

IMAGE PROCESSING, PATTERN RECOGNITION

Retinal biometric identification using convolutional neural network

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Abstract

Authentication is needed to enhance and protect the system from vulnerabilities or weaknesses of the system. There are still many weaknesses in the use of traditional authentication methods such as PINs or passwords, such as being hacked. New methods such as system biometrics are used to deal with this problem. Biometric characteristics using retinal identification are unique and difficult to manipulate compared to other biometric characteristics such as iris or fingerprints because they are located behind the human eye thus they are difficult to reach by normal human vision. This study uses the characteristics of the retinal fundus image blood vessels that have been segmented for its features. The dataset used is sourced from the DRIVE dataset. The preprocessing stage is used to extract its features to produce an image of retinal blood vessel segmentation. The image resulting from the segmentation is carried out with a two-dimensional image transformation such as the process of rotation, enlargement, shifting, cutting, and reversing to increase the quantity of the sample of the retinal blood vessel segmentation image. The results of the image transformation resulted in 189 images divided with the details of the ratio of 80 % or 151 images as training data and 20 % or 38 images as validation data. The process of forming this research model uses the Convolutional Neural Network method. The model built during the training consists of 10 iterations and produces a model accuracy value of 98 %. The results of the model's accuracy value are used for the process of identifying individual retinas in the retinal biometric system.

Keywords: blood vessels, convolutional neural network, identification, retina, segmentation.

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Introduction

Currently, individual identification is of great importance since many systems require legitimate users in access control, especially for systems that store valuable documents [1] and important data. One identification technology that is presently developing is biometric feature-based identification technology [2, 3]. The biometric identification system is a system that does identification and recognition using a biometric characteristic pattern [4, 5] that one's owned [6]. The biometric system-based individual identification technique that is developing today is fingerprints. This is because in a fingerprint there are about 40 unique characteristics [7], which enable the identification of about 1.1 trillion different individuals [8]. Apart from fingerprints, one of the body parts that can be used as a biometric system for identification is the retina. The retina is a sensitive eye organ and it functions in the ability to see. Aside from being used to see, the retina

can be used as identification as it has unique characteristics. In the retinal tissue of the human eye, there are about 256 unique characteristics [9].

Research [10] implemented the use of a Neural Network to identify individuals based on retinal biometrics. This study uses the backpropagation algorithm which consists of 3 main layers, namely input, hidden, and output layers [11, 12]. The process of identifying retinal images uses a feed forward neural network which consists of input, hidden, output. In the hidden and output sections using the sigmoid activation function. This study has a total of 233 retinal segmentation images with a resolution of 768×584 from a total of 139 individual retinal samples. Of the total number of retinas, 40 images were separated as test data. Excellent accuracy needs to be tested on the number of neurons in hidden layers, which starts from 8 hidden layers to 35 hidden layers. The highest accuracy is at 97.5 % with the number of hidden layers of 35 neurons.

The network is trained with a maximum total of 10000 epochs in each test.

Research [13] Identify biometric characteristics using deep learning. The deep learning system proposed in this study is MultiTraitConvNet whose architecture is based on a combination of Convolutional Neural Network (CNN) and Softmax classifier to extract discriminatory features from images with 5 classes, namely face, fingerprint, footprint, iris and fingerprint, respectively. Each class has 100 pictures of which 80 pictures are for training data and 20 pictures are for test data. The training procedure is carried out using the backpropagation algorithm with the Adam optimization method. The model consists of two layers which are fully connected for classification. The output of the first connected layer is fed into the softmax classifier (the last fully connected layer) which produces a probability distribution over the class N label. This architecture is built with image inputs resized to 64×64 pixels. The proposed model contains four layers of convolution and produces feature maps of 32, 64, 128, and 256 pixels respectively. Each convolution layer has a reluctant activation function to decide which neurons are activated at a certain time.

