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Palmprint Recognition Based on Edge Detection Features and Convolutional Neural Network

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***Abstract*— Research on biometric technology get much attention from researchers who interest in the recognition system. One of the biometric objects that will continue to be developed is the palmprint. The hand palm line has a unique characteristic in each person or may not be the same. The palmprint image is easy to capture because clearly visible, so it does not require a specific sensor. This paper presents the automatic extraction feature with Convolutional Neural Network (CNN) technique to get a unique characteristic of palmprint image and identify a person. CNN will get easier to classify the image database if it has many data. CNN belongs to Supervised Learning, which requires training data to create a knowledge base. In the dataset with little training data, the system must increase the training data using augmentation methods like zoom, shear, and rotate. Still, in the palmprint, that augmentation method can change the original character of the palmprint. Our proposed method is adding training data with an edge detection image from the original image. Edge detection used in our method is Canny and Sobel. The addition of Canny and Sobel edge detection for training data is the best combination scenario for palmprint recognition. The experiment results showed that palmprint recognition using Convolution Neural Network with Canny and Sobel edge detection for training data resulted in an accuracy rate of 96.5% for 200 classes, and the Equal Error Rate (ERR) value is 3.5%. This method has been able to recognize 193 palms of 200 people.**

***Keyword* — Palmprint recognition; edge detection; convolutional neural network.**

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I. INTRODUCTION

Person identification is still a fundamental problem in biometric systems. The biometric has attracted researchers' significant attention because the biometric system has grown as a reliable method for human authentication [1]. A biometric system is a technology that uses information about a person or another biological organism to identify that person [2]. The biometrics system study has moved to other scenarios, such as mobile devices authentication or internet-based systems, in line with novel deployment platforms of human-computer technology [3]. Biometric systems become popular as a measure to identify a person by measuring physiological or behavioral characteristics [4].

Today, biometric systems can use to classify characteristics in humans, such as faces and fingerprints. Many studies have conducted various experimental methods to classify biometric data. The development of biometrics technology affects several systems that utilize biometrics, such as security systems and biometric recognition systems. Many studies have conducted various experimental methods to classify biometric data. Research on biometrics has long been carried out with various new biometric objects found. The last few years of research on the introduction of individuals using biometric lines or palmprint palms are overgrowing. The lines of the palms of each person are known to be different even though identical twins. Palmprint use in a recognition system has several advantages over other human traits such as rich and stable features unlikely to change with age. Uniqueness, even twins, do not have the same palm print features, and less intrusiveness. Palm print recognition also less costly because palm possesses more features than other human traits that can be extracted even with low-resolution image capturing devices. The palm line is also difficult to change or falsify and does not have much effect on age.

Many experiments have been carried out on facial biometric objects, fingerprints, and iris in carrying out individual recognition, but the palmprint recognition tends to be a little and less popular. The palmprint recognition system has attracted many researchers because palmprint as a biometric object has distinctive features, reliable, permanent in nature, good recognition with low-resolution cameras [5]. Palmprint is relatively new in physiological biometrics [6]. The characteristics of palmprint, such as geometrical features, line features, delta, and minutiae points [7]. Palmprint is a part of the palm that has fold lines that are different from one individual to another. Palmprint has rich features, unique (even twins do not have the same features), less intrusive, can be extracted with a low-resolution image capturing device [8]. There are differences in individual palm lines with one another because of gender and age differences. In men's palms, lines are thicker and deeper because men tend to have more grip strength than women so that the image of a woman's palm is smoother than men. Based on age, the lines of children's palms are smoother and less than those of an older person. This condition happens because older people have more wrinkles on their palms so that the palm on someone who is elderly is more than the children.

As shown in Fig. 1, the palmprint image used in the experiment has been preprocessed with cropping and grayscaling technique to get more features of the palmprint image.

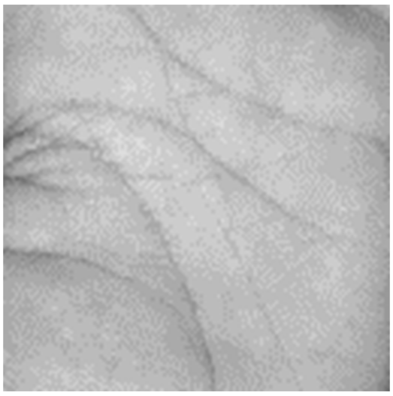


Fig. 1 A sample of palmprint image

The human hand palm has a principal line and wrinkles line, which are the main characters in palmprint recognition. However, there are other features on the hand palm if using high resolution capturing device. Palmprint image has a different level of features in different image resolution, as shown in Table 1 [9].

