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Gender Classification Based on Fingerprint Using Wavelet and Multilayer Perceptron

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Abstract: Fingerprint-based gender classification is beneficial for speeding up the fingerprint identification of criminals, accident victims, and natural disaster victims that are difficult to be recognized based on their physical characteristics. The biggest obstacle to digitally classifying fingerprints is the image's poor quality. Some methods have been developed to improve image quality through various preprocessing, such as noise removal, background segmentation, thinning, and binarization. However, as these processes increase the classification time, some methods have been developed to classify fingerprints without preprocessing. One of them that has shown excellent success is CNN (Convolutional Neural Network). The method does not require preprocessing, but the computation time is very long and requires large amounts of training data. This study proposed a new method that did not need any preprocessing by using wavelet decomposition combined with the max-pooling process to generate features. Firstly, the fingerprint image was decomposed with a Haar wavelet of 4 levels, and each level was followed by a max-pooling process with a 2×2 filter. After that, the resulting feature was used as training data for the Multilayer Perceptron (MLP) network. In this study, the training data was a dataset from NIST (National Institute of Standart and Technology), with 750 fingerprints consisting of male and female fingerprints, each as many as 375. The method could produce a total accuracy of 80.1%.

Keywords: Fingerprint; gender; multilayer-perceptron, wavelet, maxpooling

INTRODUCTION

Fingerprint classification aims to speed up the process of matching a fingerprint with a collection of fingerprints stored in a database. In general, it has been accepted that there are five classes of fingerprints, namely left-loop, right-loop, whorl, arch, and tented arch [1]. The classification is based on specific traits found in a fingerprint, namely minutiae. The minutiae can easily be detected by forensic experts but are very difficult to detect digitally.

The biggest challenge in processing fingerprints based on minutiae is when the fingerprint image quality is poor. Hsiao et al. [2] stated that in some countries, collected fingerprints are of poor quality and can not be digitally processed. It is why some efforts have been proposed to enhance the image quality. They need some preprocessing, such as noise removal, thinning, and background separation, which consumes a lot of time. Moreover, detecting minutiae is also challenging.

Some researchers, such as Rim, et al. [3], hypothesized that once a fingerprint database is classified into five classes, the matching process only takes one-fifth because the matching is directed to the appropriate class. Therefore, there will be two subclasses for each class so that the matching can reach one-tenth of it. This matching process will be even faster if each class is classified again by gender. This research aims to classify or, more correctly, estimate gender based on fingerprint without using any preprocessing. The features are generated by Haar wavelet and combined with the max-polling method before inputting to a multilayer perceptron. The research mimics what was conducted in the CNN method but with more straightforward and shorter steps.

Based on existing literature, fingerprint-based gender classification was pioneered by Acree [4]. At that time, he utilized the ridge density (RD) feature, the number of ridges on an area measuring 5×5 mm from a fingerprint. What is meant by a ridge is a dark-colored groove that forms a kind of curve on the fingerprint. The study reported that the RD of women's fingerprints is higher than that of male fingerprints. Thus the male fingerprint ridge is thicker than the ridge on the female fingerprint.

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1. Literatures Review

There were quite a lot of similar studies as conducted by Acree with various methods for calculating RD, as was found in [5], [6], [7] and also on [8]. In these studies, RD is generally calculated manually by cropping a particular area on the fingerprint image, then enlarged digitally, and then calculated manually.

The determination of the ridge-based fingerprint feature faces obstacles when done automatically with digital technology. These obstacles are related to preprocessing to improve image quality, ridge tilt detection, ridge thickness detection, and also detection of specific patterns formed from the ridge. That is why lately, digitally fingerprint-based gender research uses more frequency analysis, such as wavelets, and deep learning approaches, such as the Convolutional Neural Network (CNN). In addition to problems related to the selection of features that are reliable and easy to extract, another challenge is the selection of classifier models that can process multi-dimensional and large amounts of data.

