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Finger vein identification system using capsule networks with hyperparameter tuning

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ABSTRACT

Safety and security systems are essential for personnel who need to be protected and valuables. The security and safety system can be supported using a biometric system to identify and verify permitted users or owners. Finger vein is one type of biometric system that has high-level security. The finger vein biometrics system has two primary functions: identification and verification. Safety and security technology development is often followed by hackers' development of science and technology. Therefore, the science and technology of safety and security need to be continuously developed. The paper proposes finger vein identification using capsule networks with hyperparameter tuning. The augmentation, convolution layer parameters, and capsule layers are optimized. The experimental results show that the capsule network with hyperparameter tuning successfully identifies the finger vein images. The system achieves an accuracy of 91.25% using the Shandong University machine learning and applications-homologous multimodal traits (SDUMLA-HMT) dataset.

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1. INTRODUCTION

Personal identification is essential in many systems' safety and security, such as in a building or financial deposit system. Technology developments by hackers often follow the development of security systems. It gives its motivation so that security technology continues to be developed. One of the identification systems still developing is the biometric-based identification system [1]. Some biometric systems capable of being used in the identification process are fingerprint, face, iris, speech, and finger vein [2], [3].

The finger vein-based biometric method has some advantages in the security system. The process is suitable for identifying the authentication system that needs high accuracy and security. This finger vein image pattern will differ when a person is alive or has died, making it more challenging to fake. The finger vein images were acquired with tools utilizing a near-infrared camera system. Image acquirement uses a different contrast principle because of the deoxygenizing process on the vein's blood flow. The blood absorbs more infrared radiation than the area around it. Therefore, the finger veins will be darker than in other areas. The difference can be further processed and finally classified using artificial intelligence.

Several artificial intelligence methods have been implemented in real problems [4]–[8]. One artificial intelligence application identifies and verifies finger vein images [9]–[13]. Several available algorithms can be implemented from the deep learning method, such as convolutional neural networks (CNN) [14]–[16]. In feature recognition, CNN has an advantage in its performance and accuracy. However, CNN generally has a disadvantage because it considers spatial information in the feature extraction process [17]. When several images have the same value in a particular area, it can increase the difficulty level of pattern recognition. CNN will assume that the images are identical, although different [18], [19]. This paper proposes a finger vein identification system using capsule networks with hyperparameter tuning to overcome the problem. We optimized the capsule architectures and routing iterations at the capsule layer to find the best capsule network system to identify the finger vein images.

The rest of this paper is described as follows. First, the research method is described in detail in section 2. Then, section 3 describes the experimental results, including the training and testing of the finger vein identification system using capsule networks with hyperparameter tuning. Finally, in section 4, the conclusion of this study is offered.

2. RESEARCH METHOD

This paper shows the finger vein image identification system using capsule networks with hyperparameter tuning, as shown in Figure 1. The system consists of data preprocessing and capsule networks with hyperparameter tuning. We used the capsule networks with hyperparameter tuning as the classifier.

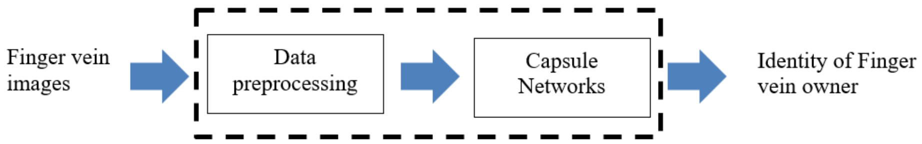

Figure 1. Finger vein images identification system using capsule networks with hyperparameter tuning

2.1. Data collection and preprocessing

We used finger vein digital images from a dataset of the Shandong University machine learning and applications-homologous multimodal traits (SDUMLA-HMT) [20], [21]. The data was divided into three parts: training set, validation set, and test set. Each class has six image data. We split the data of each type into three sections, i.e., four images for training, one for validation, and two for evaluation [19], [20]. This data preparation was carried out to prevent overfitting [22]. This research increased the training set by varying the data images by rotation and translation transformations.