TABLE I
DIFFERENT PALMPRINT FEATURES ON DIFFERENT IMAGE RESOLUTION

	100 ppi	**500 ppi**	**1000 ppi**
Features that can be extracted	Principal lines, wrinkles line	Principal line, wrinkles line, ridges, minutiae points	Principal line, wrinkles line, ridge, minutiae points, pores, ridge width

Palmprint images with low resolution or about 100 pixels per inch (ppi) are classified as texture-based images. In textured-based palmprint image, the principal line is the most visible, and the wrinkled line is visible but need to improve with edge detection filter. High-resolution palmprint image contains many features that can be extracted. In 500 ppi, ridge and minutiae points can be extracted. In 1000 ppi, palmprint image contains pores and ridge width features.

The palmprint image that already acquired by the camera must enhance by image processing technique. The image preprocessing stage is the image quality improvement to get better characteristic of the image [10]. Computer vision and pattern recognition are becoming an important trend in nondestructive detecting technologies (NDT) nowadays, which is boosting various industrial detection applications [11]. Convolution Neural Network (CNN) is one of the most successful deep learning methods applied to image recognition. The discriminative pattern features can be automatically learned from a large amount of data, and it can achieve the effect of close to human eye recognition [12]. The Convolutional Neural Network layer receives an input signal that is called convolution filters [13]. Many concepts or architecture of CNN were improved by researchers like AlexNet and ResNet. The modern architecture of CNN can classify many data and achieved high accuracy. Modern CNN architecture can classify objects, animals, disease or biometric because of the convolution layer's complexity. AlexNet has five convolutional layers, three subsampling layers (pooling), and three fully connected layers with about 60 million training parameters and 1.2 million images as training sets [14]. The Convolutional Neural Network technique becomes effective if it uses many training data. Research from [15] revealed several tips for getting good accuracy even with a small dataset:

- Reduce the dimension of the fully-connected layers, so the number of CNN parameter will reduce
- Using batch normalization and more dropout to reduce error and overfitting

Another way to improve CNN model is by filtering the image. Image filtering is done to show the main features of the image. For example, in palmprint recognition, the main features are the principal line and wrinkles line. So, the filter must have abilities to highlight a line. Image filtering method that use to highlight a line is Edge Detection technique. Edge detection can filter out unwanted information of the image so that CNN can train the image more compelling. There are many edge detection techniques for image filtering such as neural network, sparse coding, watershed and learning [16].

The most popular edge detection techniques are still Canny and Sobel Edge Detection. Canny edge detection is a popular edge detection algorithm because of its simplicity, great localisation of the edge and excellent noise reduction for many image applications [17].

$$S = I * G_x * G_y \quad (1)$$

$$S_x = S * dG_x \quad (2)$$

$$S_y = S * dG_y \quad (3)$$

$$M = \sqrt{S_x^2 - S_y^2} \quad (4)$$

Image is symbolized by I, smoothed with horizontal, Gx and vertical, Gy Gaussian filters. Then, image convolved horizontal, as shown in Equation 2, and convolved vertical, as shown in Equation 3. The dG_x and dG_y parameter are the derivatives of the Gaussian. The magnitude of the gradient, *M,* is given in Equation 4.

