage, a flattening or reshaping operation must be performed on the previous layer's created feature map or activation map. The flattened operation's output is a vector utilized as input by the ultimately linked layer. This layer contains hidden layers, action functions, output layers, and loss functions [30]. Figure 3 depicts a fully connected layer. (4) Dropout. Due to multiple layers, the learning process can be slow; consequently, a dropout procedure is needed. In addition to accelerating the learning process, this method can also prevent overfitting. Overfitting is a phenomenon that occurs when the accuracy acquired during the training phase is high, but a prediction error occurs [30]. In its application, dropout will randomly delete hidden and exposed neuron layers. Every neuron will be assigned a probability between 0 and 1 [29].

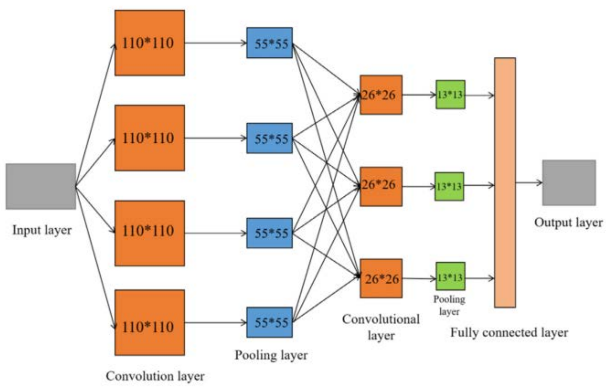

Figure 1. The Structure of CNN [31]

3.2. Residual Network or ResNet

A residual network (ResNet) is a deep convolutional network architectural type. ResNet is considered a continuation of deeper networks since it introduces the optimal training theory for deeper networks [32]. ResNet connects the new layer with a duplicate of the preceding layer, as depicted in Figure 2, because the model is constructed with the assumption that the number of layers organized in a row does not ensure an increase in precision.

If the additional layers are built as identity mappings, the basic operating principle states that a deeper model should not have any more training error than the equivalent shallower model if the deeper model is built on top of it [33]. Instead of directly stacking layers to conform to a specific underlying mapping, the layers are stacked to accommodate a residual mapping. Let H(x) represent the required underlying mapping; the nonlinear layers are designed to correspond to a different mapping in such a way that [34]:

$$F(x)=H(x)-x \qquad (1)$$

$$\rightarrow H(x)=F(x)+x \qquad (2)$$

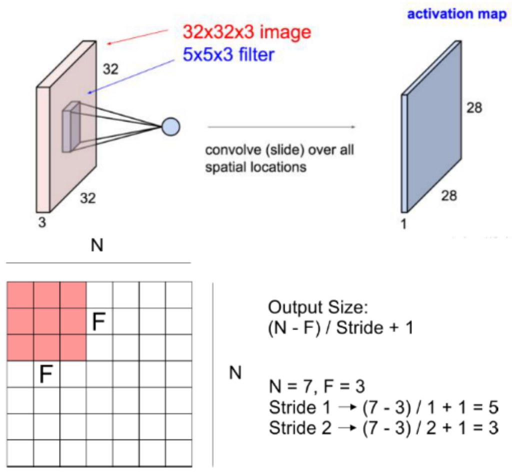

Figure 2. Convolution Layer [30]

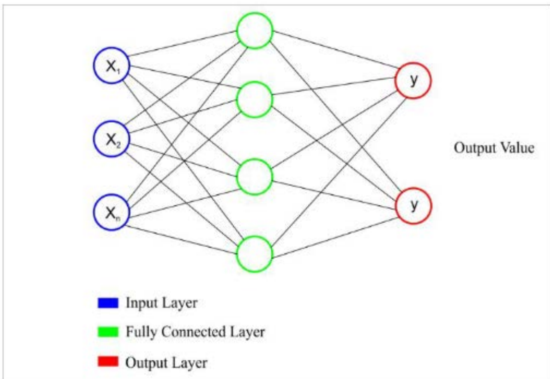

Figure 3. Fully Connected Layer [30]