The finger veins images of one finger are chosen for each subject. The number of images is 636, with 106 classes. The finger vein images were preprocessed in two stages: the extraction of the region of interest (ROI) and image enhancement using contrast limited adaptive histogram equalization (CLAHE) method [23]–[25]. Figure 2 shows the ROI extraction process. ROI extraction was conducted by determining the exact area where the finger vein images were taken. The site is obtained by determining the location of the finger edge contour. Cutting the ROI area produces an image of 180×100 pixels. This ROI extraction is conducted to reduce class variations caused by image capture errors.

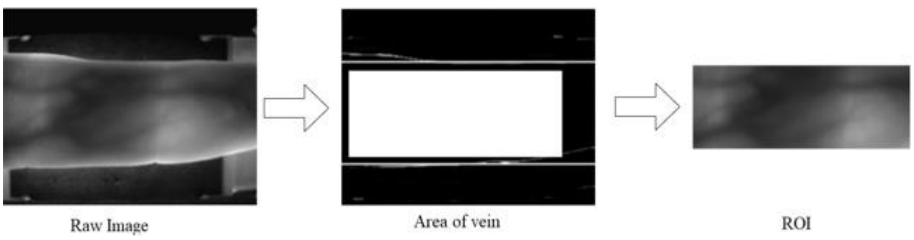

Figure 2. ROI extraction process [21]

The CLAHE method is implemented using open-source computer vision (OpenCV) library. OpenCV is a library of many tools provided for dynamic image processing by Intel [26], [27]. CLAHE improves the adaptive histogram equalization by applying the clip limit on the histogram to decrease the possibility of contrast. Figure 3 shows an example of the input and output of finger vein image contrast enhancement using CLAHE.

Figure 3. Example of the input and output of finger vein image contrast enhancement using CLAHE [21]

2.2. Design of capsule networks with hyperparameter tuning

This research implements capsule networks as the finger vein identification system [28], [29]. We used several libraries in the Python language, such as tensor flow, Numpy, Pandas, Keras, and Scikit-learn [22], [30]–[33]. The hyperparameter variations in the model are the augmentation, the parameters of the capsule layer, and the convolution layer. There are variations in capsule architectures and routing iterations at the capsule layer. The convolution layer is used as an image feature extraction. We varied the number of convolution layers and other parameters such as stride, kernel size, and input image size.

The model was trained using Google Colaboratory [34]. Training on each variation is carried out to get the best variation in each layer. The better model architecture will be rearranged into a new model using the best parameters for each variation. Each training stage is optimized using an Adam optimizer with a learning rate of 0.001 and evaluated using a margin loss function.

3. RESULTS AND DISCUSSION

The finger vein identification system's results and performance are explained as follows. We present the performance of the baseline model, the image processing with ROI Extraction and CLAHE, and the augmentation effect. We also offer the model's performance with routing iterations, the variation of the capsule layer architecture, and the convolution layer variation.

3.1. Baseline model

The baseline model used as a reference was based on what Sabour *et al.* [35] and Hinton *et al.* [36] proposed. The accuracy obtained from the model training shows that the baseline model cannot recognize all images correctly. It can be improved by giving the batch normalization function to the convolution layer in the model [37]. Batch normalization is used to normalize the input in the activation values by normalization of the mean and variance values. The baseline model performance after the batch normalization is shown in Figure 4. The model using batch normalization increases the accuracy of the baseline model.