Research [14] identify the individuals' retina with Diabetic Retinopathy (DR) eye disease which was classified into 5 classes, namely No DR (0), Mild DR (1), Moderate DR (2), Severe DR (3), Proliferative DR (4). Research [7] uses the DR dataset provided by EYEPACS. The number of images in the dataset contains 88.702 images from 44.351 patients for the left and right eye. This study only took 35.126 images which were divided into training data and test data, each of which had a percentage of 80% training data, 20% of the test data used 3 CNN models with each using the ReLu activation function. This study addresses the problem of overfitting in pooling layers by using max pooling to reduce image dimensions [15, 16] and accelerate the learning process. After that, just do the classification into 5 types of DR.

Research [17] conduct a segmentation process for retinal blood vessels by implementing a CNN-based deep learning algorithm. This study evaluated the results in two aspects, namely the accuracy and sensitivity of the retinal blood vessel segmentation images. In its implementation, this study uses a built-in library from deep learning, namely the caffe library. The dataset used comes from the ARIA Dataset which contains 143 retinal fundus images with an initial resolution of 768×576 . Each image shape is changed by a rotation process and also a flip from every angle in the image so that during the training process, the amount of data being trained becomes a lot with various shapes. Previously, the image resolution was reduced to 565×584 and then trained 10.000 times. The purpose of this study is to compare the accuracy and sensitivity of the two existing dataset sources, namely STARE dataset and DRIVE dataset, where these two types of datasets are processed by experts from various countries specifically for implementing the retinal segmentation process.

In this research, a biometric identification by retinal fundus image feature was carried out by utilizing the feature segmentation results of the retinal fundus image, specifically the retinal fundus image blood vessel pattern. The results of feature extraction are then used in the training and testing process with a convolutional neural network algorithm. This research will also calculate the accuracy value of the retinal identification process to observe the performance of the algorithm. The results of this research are expected to identify the retina through the retinal biometric system with a rapid process and high accuracy.

1. Methods

This research consists of several stages, firstly, the retinal fundus image collection stage and the preprocessing stage where the preprocessing operations of changing the RGB image to a green channel image and the Histogram leveling by adaptive histogram equalization method and the filtering process to remove non-blood vessel objects in the retinal fundus image are carried out. After that, in the feature extraction phase, a retinal fundus image segmentation operation is performed and then a rescaling process is done to change the output dimensions of the retinal fundus image. The next process is the process of forming a model using a convolutional neural network algorithm to identify the fundus image biometric features. The process of forming a neural network model consists of two main processes, first is the training set process that is conducted to train the convolutional neural network layer that is built to be able to recognize biometric features of fundus images.

The he stages that follow after the training process is the testing set process that aims to test the results of the training model that has been done. The total retinal fundus image dataset divided into 9 classes where each class has 21 fundus images with different fields of view with angles of $-2, -5, -10, -15, -20, -25, -30, -35, -40, -45, 0, 2, 5, 10, 15, 20, 25, 30, 35, 40, 45$. The training and testing process uses an 8:2 ratio in the fundus image dataset. The final stage of retinal fundus identification is the processing of identification results where at this stage the accuracy of the identification process is calculated. Examples of retinal fundus images used can be seen in fig. 1.

1.1. Fundus retina image preprocessing

The initial stage is done by changing the image of the RGB into a green channel image. The selection of green channel as an image that will be used in image processing is because the image on the green channel has an intensity value that is neither too bright and nor too dark [19]. The result of green channel extraction then goes through incomplement process [20] which aims to invert the pixel intensity value in the image. The equation of the incomplement process can be seen in formula 1 where i is the result of intensity, x is the value of image

intensity at position x . The constant 255 is the highest intensity value in an image as follows :

$$i = 255 - x. \quad (1)$$

After obtaining an incomplement image, histogram leveling is carried out using adaptive histogram equalization to evenly increase the image intensity. The stage following the histogram equalization process in preprocessing is the filtering process. The filtering process aims to eliminate non-blood vessel objects in the retinal fundus image including optical disks and noise. The filtering process begins with the formation of the foreground or upper layer. This layer serves as a layer that will be used to eliminate non-blood vessel objects by the process of separating the foreground with the background image. The formation of the foreground layer is done by initializing a ball form layer with a size of 8×8 . The foreground formation process is done by an open morphological process between the histogram equalization result image and a ball object of size 8×8 .