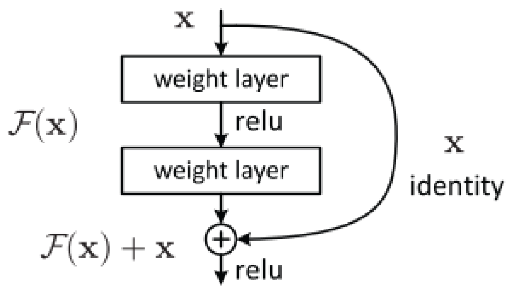

Figure 4. Residual Network Structure [33]

3.3. Squeeze-and-Excitation Networks or SENet

SENet is a deep convolutional network like ResNet. SENet improves the quality of network representation by explicitly describing the reliance between channels. Therefore, SENet can adaptively recalibrate the relationship between channels' responses [35]. SENet comprises five continuous progressions: channel-wise global average pooling, a fully connected (FC) layer, a ReLU, and an FC layer followed by a sigmoid [36]. Figure 5 shows the structure of SENet.

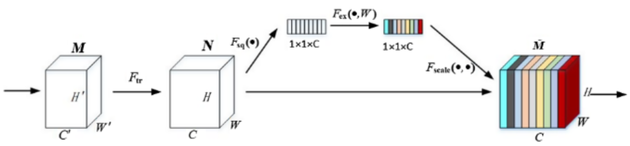

Figure 5. The SENet Structure [37]

Similar to ResNet, SENet's layer mapping principle is to build blocks. The blocks formed in the SENet design are known as SE blocks. The block is intended to include global data. Subsequent layers can examine this information to be more selective in selecting helpful information while focusing on managing the most useful information. This architecture may be combined with other designs using the block idea; one of the architectures that can be combined with this architecture is ResNet [35]; Figure 6 depicts the layer combination in ResNet.

3.4. VGGFace2

VGGFace is a vast facial image database. VGGFace has undergone two phases of development. Initially, 2.6 million photographs with 2,622 distinct identities were collected. Then, in 2018, VGGFace entered its second publication phase, also known as VGGFace2, comprising 3.31 million photos with 9,131 unique identities [38]. VGGFace2 is a large-scale FR dataset in which the photos are downloaded from Google Image Search and exhibit substantial pose, age, illumination, and ethnicity differences [39]. VGGFace was initially evaluated using the Deep Face or VGG 16 architecture [40], whereas VGGFace2 was assessed using the ResNet 50 and SENet 50 architectures. Based on the VGGFace2 test results on the IJB-A dataset, the SENet 50 architecture outperforms ResNet 50 in terms of accuracy [38].

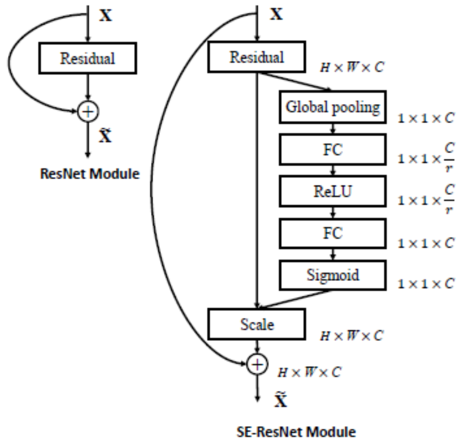

Figure 6. ResNet block architecture (left) and ResNet blocks combined with SENet SE blocks (right) [35]

4. Result and Discussion

The author examined three face detection algorithms: Viola Jones [41], Multitask Cascaded Convolutional Networks (MTCNN) [42], and ResNet 10. Google Colab was used to select and collect ten volunteers' photographs as a test dataset. Figure 7 illustrates the dataset, while Figures 8, 9, and 10 show the face detection result using Viola Jones, MTCNN, and ResNet 10, respectively.