Research on fingerprint-based gender classification using CNN has been widely carried out. Iloanusi and Ejiogu [9] built a CNN model to examine all five right-handed fingerprints as the basis for determining the gender of their owners. The samples used were taken from 392 people, each of which was taken 20 times, bringing the total to 7840 fingerprints. Their CNN architecture has 20 layers consisting of five convolutional layers, six Rectified linear unit (ReLu) layers, five max-pooling layers, two fully connected layers, one softmax layer, and one classification layer. This study found that each finger's fingerprints produce different accuracy when used as a basis for classification. Based on this fact, they combined three fingerprints of the little finger, middle finger, and thumb as the basis for classification. Through this combination, the CNN model they built produced accuracy for men's fingerprints at 94.7%, for women's fingerprints at 88.0%, and overall at 91.3%.

Jayakala and Sudhab [10] build a simple CNN consisting of only three convolutional layers and a fully connected layer. They compared ReLu and Tanh activation functions on all layers to determine which was better. Using a sample of 4000 from the NIST (National Institute Standard and Technology) dataset, the model they built was able to produce an accuracy of 99% using the ReLu activation function and 87.6% when using the Tanh activation function.

In addition to building the CNN model from scratch, some studies make use of the existing CNN model created by previous researchers. CNN models can be distinguished by the number of convolution layers, filters on each player, the type of pooling layer, the number of fully connected layers, the activation function used, and the number of neurons in the classification layer. These existing models have generally been trained with massive datasets so that the training time will be shorter if used in subsequent studies. This kind of concept is called pre-trained or transfer learning.

Three existing CNN models, namely VGG16, Inception-v3, and Resnet50 were used by Hsiao et al. [2], to predict fingerprint-based gender. In the study, they used 1000 samples consisting of 500 female and male fingerprints. Based on the results of the study, they found that the VGG16 model provided the highest accuracy of 79.2%. This result is less high than similar studies because the number of samples used is less, which is generally at least 10000.

Rim et al. [3] also utilize existing models, namely VGG-19, ResNet-50, and EfficientNet-B3. They used 8000 training data, 1520 validation data, and 360 test samples. The data was obtained directly from 494 male and female volunteers, and each person's fingerprints were taken from all ten fingers. The best accuracy was obtained from the experiments they conducted on the EfficientNet-B3 model of 97.89%.

The ResNet-50 model was implemented by Miranda et al. [11] to classify fingerprints using. Using the NIST dataset and implementing Contrast Limited Adaptive Histogram Equalization (CLAHE) resulted in an accuracy of up to 95.05%. Meanwhile, Listio [12] implemented CNN to detect gender based on eye image. She compared two models of CNN, namely Inception-V3 and MobileNet to analyze a dataset of 1251 male and 1430 female eyes. This study found that the Inception-V3 method has higher accuracy than the MobileNet method, which is 91.82%.

Due to its success, CNN has been implemented for some purposes. Andrew and Santoso [13] used three models, namely VGG19, ResNet50, and Inception-V3, to analyze the rating of online food orders. Their research found that the accuracy of VGG19 is 96.86, Resnet50 is 97.29, and Inception_v3 is 97.57. Some researchers, such as Jatmika and Saputra [14], used CNN to identify rice plant diseases, Untoro and Muttaqin [15] applied CNN to detect malaria, and Sze et al. [16] implemented CNN to review five-star hotels.

The use of the CNN model produces a high accuracy; however, CNN requires a very long computational time. The main factor influencing computational time is CNN's highly complex architecture. A CNN model can consist of many layers, and each layer can use many filters or kernels. To increase accuracy, the model designers commonly increase the number of layers and filters. In addition, CNN requires a large number of datasets.

This study proposes a fingerprint-based gender classification model by utilizing features generated by Haar wavelet decomposition and combined with the max-pooling method. The resulting feature is used as training data for the Perceptron Multilayer, which consists of only one hidden layer and an output layer.