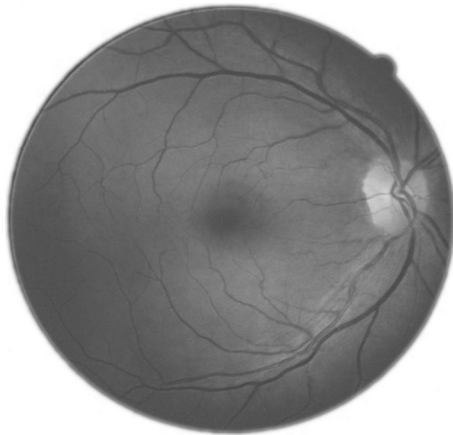


Fig. 1. Retinal fundus image [18]

The separation between the foreground and the background of the fundus retinal image is done by reduction elimination between the of the histogram equalization image with the foreground image. The results of the filtering process with a median filter are then brought to the process of image edge sharpening with the imsharpen function. The parameters used in the edge sharpening process are the image sharpening radius with the value of 25 pixels and the the image sharpening with the value of 2 pixels. The stages of preprocessing can be seen in fig. 2.

1.2. Feature extraction

The feature extraction process is a process to obtain characteristic biometric features of retinal fundus images to be used in the fundus image identification process using the built neural network architecture. The characteristic feature used is the segmentation of blood vessels in the retinal fundus image. The method used in segmenting the blood vessels of the retinal fundus is using the thresholding process. The thresholding process results are used in the formation of binary images that have a value of 1

and 0 for each pixel. The area opening process is carried out for elimination in case there are still objects with pixel values below 100. The purpose of the area opening process is to centralize the results of blood vessel segmentation without the non-blood vessel objects. The feature extraction process results in the form of blood vessel segmentation of the fundus image can be seen in fig. 3.

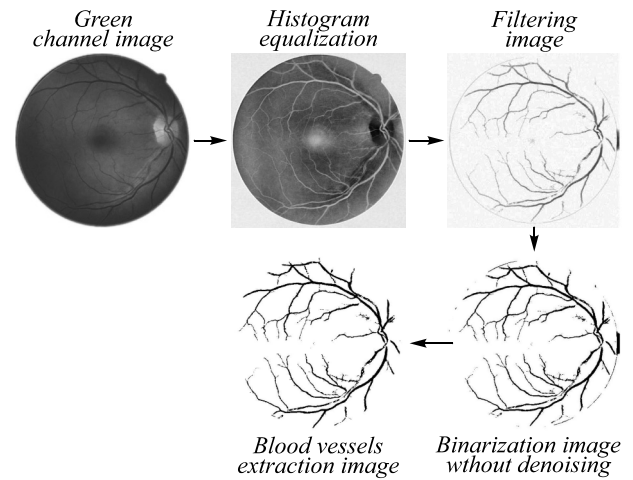


Fig. 2. Preprocessing steps

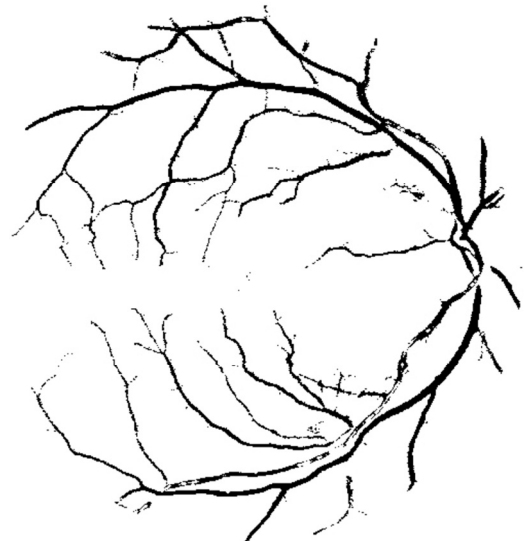


Fig. 3. Results of retinal blood vessels extraction

Fig. 3 is a binary image needed for the process of blood vessel segmentation. The white pixels are the blood vessel and not a background. Therefore it can't be inverted as the object (blood vessel) must be the foreground.