The study was conducted by [18] that creating palm print recognition with Gabor Filter and KNN matching. They used different wavelength and orientation with the Gabor Filter to extract the features. The Gabor filter method allows us to set various parameters such as orientation, wavelength, and scale, so the Gabor filter method is relatively useful for edge detection or texture detection. In contrast, the KNN (K-Nearest Neighbor) method is an algorithm that functions to classify data based on learning data (train datasets), which is taken from the nearest neighbor. The experimental result of this research showed that their proposed method gets 99% accuracy. Palm print recognition can be used 3D features like research that proposed by [19]. They propose a complete binary representation (CBR) for the 3-D palm print multiple dimensional feature representation and recognition. The 3D feature is a new type of feature used in image classification because not many images can be mapped into 3D images. The result showed that they got EER (Equal Error Rate) 2.27%. The equal error rate is the percentage of error that system achieves. Smaller ERR value that achieved, the recognition system was more effective. Another research about palm print recognition was proposed [20] that used the Deep Scattering Network. Scattering network is a convolutional network where its architecture and filters are predefined wavelet transforms. Wavelet transforms use wave signal to transforming image to wavelet image. Scattering transform is designed so that the features in its first layer are like SIFT descriptors and the higher layers feature captures higher frequency content of the signal lost in SIFT. They claim their proposed method get 99.9% accuracy using an SVM classifier. SVM classifier is Support Vector Machine that used in object classification or recognition. SVM was well known in high accuracy recognition because of its complexity algorithm. Another study [21] has argued that employing one-to-one matching strategy and binary representation for the feature is more useful for palmprint identification. The one-to-one matching strategy is used in the verification system because it checks one image to one other image claimed in the same class. So, in verification technique system can get a percentage that represents the matching score of the image was declared to the class. They used 2-D and 3-D palm print features and got FAR (False Acceptance Rate) better than orientation. Research by [22] that implement CNN methods in the automation of the robotic system.

The CNN used in the detection and classification of the pentominoes in the work environment, using a database. The R-CNN trained accuracy represents a critical factor in the algorithm's operation because an erroneous prediction or loss of information in that stage generates errors. In [23] introduce an RPN (Region Proposal Network) that can shares full-image convolutional features with the detection network. RPN method was essential to analyze the feature of the Fast R-CNN. RPN with Fast R-CNN was able to run an object detection system at 5 – 17 fps or 200ms per image. They also give a screenshot of a system that was implemented which shows the real-time object tracking. In [24] experiment about the biometric system was done with finger knuckle. Finger knuckle patterns were believed to be unique in establishing human identities. The finger knuckle image is processed by segmentation, edge detection before transforming to 3D-Representation. The recognition performance visualized with ROC curve and achieved an EER score of 9%.

II. Material and Method

In this section, this experiment will provide a palmprint recognition based on Convolutional Neural Network and Edge Detection Feature as a problem solving from the difficulty of getting good accuracy in training with CNN if the number of datasets is small. As mentioned above, CNN will get higher accuracy when used many datasets of each class. Dataset of each class means how many images consist of each class that represent people.

A. Enrollment

The enrolment process begins by loading the entire palmprint image. One person or one class must have an extensive and varied training data so that the CNN model can extract each class's features correctly and get high accuracy in recognition. Image filtering does after loading the dataset. Image processing method that uses in this study is contrast stretching. The contrast stretching method can transform the image to sharpen the image, reduce noise, and show the image's highlighted object. The contrast stretching uses to highlight the line of a hand palm. The image processing stage only uses contrast stretching method because the palmprint dataset has been processed by cropping and grayscale. Cropping is the primary image processing which removes the object that cannot be interested. Example of cropping technique is Region of Interest (ROI). In the ROI technique, the system can detect an object and create a region of a selected object; even the image is skew or has been rotated.

Feature extraction does after image preprocessing stage. Feature extraction is the way to get the unique characteristic of each class. The unique characteristic can transform into an array with a mathematical function to classify each image. Additional feature extraction that uses in this experiment is edge detection method such as Canny and Sobel. Canny was popular edge detection technique that uses to find the edge of the object in the image. In palmprint recognition, edge detection used to highlight the principal line and wrinkles line in palmprint image. Sobel edge detection also a popular edge detection method for texture analysis. Sobel has a parameter that can adjust to highlight vertical texture or horizontal texture. Edge detection image outputted to palmprint dataset to increase the number of training data.

B. Identification

The identification process begins by loading a single image. In the identification stage, the system only loads a single image because the identification process will predict who has the palmprint image. The palmprint image was predicted by CNN method after processed by contrast stretching. This experiment's testing image was transformed to Canny and Sobel edge detection because the dataset used in the enrolment process contains the palmprint image that has been processed with Canny and Sobel edge detection. The matching process requires a feature database from the enrollment process to calculate the prediction. The result of the prediction will appear as a class name. The complete process of enrolment and identification stage was shown in Fig 2.