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2. METHOD

In principle, this study is a binary classification, which groups datasets into men and women. This study used a fingerprint dataset from NIST of 750 fingerprints consisting of 375 male fingerprints and 375 female fingerprints. Each sample is 512×512 pixels in size. Because the image size is quite large when used directly as input for MLP, the number of parameters is enormous and needs a long computation time. Considering these facts, the first to do is to convert the image into a feature.

In this study, the features were generated by decomposing fingerprint images by a 4-level Haar wavelet, and a max-pooling process followed each level. Haar wavelets were chosen because their computation is relatively simple compared to other wavelets. For each decomposition level, the image size will be half. Although the wavelet decomposition produces four components: average, horizontal, vertical, and diagonal, only the average component is processed by max-pooling. The max-pooling filter size is 2×2, so the image size will be half again.

With an original image size of 512×512 pixels, after the decomposition of four levels and each processed with max-pooling size 2×2, a matrix of size 8×8 will be produced. This matrix is then reshaped into a vector of size 64.

Figure 1 is a flowchart of the proposed method.

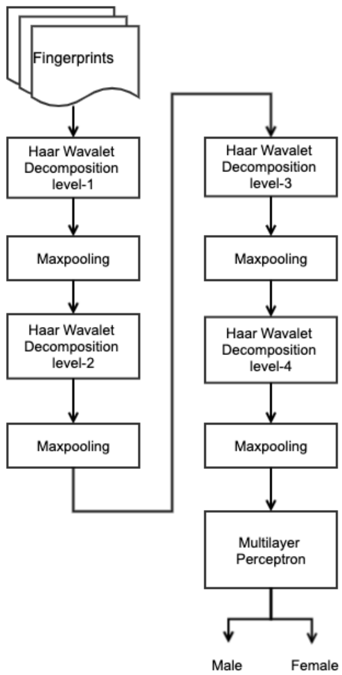

Fig. 1 Flowchart of the proposed method

It can be seen in Fig. 1 that the final max-pooling output is used as training data for the MLP. This MLP network serves as a classifier, and its architecture can be seen in Fig. 2. It is composed of an input layer of size 64, a hidden layer of size n, and an output layer of size two. The activation function of the hidden layer is sigmoid, whereas the output layer uses the softmax function.

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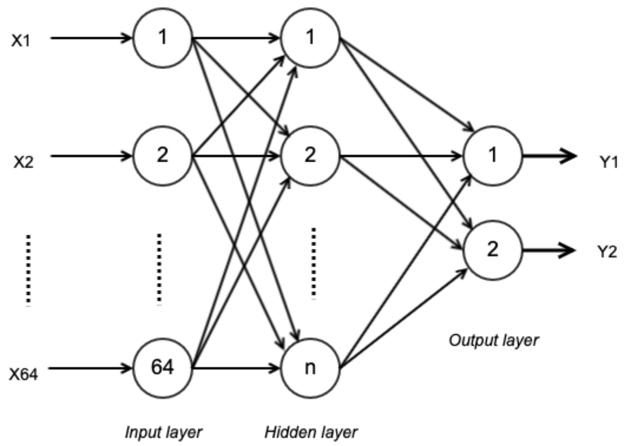

Fig. 2 MLP Architecture

The neuron number of the input layer is related to the size of the final max-pooling output. In this research, the neuron number of the hidden layer was tested from 10 to 100 with the step of ten. The output layer was chosen as two because the layer is designed to classify two classes.

Training data was prepared as a matrix with the size of 750×64, where 750 is the number of samples, and 64 is the number of features. The target matrix was the size of 750×2, where 750 is the number of samples, and two is the correlated class category of each sample. A confusion matrix would evaluate the result of the method. The proposed method was implemented in MATLAB R2022a utilizing Wavelet and Neural Network Toolboxes.

3. RESULT

Table 1 shows the result of the experiment implemented in the proposed method. It showed prediction accuracy of the male and female fingerprint with various hidden layer neuron numbers. Fig. 3 presents this table as a chart, and Fig. 4 shows the confusion matrix. The table and the figures show the prediction accuracy when the number of neurons in the hidden layer is varied.