1.3. Convolutional neural network models design

The design of deep convolutional neural network models is used to identify biometric features in retinal fundus images. The model design uses two main libraries namely Keras as high-level neural networks API and Tensorflow as backend engines. The formation of a neural network model and the determination of each hyperparameter is the results of trials on each value and model to obtain a model with the highest accuracy value

and the lowest error rate. The following are the model formation phases for the identification of retinal biometrics using convolutional neural networks.

1. Define the model on Keras. This research uses a sequential model. Layer modules are used in neural network design. The optimizer module is used to optimize with the aim of minimizing error rates and maximizing the accuracy of the neural networks.
2. Conducting a rescaling process to change the image size of the blood vessel segmentation results. Rescaling is done with the aim of reducing load and computation in the neural network architecture training process. The results of the image rescaling process will be stored in a multi-dimensional matrix of size (189, 256, 256) where 189 is the total dataset used in this research and the value 256 is the image size of 256×256 pixels.
3. Labeling the dataset aims to represent images in the form of variable categories that can be read by the program in the dataset training process. Labeling each image is done by a one-hot encoding technique where each image class will have a value of 1 while the other bit values are 0. Each bit that has the value 1 in one-hot represents the class of the fundus retinal dataset. This study has a total dataset of 9 classes consequently there are 9 one-hot categories. One example in Tab. 1 is class 1 has a one-hot value label of 100000000.

Tab. 1. One hot label for each class

Class	One-hot
Class 1	100000000
Class 2	010000000
Class 3	001000000
Class 4	000100000
Class 5	000010000
Class 6	000001000
Class 7	000000100
Class 8	000000010
Class 9	000000001

One hot encoding is a method used to represent variables. The target class is 9 classes which are 9 people with different binary code formation patterns. One hot label encoding is used because CNN cannot work automatically directly to categorize the person into 9 target classes. Then the categorical data will be converted into a number that can be recognized on the CNN model. For example in class 1 with One hot label: 100000000 recognized as target retina person 1, Class 2 with One Hot label: 010000000 recognized as target retina person 2 and so on until class 9. One hot label will adjust the changes in binary position according to the target class which will be recognized.

1.4. Convolutional neural network architecture

The formation of the architecture model convolution layer in this study has several layers where the first layer

is the input layer which has an input image size of 256×256 pixels. The parameter in each convolution process is the number of features that can be learned by *neural network* models in performing an identification. The parameter calculation process uses as follows :

$$Parameter = (hxwxc + 1)xf. \tag{2}$$

In formula 2, the parameter value in a convolution layer is determined by the kernel size ($h \times w$), the number of channels (c) and the filter size (f) value used. Parameter values calculation for the next convolution layer uses the same equation, formula 2. Based on equation 2, the parameter values contained in a convolutional layer can be determined from the size of the kernel size, the number of channels, and the filter value used. An example of the first convolutional layer found in the neural network Figure x uses a kernel size of 3×3 with a channel input of 3, and a filter size of 256. The calculation of parameters in the first convolutional layer can be seen in the following calculation (1)

$$Parameter = (3 \times 3 \times 256 + 1) \times 256, \\ Parameter = 5900080.$$

The following is the calculation of the parameters of each convolutional layer process in the neural network architecture that is made, it can be seen on tab. 2.