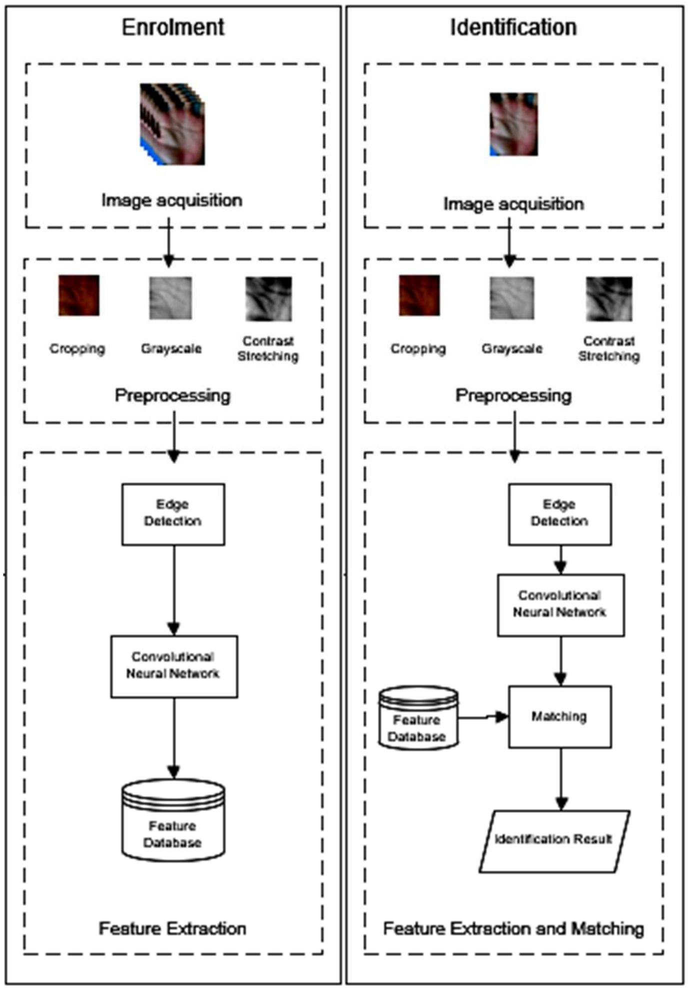


Fig. 2 Overview diagram of enrollment and identification process

This experiment was not using the Convolutional Neural Network pre-trained network, for example, VGG, AlexNet or ResNet, because we want to test the efficiency of adding edge detection training data on ordinary CNN models. As shown in Fig 3, the CNN model used has three convolution layers and three pooling layers, two fully connected layers with ReLu and finally a Softmax activation. The CNN model is shown in Fig 3.

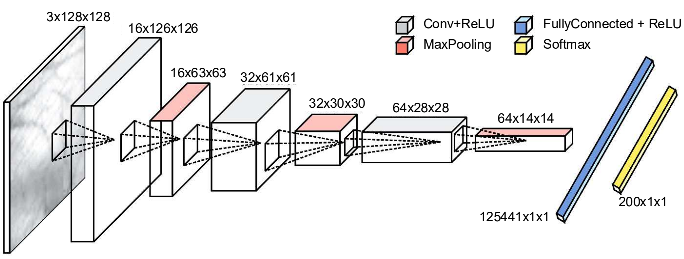


Fig. 3 CNN architecture

Table 2 shows the layer type, output shape, and several parameters. The CNN model that was used in this experiment contains three convolution layer and two fully-connected layers. First convolution layer has outputted shape 126 x 126 x 16 with 448 params. First pooling layer transforms the image to the size of 63 x 63 x 16. Second convolution layer has outputted shape 61 x 61 x 32. The second pooling layer transforms the image to a size of 30 x 30 x 32. Third convolution layer filtered the image to the size of 28 x 28 x 64. The last pooling layer gets outputted shape of 14 x 14 x 64. Flatten was done after the convolutional stage. The flatten layer transforms the three-dimensional image to one dimension, so the number of features in the first layer is 1 x 12544. The first dense layer is to define how many features that will used in the network. Dropout stage is to prevent overfitting. The last dense layer is some class used in the experiment.

TABLE II
CONVOLUTIONAL NEURAL NETWORK MODEL

Layer (type)	Output shape	Param #
Conv2d_1	(None, 126, 126,16)	448
Max_pooling2d_1	(None, 63, 63, 16)	0
Conv2d_2	(None, 61, 61, 32)	4640
Max_pooling2d_2	(None, 30, 30, 32)	0
Conv2d_3	(None, 28, 28, 64)	18496
Max_pooling2d_3	(None, 14, 14, 64)	0
Flatten_1	(None, 12544)	0
Dense_1	(None, 256)	3211520
Dropout_1	(None, 256)	0
Dense_2	(None, 200)	25700

III. RESULTS AND DISCUSSION

Palmprint recognition tested with several scenarios such as various class number, and various type of testing image. Palmprint recognition was implemented using Intel Core ™ i3 ~1.8 GHz processor, 4 GB RAM, 500 GB hard disk. Keras library in Tensorflow uses to implement all the Convolutional Neural Network computations.