Figure 1. Face Dataset

Figure 2. Face Detection using Viola Jones

Figure 3. Face Detection using MTCNN

Figure 4. Face Detection using ResNet10

The authors conclude that the ResNet 10 algorithm is superior to the other two algorithms due to its higher accuracy than Viola Jones and faster execution time than the MTCNN algorithm. The test results are summarized in Table 1.

Table 1. Face detection algorithm test results

Algorithm	**Accuracy**	**Execution Time (second)**
Viola Jones	90%	2.67
MTCNN	100%	45.64
ResNet 10	100%	3.16

ResNet 10 is implemented using the Flask framework. The application sends the photo to the web service in base64 format. Then, base64 is converted back to an image and passed directly to the crop function. The author will first detect the image using ResNet10 and then determine the face's width, as the human face's width is less than the height of the face. Choosing the shortest value is necessary to ensure that the cropped face has the least amount of noise possible. Then, based on the midpoint of the face width and height, the face-cutting area is shifted to the center of the face, ensuring that the face-cutting results contain all face components.

The authors of this study compare several network architectures for face recognition, including VGG 16, ResNet 50, and SENet 50. VGG 16 and ResNet 50 use ImageNet and VGGFace2 pretraining models (weights), whereas SENet 50 only uses VGGFace2 weights. The author omitted the fully connected layer and instead used average pooling as the pooling layer in these models.

The author uses Cosine to compare two vectors in this study. When Cosine approaches zero, the two face images become increasingly similar. The author conducted a five-person test.

Using the One Shot Learning concept, each individual is represented by a single-face image. After that, the face images were compared to ten photos of faces with various expressions and conditions. The author uses Keras to obtain ImageNet weights, while VGGFace weights are obtained from https://github.com/rcmalli/hard-vggface.git. This test measures speed, accuracy, and the shortest possible distance (*min_dist*). *min_dist* is the value returned by a minor Cosine calculation performed on the entire database compared to the vector value of the testing data. Table 2 contains the test results.

Table 2. Face recognition model test results

Model	**Accuration**	**Execution Time (second)**	***min_dist* (average)**
VGG 16 (ImageNet)	74% (37/50)	26.34	0. 105
ResNet 50 (ImageNet)	70% (35/50)	14.64	0.0888
VGG 16 (VGGFace)	86% (43/50)	26.2	0. 1386
ResNet 50 (VGGFace2)	100% (50/50)	14	0. 186
SENet 50 (VGGFace2)	100% (50/50)	14.49	0. 1476

Along with face recognition, the built model must recognize faces that are not stored in the database. This model is accomplished by setting the *min_dist* limit as the margin value used to determine whether the photo is in the database. The authors will use correct data to determine the *min_dist* margin and test the model using face data that are not currently in the database. The dataset used to represent an unknown face consists of 50 images of faces with five distinct identities. Additionally, the photographs feature a variety of poses and expressions. The following are the test results: ResNet 50 has a smaller *min_dist* than SENet 50 by 0.0079. This indicates that SeNet 50 is slightly more accurate than ResNet 50 at recognizing previously unrecognized faces. As a result, this study employs SENet 50 as a model for facial recognition. The author uses the Flask framework to implement the SENet 50 model with weight VGGFace2 and the Caffe model from ResNet 10. Flask will handle only model-related transactions. Patient registration, patient verification, and patient deletion are all model-related transactions.

This system must recognize faces already in the database and distinguish between faces not yet in the database; thus, determining the *min_dist* margin is critical when testing this system. The authors use a value of 0.2 as the minimum and 0.35 as the maximum.

Table 3 contains the test results. The test results demonstrate that as the MD increases, the T value increases while the U value decreases, but there is an F value at MD > 0.35. As a result, MD > 0.35 will not be used in the subsequent test. The second test consisted of two stages: removing data from the first five volunteers and testing it on five additional volunteers, while the second involved the reversal. Table 4 summarizes the results of the first and second stages of testing. According to the second test results, one identity has been identified as F, even though the associated data are not in the database. When MD is set to 0.3, the error occurs. As a result, the third stage will consist of testing MDs of 0.26, 0.27, 0.28, and 0.29 with the same flow and steps. Tables 5 and 6 contain the results of this third test.