Tab. 2. Calculation result of convolution layer parameter

Layer	The calculation	Parameter value
1	$(3 \times 3 \times 3 + 1) \times 256$	7168
2	$(3 \times 3 \times 256 + 1) \times 256$	5900080
3	$(3 \times 3 \times 256 + 1) \times 128$	295040
4	$(3 \times 3 \times 128 + 1) \times 64$	73792
5	$(3 \times 3 \times 64 + 1) \times 32$	18464

Weight output for each convolution process is a calculation between input image size, kernel size, padding and stride as hyperparameter. The weight output on a neural network layer as follows :

$$Weight = (W - F + 2P) / S + 1. \tag{3}$$

An example of calculating the weight value contained in the first convolutional layer with the initial image input value 224×224 , the kernel filter value 3×3 , the padding value 0, and the step value 1 can be seen in equation 3 where $Weight = (224 - 3 + 2 \cdot 0) / 1 + 1 = 222$. The calculation of the weight value of the merging layer uses the input value resulting from the previous convolution process, the value of the filter kernel 2×2 , the value of padding 0, and the value of step 2 can be seen in equation 3 where $Weight = (222 - 2 + 2 \cdot 0) / 2 + 1 = 111$.

The architecture that is built on all layers does not use padding or what is commonly called as zero padding. Tab. 3 is the calculation result of the weight value of each convolution layer process and the pooling layer in the neural network architecture created.

Tab. 3. Weight output

Layer	Layer type	Input	Kernel filter	Stride	Weight value
1	Convolution	224	3	1	222
1	Maxpooling	222	2	2	111
2	Convolution	111	3	1	109
2	Maxpooling	109	2	2	54
3	Convolution	54	3	1	52
3	Maxpooling	52	2	2	26
4	Convolution	26	3	1	24
5	Convolution	24	3	1	22

The first convolution layer has a filter size of 256 with a 3×3 pixel kernel, and the input channel is 3. This first convolution process uses an image input measuring 244×244 pixels. The activation function is used for the entire convolution layer using ReLu. The next layer is batch normalization to keep the data from the first convolutional process. After that, there is a pooling layer with the max pooling type which has a 2×2 filter kernel. The purpose of this pooling is to reduce pixel dimensions in the image. Then the next layer is dropping out of school with a value of 0.5 to minimize excess losses from the previous layer processes. The formation of a convolutional neural network architecture in detail can be seen in tab. 4. As can be seen in tab. 4, the architectural process flow in each layer is more or less the same as the first convolutional layer. First convolutional layer then the normalization layer, then the max pooling layer, and lastly the dropout layer. The only difference is in the filter size of each convolution layer where in the second convolution layer to the fifth convolution layer the filter size is 256-256-128-64-32 respectively. The model used is sequential so the weight results obtained in the convolutional layer use the results of the weights from the previous convolutional layer. Next is the flatten process where all the feature maps obtained are accumulated and put together into single fully connected layers. The next layer is dense, which is a regular layer function that bridges the integrated feature maps with the output parameter values of the previous layer. Dense also adds a layer that is fully connected with units or the number of nodes, which is 32. The activation function used in dense is ReLu and then batch normalization and dropout is carried out like the previous layer. Finally, the fully connected feature maps are categorized into 9 classes according to the number of datasets that have been determined at the beginning of the activation function used, namely softmax.

2. Result and discussion

This study conducted 10 epoch model training with batch size score 15 using a dataset with a ratio of 80% or 151 images used as training data and 20% or 38 images were used as validation data. Further, this study has conducted trials with several epoch values, and within this paper it also showed 10 epochs with the highest accuracy value.

2.1. Blood vessel segmentation result

The examples for feature segmentation of retinal fundus image biometric features in the form of fundus images blood vessel segmentation can be seen in tab 5.