Palmprint database that used in this experiment got from [6]. The palmprint image database has 600 images of 200 people. Each person has three images separate into training data and testing data with a ratio of 2:1 so that there are 1 test image and two training images. The image conditions in palmprint dataset have been cropped and grayscaling, and have 128 x 128 shape in grayscale format.

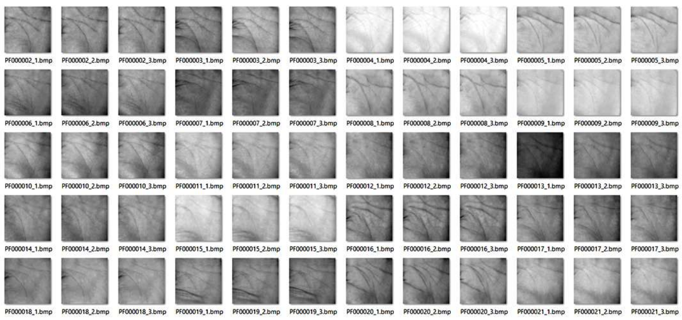


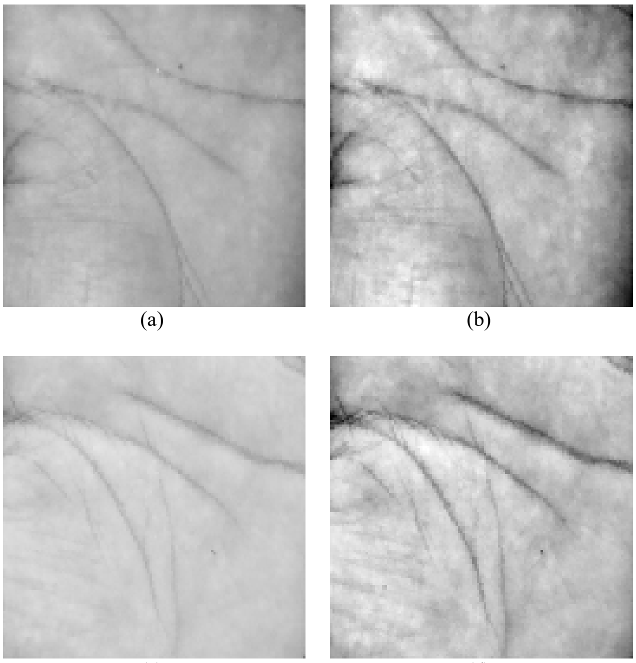
Fig. 4 Screenshot of the image dataset

Fig 4 is the screenshot of palmprint dataset in file explorer windows 10. The name format of each image is PF00<class_number>_<image_number>.bmp. With this file name scheme, the system can classify each class with section <class_number>. Then, the system split them into training data and testing data with a ratio of 2:1.

The image on the dataset is somewhat blurry. The preprocessing stage needs to filter the image. The contrast stretching technique that uses in this study shown in Fig 5. Contrast stretching technique is an image filtering method that transforms image to sharpener image. The contrast stretching was used to highlight the line of a hand palm. The preprocessing image stage is only a contrast improvement because the palm print dataset used has gone through the process of cropping and grayscale. The following equation is a contrast stretching formula.

$$\frac{\text{gray value} - \text{MIN(gray value)}}{\text{MAX(gray value)} - \text{MIN(gray value)}}\ x\ 255 \tag{5}$$

Contrast stretching is a way to increase the contrast of a blurred image by stretching the frequency of images that have previously accumulated at a specific range, to stretch from 0 to 255. Fig 5 (b) is the result of a palmprint image that has been processed with a contrast stretching technique.