Table 3. System and Model Test Results

Name	System			Google Colab								
	MD > 0.2			MD > 0.25			MD > 0.3			MD > 0.35		
	U	T	F	U	T	F	U	T	F	U	T	F
Calfa	3	7	0	2	8	0	1	9	0	1	9	0
Ninna	4	6	0	2	8	0	0	10	0	0	10	0
Patricia	1	9	0	1	9	0	0	10	0	0	10	0
Raya	3	7	0	1	9	0	0	10	0	0	10	0
Riandy	5	5	0	2	8	0	0	10	0	0	10	0
Rius	1	9	0	0	10	0	0	10	0	0	10	0
Shen	5	5	0	5	5	0	5	5	0	3	6	1
Yulius	3	7	0	2	8	0	1	9	0	0	10	0
Yafet	4	6	0	3	7	0	2	8	0	1	9	0
Yudho	1	9	0	1	9	0	1	9	0	0	10	0

Table 3 description:

- MD or *min_dist* margins.
- U or unknown is a facial condition not recognized by MD.
- T or true is the condition of the face that is known and constitutes the identity.
- F or false is a facial condition known but not its identity.

Based on the results of all tests, the best MD for the dataset is 0.28. MD>0.28 is determined only when verifying the patient's face, whereas *min_dist* will have a margin of 0.35 during patient registration to make registration more difficult. After establishing the *min_dist* margin, the author conducts further testing directly using the newly created system. Table 7 summarizes the first test's results, while Table 8 summarizes the second test's results.

Table 4. Second system and model test results

Name	Google Colab								
	MD > 0.2			MD > 0.25			MD > 0.3		
	U	T	F	U	T	F	U	T	F
Calfa	10	0	0	10	0	0	10	0	0
Ninna	10	0	0	10	0	0	10	0	0
Patricia	10	0	0	10	0	0	10	0	0
Raya	10	0	0	10	0	0	7	0	3
Riandy	10	0	0	10	0	0	10	0	0
Rius	10	0	0	10	0	0	10	0	0
Shen	10	0	0	10	0	0	10	0	0
Yulius	10	0	0	10	0	0	10	0	0
Yafet	10	0	0	10	0	0	10	0	0
Yudho	10	0	0	10	0	0	10	0	0

Table 5. Third system and model test results (Phase One)

Name	Google Colab											
	MD > 0.26			MD > 0.27			MD > 0.28			MD > 0.29		
	U	T	F	U	T	F	U	T	F	U	T	F
Calfa	2	8	0	2	8	0	1	9	0	1	9	0
Ninna	2	8	0	2	8	0	0	10	0	0	10	0
Patricia	1	9	0	1	9	0	0	10	0	0	10	0
Raya	0	10	0	0	10	0	0	10	0	0	10	0
Riandy	2	8	0	2	8	0	2	8	0	0	10	0
Rius	0	10	0	0	10	0	0	10	0	0	10	0
Shen	5	5	0	5	5	0	5	5	0	5	5	0
Yulius	2	8	0	2	8	0	1	9	0	1	9	0
Yafet	3	7	0	3	7	0	2	8	0	2	8	0
Yudho	1	9	0	1	9	0	1	9	0	1	9	0

Table 6. Third system and model test results (Phase Two)

Name	Google Colab											
	MD > 0.26			MD > 0.27			MD > 0.28			MD > 0.29		
	U	T	F	U	T	F	U	T	F	U	T	F
Calfa	10	0	0	10	0	0	10	0	0	10	0	0
Ninna	10	0	0	10	0	0	10	0	0	10	0	0
Patricia	10	0	0	10	0	0	10	0	0	10	0	0
Raya	10	0	0	10	0	0	10	0	0	7	0	3
Riandy	10	0	0	10	0	0	10	0	0	10	0	0
Rius	10	0	0	10	0	0	10	0	0	10	0	0
Shen	10	0	0	10	0	0	10	0	0	10	0	0
Yulius	10	0	0	10	0	0	10	0	0	10	0	0
Yafet	10	0	0	10	0	0	10	0	0	10	0	0
Yudho	10	0	0	10	0	0	10	0	0	10	0	0