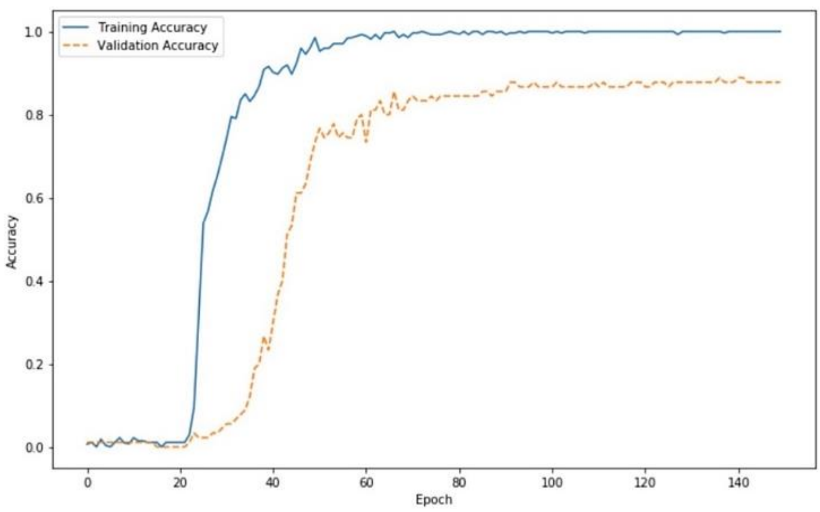

Figure 4. The accuracy of the baseline model using a batch normalization [21]

3.2. Image processing with ROI extraction and CLAHE

In this research, the image processing conducted using ROI extraction and CLAHE increases the model accuracy. Data with image processing has more apparent and more precise features. It makes it easier for the model to recognize the features. The test is conducted on two images representing each class. The system will choose the highest value as the predicted output of the system.

3.3. Augmentation effect

The augmentation of the training set is conducted to decrease overfitting because of the relatively small number of the training set. The augmentation uses the principle that each image batch is augmented for each epoch so that each trained data will have a new variation for each epoch. We augmented the finger vein images with rotation and translation transformations. The process has been performed with an angle of 5 degrees. The translation transformation is undertaken with five percent of the image's horizontal and vertical position differences. The augmentation effects on the training loss of the model are shown in Figure 5. Although achieving minimal error was a little slow, capsule network were successfully trained even by using data augmentation in the training phase.

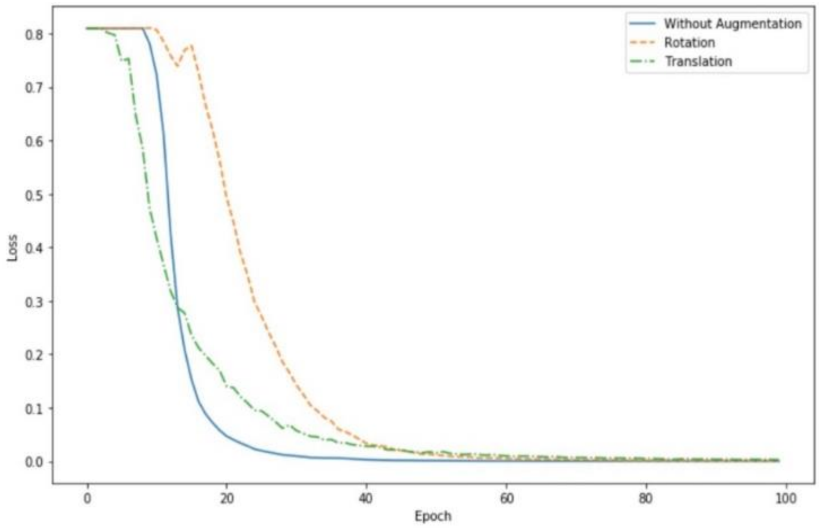

Figure 5. Training loss of capsule network model of finger vein identification with augmentation variation

3.4. Routing iterations and capsule layer architecture

This paper optimizes the number of routing iterations and the capsule layer architecture. The term routing in capsule networks can be found in several references [38]–[40]. In this paper, the identification system uses three variations in the number of routing iterations at the capsule layer, i.e., three, four, and five. Figure 6 shows the effects of several routing iterations on the validation loss. The system achieved the highest accuracy with four routing iterations. Another variation of the capsule layer is its architecture. The capsule architecture in the baseline is eight capsules in the primary capsule layer and 16 capsules in the digitcaps layer. Table 1 shows the variation of the capsule architecture.