(a) (b)

(c) (d)

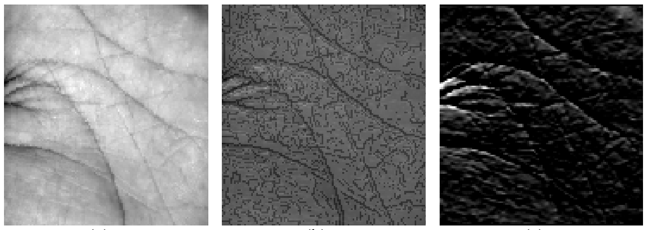
Fig. 5 Contrast stretching image preprocessing, (a, c) original image (b, d) contrast stretching image

Contrast stretching image is outputted to the same directory as the original image to increase the training data. Training data has been increased to 4 images, and the testing data increase to 2 images. As shown in Fig. 5, the line of hand palm each person is different from the heart line's length and curvature, headline, and lifeline on the hand palm. The line in palmprint image after contrast stretching filter is more clearly visible in both the principal line and the wrinkle's line.

In this study, edge detection is used to find the line of palmprint images and add training data to help CNN get better recognition. CNN will easier classify image if many training data used in the dataset. The edge detection image will be created in the same directory as the original image. The edge detection method used is Canny and Sobel. The canny images used will be stacked with contrast stretching results, so that the images displayed are more original with additional lines. The following formula is the Sobel edge detection filter.

$$G_x = \begin{bmatrix} -1 & 0 & +1 \\ -2 & 0 & +2 \\ -1 & 0 & +1 \end{bmatrix} x\ A \text{ and } G_x = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ +1 & +2 & +1 \end{bmatrix} x\ A \tag{6}$$

The implementation of Canny and Sobel edge detection is shown in Fig 6. The OpenCV library is used to filtering the image, which is run using the Python programming language 3.6. Canny filter that created detect thick lines on the palms by adjusting the kernel size parameters. The line thickness on Canny set to 3 pixels. Whereas in Sobel, the kernel flow (x = 0, y = 1), with a size of 3 x 3.



(a) (b) (c)

Fig. 6 Edge detection process, (a) Contrast stretching image (b) Canny image (c) Sobel image

After edge detection stage, dataset now has six training data for each class. The edge detection method was added to the testing image and replaced the original image with a contrast image. So, the system now has one testing image for each class. The complete training data before feature extraction is shown in Fig 7.

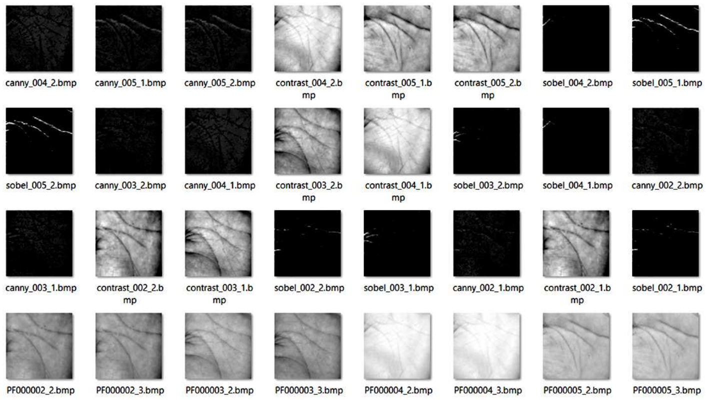


Fig. 7 Combination of image filtering in data training

The combination of the original image, contrast stretching image, canny edge detection and Sobel edge detection are collected in one folder into training data. Training data increased four times to 1600 images. In this study, 200 epoch training was done about 20 minutes.

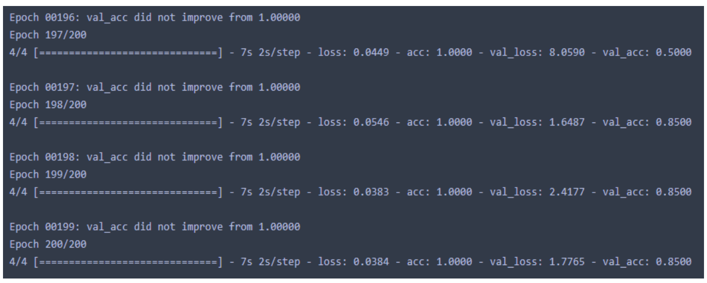


Fig. 8 Training Process

As shown in Fig 8, the Jupyter notebook environment's training process displays statistics such as accuracy, loss, and time obtained for each epoch. The statistics are beneficial for the analysis. If the training process were done, the system would get a feature database. Feature database is used for matching to find out the accuracy of recognition of the knowledge base from the palmprint dataset.