Table 7. Patient registration test using min_dist margin 0.35

Name	Experiment (Face Condition)				
	Straight	Left 45 Degree	Right 45 Degree	Close Eyes	Smile
Niken	Succeed	Succeed	Succeed	Succeed	Succeed
Aga	Succeed	Fail	Succeed	Succeed	Succeed
Yudho	Succeed	Succeed	Succeed	Succeed	Succeed
Agung	Succeed	Succeed	Succeed	Succeed	Succeed
Rein	Succeed	Succeed	Succeed	Succeed	Succeed
Ryandi	Succeed	Succeed	Succeed	Succeed	Succeed
Geo	Succeed	Succeed	Fail	Succeed	Succeed
Dewa	Succeed	Succeed	Succeed	Succeed	Succeed
Vanessa	Succeed	Succeed	Succeed	Succeed	Succeed
Panda	Succeed	Succeed	Succeed	Succeed	Succeed

Table 8. Patient verification test using min_dist margin 0.28

	nkn	aga	ydh	agn	rn	ry	geo	dw	vns	pd
nkn	T	F	F	F	F	F	F	F	F	F
aga	F	T	F	F	F	F	F	F	F	F
ydh	F	F	T	F	F	F	F	F	F	F
agn	F	F	F	T	F	F	F	F	F	F
rn	F	F	F	F	T	F	F	F	F	F
ry	F	F	F	F	F	T	F	F	F	F
geo	F	F	F	F	F	F	T	F	F	F
dw	F	F	F	F	F	F	F	T	F	F
vns	F	F	F	F	F	F	F	F	T	F
pd	F	F	F	F	F	F	F	F	F	T

According to Table 7, registration of patients with a straight face, closed eyes, or smiling condition can have an accuracy of up to 100%. However, if the registrant looks to the left or right by 45 degrees, the accuracy is 90%. As shown in Table 8, all patients have true positive values, indicating that face verification is 100% accurate.

The author concludes from the system test results that the model and system still have weaknesses in recognizing faces. This is because the *min_dist* margin is still relatively high, 0.28 and 0.35. As a result, the authors conducted additional testing on several uncommon conditions, including users who faked facial registration or verification using printed patient photos and patient registration with identical twin faces.

The advantage of this system is the model's accuracy, which ranges from 90% to 100% in the face identification process. It only takes one photo to recognize a face when it is turned 45 degrees to the left or right, facing the camera straight, smiling, or eyes closed. Meanwhile, the system's limitations include the inability to detect printed photographs, the failure to distinguish identical twin faces, and the fact that the light conditions under which the patient's photo is taken significantly affect the model's prediction results.

5. Conclusion

Patient identification is one of the most critical aspects of the hospital process. Patient identification errors can have fatal consequences. Therefore, we require a tool that aids in patient identification. Using facial recognition to identify patients is one method. Numerous algorithms may be used to recognize human faces. The first step for face recognition is preprocessing.

In this study, we used ResNet 10 to perform image preprocessing with the Caffe model. The algorithm is used to identify faces in a photograph. As one of the preprocessing steps, the photo is cropped after the face has been spotted. Face cropping is performed by calculating the midway of the face to crop the picture with a complete face condition. After cropping, the face-only image continues the face-recognition process. After preprocessing, the image is loaded into the SENet 50 model using the pretraining model VGGFace2 to identify the patient's face using the vector value. In the implementation of the facial recognition model, a minimum distance of 0.35 is used for patient registration, and a minimum distance of 0.28 is used for patient verification. The system and model's final findings are between 90 and 100 percent accurate regarding patient registration, while patient verification is 100 percent accurate.

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