As for the digitcaps layer, the number of computational complexities is influenced by the number of classification classes, vector dimensions, and input matrix channels of the primary capsule layer. The effect of the capsule architecture variation on the validation accuracy of the model is shown in Figure 7. The accuracy of the interpretation of the capsule architecture gets the same results for architectures 1 and 2. Still, the accuracy convergence on the baseline architecture occurs faster, and accuracy with architecture 2 is more challenging to achieve stability. Optimal accuracy is obtained from the model that uses capsule base dimensions, namely eight capsule dimensions on the main capsule layer and 16 vector dimensions on digitcaps with three routing iterations.

3.5. Convolution layer variation

The number of computational complexities in the convolution layer depends on several factors, including Kernal size, the number of features, stride number, and image size. Variations in the convolution layer focus more on the influence of the kernel, stride, and number of layers. Table 2 shows the convolution model of the capsule network's finger vein identification system. Kernel and stride size may affect the feature extraction. The smaller the number of strides, the better the feature extraction is. Thus, the number of strides in the variation is chosen, limiting the number of computational complexities still capable of hardware computing. The sizes of the kernel are 3×3, 5×5, and 9×9. The larger the kernel size, the higher the computational parameters needed. The effect of the convolution layer variation on the validation accuracy is shown in Figure 8. The convolution model 3 achieves an accuracy of 91.25%, the highest in the experiments.

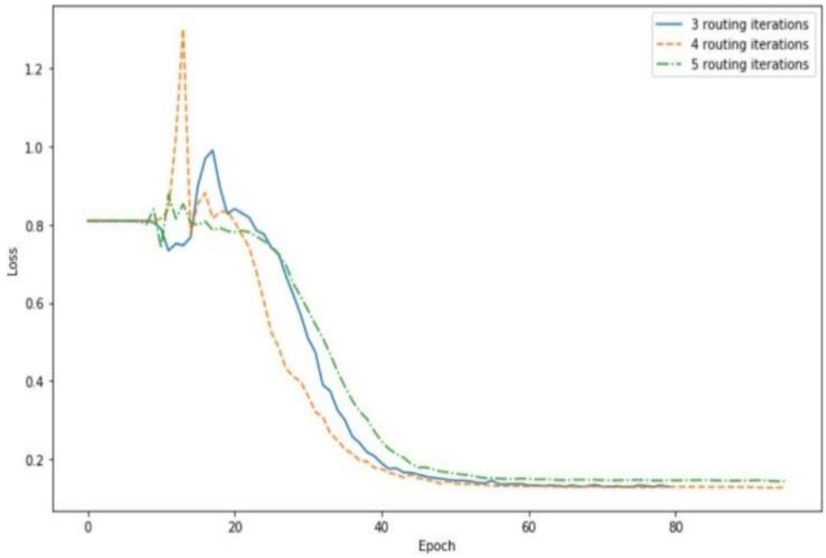

Figure 6. The effect of the number of routing iterations on the validation loss [21]

Table 1. Architecture type of capsule layer of the finger vein identification system

No	Architecture type	#Primary capsule layer	#Digitcaps layer
1	Baseline architecture	8	16
2	Architecture 1	8	8
3	Architecture 2	4	8
4	Architecture 3	10	20