Tab. 4. Convolutional neural network proposed

Layer (Type)	Input	Output
Conv2d_1 Input Layer	(None, 224, 224, 3)	(None, 224, 224, 3)
Conv2D_1: Conv2D	(None, 224, 224, 3)	(None, 222, 222, 256)
Batch normalization_1	(None, 222, 222, 256)	(None, 222, 222, 256)
Max_pooling2D_1	(None, 222, 222, 256)	(None, 111, 111, 256)
Dropout_1	(None, 111, 111, 256)	(None, 111, 111, 256)
Conv2D_2: Conv2D	(None, 111, 111, 256)	(None, 109, 109, 256)
Batch normalization_2	(None, 109, 109, 256)	(None, 109, 109, 256)
Max_pooling2D_2	(None, 109, 109, 256)	(None, 54, 54, 256)
Dropout_2	(None, 54, 54, 256)	(None, 54, 54, 256)
Conv2D_3: Conv2D	(None, 54, 54, 256)	(None, 52, 52, 128)
Batch Normalization_3	(None, 52, 52, 128)	(None, 52, 52, 128)
Max_pooling2D_3	(None, 52, 52, 128)	(None, 26, 26, 128)
Dropout_3	(None, 26, 26, 128)	(None, 26, 26, 128)
Conv2D_4: Conv2D	(None, 26, 26, 128)	(None, 24, 24, 64)
Batch Normalization_4	(None, 24, 24, 64)	(None, 24, 24, 64)
Dropout_4	(None, 24, 24, 64)	(None, 24, 24, 64)
Conv2D_5: Conv2D	(None, 24, 24, 64)	(None, 22, 22, 32)
Batch Normalization_5	(None, 22, 22, 32)	(None, 22, 22, 32)
Dropout_5	(None, 22, 22, 32)	(None, 22, 22, 32)
Flatten_1	(None, 22, 22, 32)	(None, 15488)
Dense_1	(None, 15488)	(None, 32)
Batch Normalization_5	(None, 32)	(None, 32)
Dropout_6	(None, 32)	(None, 32)
Dense_2	(None, 32)	(None, 10)

2.2. Convolutional neural network model training result



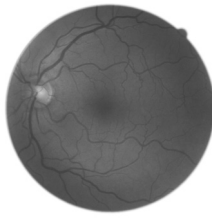
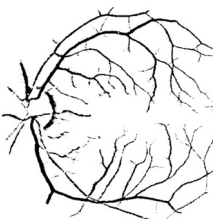

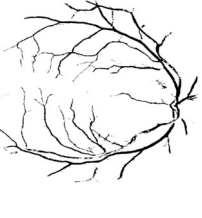
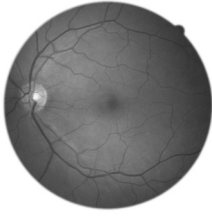


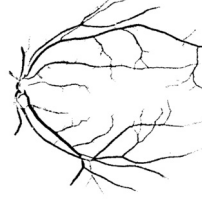



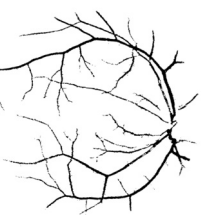
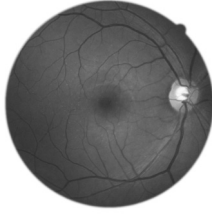


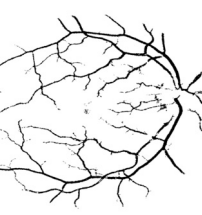
The formed model architecture is then brought into a compilation process with the purpose to enable the model to be used in the training process. Loss function is a function that used to measure how well the CNN model performs in identifying retinal fundus images. Details of performance during the training process can be seen in tab. 6.

Based on the results of the model training in Tab. 6, it can be seen that at the beginning of the training process the validation loss increased significantly and the validation accuracy did not show a significant increase either. However, the 4th epoch process onwards began to show

improvement in the training process until the 9th epoch process showed the validation accuracy value which touched the best number, namely 1. A slight decrease oc-

curred in the last epoch process. From the training results, the train results and val results were carried out on the training data and validation data used during the training.

Tab. 5. Retinal blood vessels segmentation result

Label individu target class	Retinal fundus	Blood vessels segmentation	Label individu target class	Retinal fundus	Blood vessels segmentation
Class 1			Class 6		
Class 2			Class 7		
Class 3			Class 8		
Class 4			Class 9		
Class 5					

Based on the results in tab. 5, it can be concluded that the model training performance is very good because it has a high degree of accuracy and a low level of losses. A good loss function is one that produces the lowest expected error. The results of the training also show that the validation set has a greater accuracy value of about 0.313% when compared to the training set. This shows that during the training process the validation set did not experience overfitting, hence it was able to produce higher accuracy values than the results of the training set as can be seen in fig. 4.