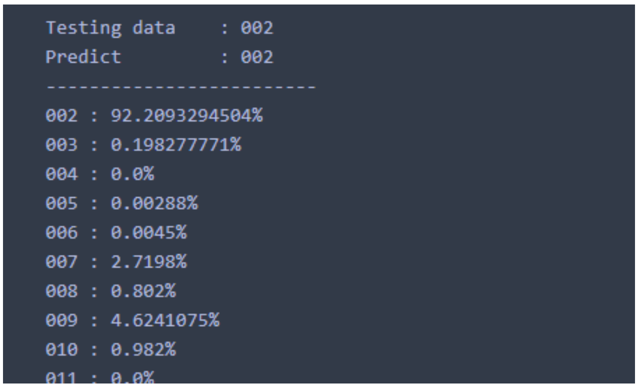


Fig. 9 Identification Process

The identification process uses images which is not in the training data. As shown in Fig 9, the result of matching shows the percentage of predictions for each class. Class prediction with the highest percentage is set to be the result of identification. The recognition system has conducted training in imagery with edge detection and without edge detection to know the impact of edge detection in palmprint recognition. Table 3 is an experimental result for the different dataset.

TABLE III
EXPERIMENTAL RESULTS FOR DIFFERENT DATASET

Data	**Testing Accuracy**	**Training Accuracy & Loss**	**Validation Accuracy & Loss**
Raw dataset	0.5%	0.5 & 12	0.01 & 15
Edge detection dataset	96.5%	0.96 & 0.2	0.95 & 0.02

The experimental results show that the recognition accuracy will improve by adding training images with edge detection images. Edge detection helps the CNN model extract features and adds training images, so there is more. Before the edge detection was added to the dataset, CNN only gets 0.5 accuracies and gets 12 scores of loss value, and it means CNN cannot classify each class and cannot get the different feature of each class. After the edge detection was added to the dataset, the system got higher accuracy with 96.5% testing accuracy, 0.96 training accuracy with only 0.2 loss accuracy. Testing accuracy means the number of correct predictions of each testing image each class.

The recognition system tested the recognition accuracy with variations number of classes, such as 100 and 200 for training data that had gone through the edge detection stage. This experiment used 100 and 200 classes to find out the effectiveness of the classification done by CNN. If dataset that used only 10 or 20 classes (less than 50 classes), it does not guarantee that the accuracy obtained is the same as using many classes, for example, 100 or 200 classes, performed on the same number of epochs, which are 200 epochs, and the same model architecture.

The experimental results show that with the addition of edge detection images, the results of accuracy for different classes of numbers remain high. The accuracy of 100 epochs is 93%. Table 4 is experimental results for different class number (100 classes and 200 classes).

TABLE IV
EXPERIMENTAL RESULTS FOR DIFFERENT CLASS NUMBER

Class Number	**Testing Accuracy**	**Training Accuracy & Loss**	**Validation Accuracy & Loss**
100	93%	0.93 & 0.34	0.92 & 1.07
200	96.5%	0.97 & 0.09	0.98 & 0.2

The testing accuracy in 100 classes is 93% while testing accuracy for 200 classes is 96.5%. This condition is rather strange where the testing accuracy of 200 classes is better than the accuracy testing 100 classes. The accuracy of 200 class is higher than 100 class because the first 100 class achieved higher error identification than the next 200 class.

Another experiment was done by varying the amount of testing data to determine the accuracy of palmprint recognition. The first test, the number of testing data that use is only 1 with contrast stretching type. On the second test, the number of testing data that use is three images such as contrast stretching, canny edge detection image, and Sobel edge detection image. Table 5 is experimental results for a different amount of testing data.