Tabel 1 The Experiment Result

Neuron number in *hidden layer*	Prediction Accuracy		Total Accuracy
	Male	Female	
10	37.6	36.9	74.5
20	38	37.3	75.3
30	32.4	39.5	71.9
40	35.6	39.3	74.9
50	37.3	37.2	74.5
60	35.6	30.0	65.6
70	40.5	37.7	78.2
75	40.4	39.7	80.1
80	38.7	39.3	78.0
90	34.8	36.9	71.7
100	34.3	28.8	63.1

4. **DISCUSSIONS**

It can be seen from Table 1 and the chart in Fig. 3 that there was no regular pattern related to the prediction accuracy of a male or female fingerprint when the number of neurons in the hidden layer was varied. The result is different even when the same number of neurons is applied. The case is typical because, in MLP, the initial synaptic weights are randomly generated.

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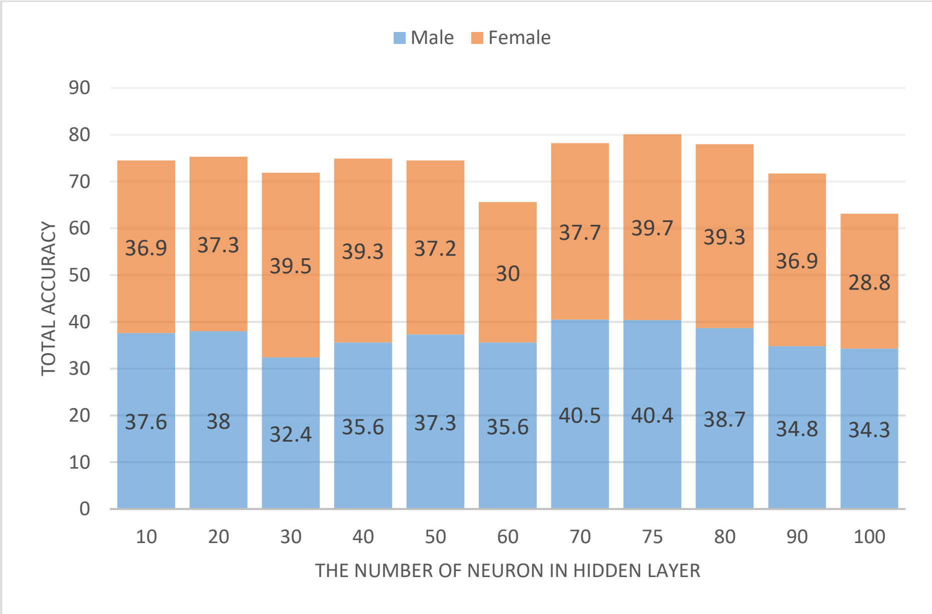

Fig. 3 Chart of the experiment result

By determining Fig. 3, it can be seen that the accuracy is moderate when the number of neurons in the hidden layer is 10 or 20. It means that when speed is concerned, a small number of it is a good choice. However, the experiment showed that the highest prediction accuracy for total accuracy was 80.1% when the number of neuron in hidden layers is 75.

Output Class \ Target Class	Male	Female
Male	**303** 40.4%	**77** 10.3%
Female	**72** 9.6%	**298** 39.7%

Fig. 4 Confusion matrix of the experiment result

Fig. 4 shows the confusion matrix, where the prediction and the actual class are compared. From 375 male fingerprints, 303 of them are correctly predicted. Meanwhile, for females, 298 fingerprints are perfectly predicted among 375 fingerprints.

5. CONCLUSION

The proposed method showed a good result, even lower than the CNN model. However, the technique showed better speed and simpler architecture. The MLP classifier showed the best result when its hidden layer had 75 neurons. However, when the speed is more concerned, two or twenty neurons are an excellent choice. The MLP classifier can be replaced by other classifiers, such as Support Vector Machine or Naive Bayes, which may improve the proposed model.

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