The results of the graph of the accuracy value shown in fig. 4 show that the training accuracy movement is very good with an increase in each iteration steadily, while in the validation accuracy the graph movement is quite increasing but not as good as training. Then the graph shows that the result of validation accuracy is higher than training accuracy as can be seen in the validation lost accuracy graphic fig. 5.

Based on the Validation Lost Accuracy Graphic in fig. 5, it shows that the training loss movement is very good with a steady decrease in each iteration. Meanwhile,

in the validation loss, the movement of the graph tends to fluctuate with a significant increase in the 1st and 2nd iterations. But after that the movement gradually decreased until it became almost equal to or even exceeded the training loss.

Tab. 6. Lost neural network and accuracy value result

Epoch	Val accuracy	Val loss	Train accuracy	Train loss
1	0.1569	3.3044	0.2108	2.3108
2	0.2097	8.8454	0.5185	1.3215
3	0.2189	10.4002	0.7258	0.7878
4	0.5056	1.7704	0.8332	0.5091
5	0.5789	1.7350	0.8888	0.3493
6	0.6617	0.5951	0.9261	0.2463
7	0.8733	0.4007	0.9369	0.2039
8	0.8722	0.4876	0.9463	0.1701
9	1.0000	7.2601	0.9525	0.1502
10	0.9806	0.1926	0.9583	0.1379

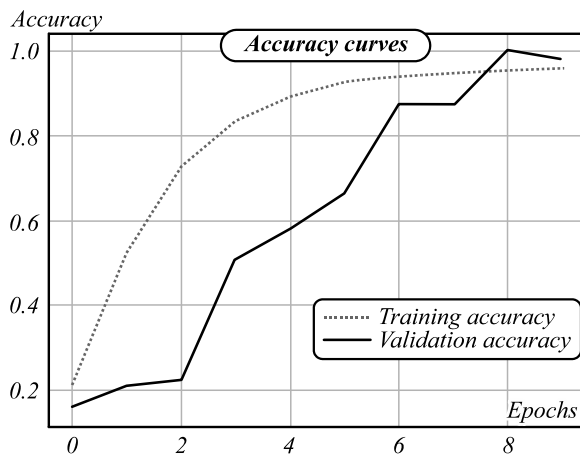


Fig. 4. Train accuracy graph

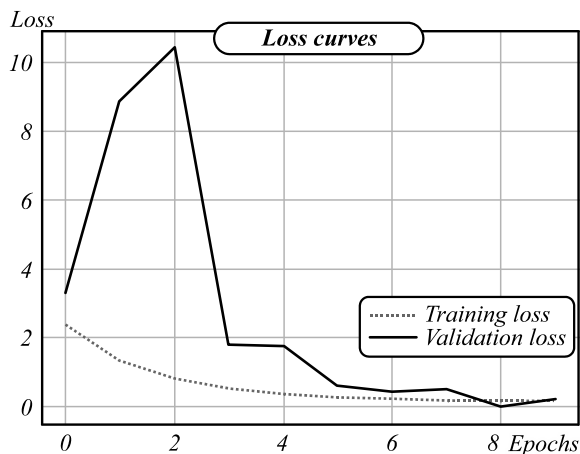


Fig. 5. Validation lost accuracy graph

Conclusion

The design of the CNN model was successfully created with 5 layers of convolution layers, 3 layers of max pooling, 6 batch normalization layers, 6 dropout layers, 1

flatten layer, and 2 dense layers. Image input in the formation of a model measuring 224×224 pixels and total parameters totaling 1483594 variables. The training and validation process uses the CNN algorithm method with a ratio of 8: 2, where the total existing images are 189 with details of the distribution of the dataset as many as 80 % or 151 images as training data and 20 % or 38 images as validation data. Model training produces a test accuracy value of 98 % and from the training results the model is used to carry out the individual identification trial process. The results of the identification trial were 10 times of randomized trials and resulted in 9 correct identifications.

Further development can be done to perfect the process of biometric identification of the retinal and using GPU can speed up the training process.

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