TABLE V
EXPERIMENTAL RESULTS FOR DIFFERENT CLASS NUMBER

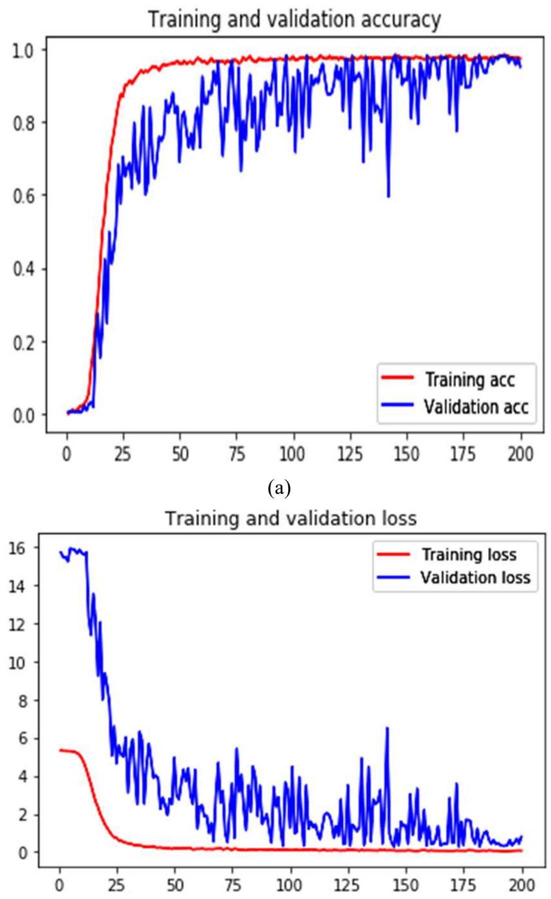
Class Number	**Testing Data**	**Type**	**Testing Accuracy**
200	1	Contrast stretching	96.5%
200	3	Contrast stretching, Canny, Sobel	93%

In the experimental result for different class number, testing with one image (only contrast stretching) per class obtaining testing accuracy 96.5% while with three testing images (contrast stretching, Canny and Sobel) each class get 93% testing accuracy. It means testing using contrast stretching image is better than testing using edge detection methods like Canny and Sobel.

The training process of the model created was analysed by looking at changes in acc, loss, val_acc, and val_loss values at each epoch. This process aims to identify training trends, whether they are increasing.

Fig 10 shown the accuracy that the system gets every step or every epoch. The training trend at 200 epochs showed a significant increase in accuracy for the first 50 epochs. The loss at 200 epochs showed a drastic decrease in the first 50 epochs. This result shows that at the first 50 epochs CNN has been able to classify the features of each class, the rest of the epoch will look for the best accuracy and worst loss.

FAR (False Acceptance Rate) and FRR (False Rejection Rate) calculations were used to determine the error rate of the system that was made. The system needs to find out how many images should be wrong to calculate the FAR value, but are considered correct at a certain threshold, so the number of matches exists (number of classes * number of test data per class - number of test data per class) * number of classes. As for calculating FRR values, the system needs to find out how many images should be correct but are blamed on a certain threshold, so the number of matches in FRR is the number of classes * the number of test data each class.



(b)

Fig. 10 Training and validation accuracy and loss, (a) Training and validation accuracy (b) Training and validation loss

The equal error rate (EER), a point where the false acceptance rate (FAR) is equal to the false rejection rate (FRR), is utilized to evaluate the performance of verification algorithms. In this experiment, the EER value that was obtained is 3.5%, as shown in Fig 11.

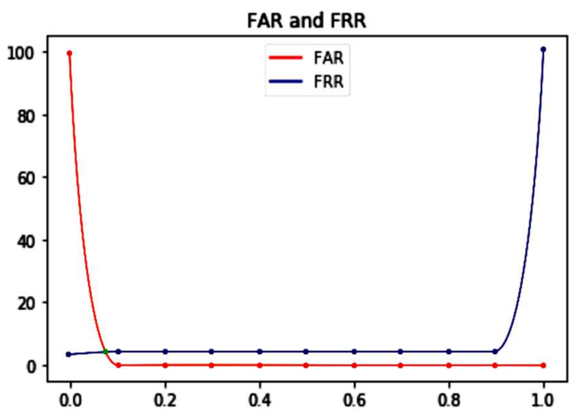


Fig. 11 FAR and FRR

IV. Conclusion

In this paper, an effective method for palmprint recognition with small datasets was proposed. Our work demonstrates that using the addition of training data in the form of edge detection images. Without using architectural models, the system can achieve 96.5% accuracy for 200 classes. By analyzing different datasets, with the addition of edge detection produces higher accuracy than without edge detection. By analyzing a different number of classes, the accuracy obtained for 100 classes and 200 classes with the same combination of edge detection results in almost the same accuracy (93% and 96.5%). By analyzing testing data, testing with one image (contrast stretching) is better than using three images (contrast stretching, Canny and Sobel image). In the future, how to use pre-trained CNN base on palmprint recognition will be studied.

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