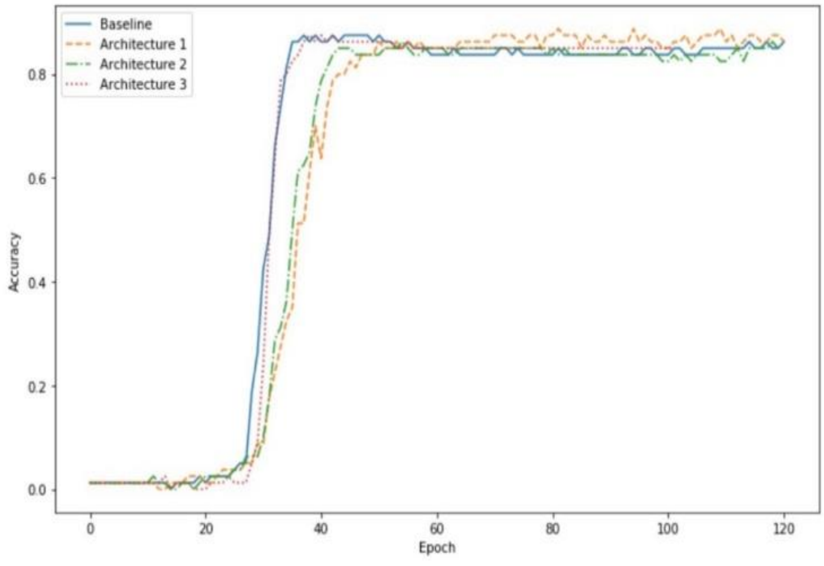

Figure 7. The effect of capsule architecture on the validation accuracy of the model [21]

Table 2. Convolution model of the finger vein identification system using capsule networks

Convolution layer model	Convolution layer	Specification
Baseline Model	First Layer	Nine kernels, one stride, ReLu
Convolution Model 1	First Layer	3 kernels, 2 strides, ReLu, Batch Normalization
	Second Layer	3 kernels, 2 strides, ReLu, Batch Normalization
	Third Layer	3 kernels, 2 strides, ReLu, Batch Normalization
Convolution Model 2	First Layer	9 kernels, 2 strides, ReLu, Batch Normalization
	Second Layer	5 kernels, 2 strides, ReLu, Batch Normalization
	Third Layer	3 kernels, 1 stride, ReLu, Batch Normalization
Convolution Model 3	First Layer	3 kernels, 1 stride, ReLu, Batch Normalization
	Second Layer	3 kernels, 1 stride, ReLu, Batch Normalization
	Third Layer	3 kernels, 2 strides, ReLu, Batch Normalization
	Fourth Layer	3 kernels, 2 strides, ReLu, Batch Normalization
	Fifth Layer	3 kernels, 2 strides, ReLu, Batch Normalization

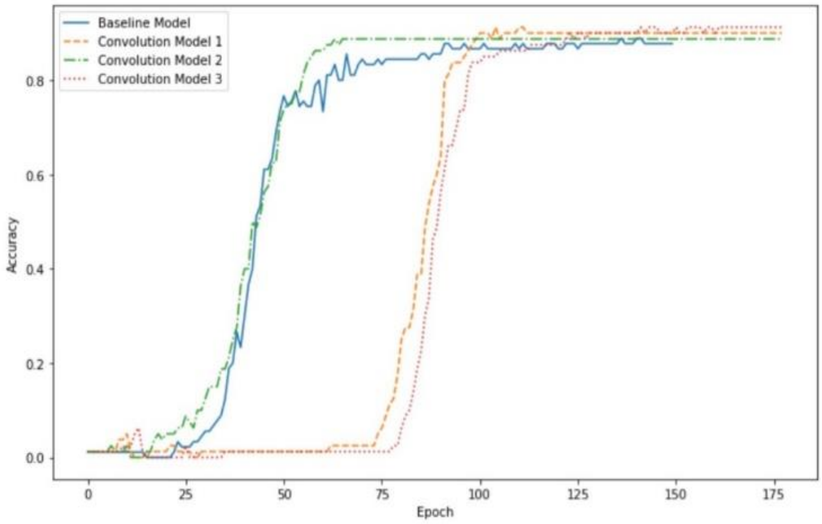

Figure 8. The effect of the convolution model type on the validation accuracy [21]

4. CONCLUSION

This paper describes a finger vein identification system as a security system. Hyperparameter tuning was carried out on the capsule networks, including variations in the capsule networks' architecture and the convolution layer. The number of routing iterations and image preprocessing was also investigated. The capsule network's finger vein identification system achieved an accuracy of 91.25% using the SDUMLA-HMT dataset.

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