

## Pre-trained based CNN model to identify finger vein

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### ABSTRACT

In current biometric security systems using images for security authentication, finger vein-based systems are getting special attention in particular attributable to the facts such as insurance of data confidentiality and higher accuracy. Previous studies were mostly based on finger-print, palm vein etc. however, due to being more secure than fingerprint system and due to the fact that each person's finger vein is different from others finger vein are impossible to use to do forgery as veins reside under the skin. The system that we worked on functions by recognizing vein patterns from images of fingers which are captured using near Infrared (NIR) technology. Due to the lack of an available database, we created and used our own dataset which was pre-trained using transfer learning of AlexNet model and verification is done by applying correct as well as incorrect test images. The result of deep convolutional neural network (CNN) based several experimental results are shown with training accuracy, training loss, Receiver Operating Characteristic (ROC) Curve and Area Under the Curve (AUC).

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## 1. INTRODUCTION

Biometric identification-based technology has seen an outstanding growth in the recent years and among them finger vein-based identification is mention worthy due to its efficiency in providing security and accuracy [1]. The security is ensured in this system from forgery and interference due to the fact that the vein network is located internally within the body and cannot be affected by outside disturbances such as dirtiness, humidity [2, 3]. Finger vein-based systems have benefits in comparison to other conventional techniques since it is non-intrusive and device size is smaller. Thus, it possesses great future prospects in the biometric technology field [4].

Locating veins under the skin means revealing venous networks using sophisticated camera technologies in order to make these networks distinguishable and a technology which can accomplish this feat is known as line tracking technique [5]. Among other mention-worthy techniques such as Far-infrared (FIR) and Near-infrared (NIR) is able to detect finger veins accurately. NIR and FIR both camera technologies possess the capability of infiltrating 5mm under the skin tissue and illuminating 740-940 nanometers [6] whereas human eyes are only able to see in between 380-720 nanometers in the visible light spectrum [7]. FIR detects tissues with higher temperature adjacent to the outside skin while NIR captures venous networks which carries blood due to the blood having the ability to absorb infrared radiation. [8].

Though the advances in the finger-vein based biometric technology are terrific but still processes for vein extraction from fingers remains dependent on four methods which are local-invariant based methods [9, 10], statistical based methods [11], sub-space learning-based techniques [12] and vessel extraction [13, 14]. It is possible to extract venous networks as a line like structures [15], as minutiae [16], as curvature

[7, 8] or as a network of dark lines as apart of vessel extraction. Besides these techniques, there are other ways of recognition such as tracking times and curvature values, thresholds and neighborhood number. [17]

In a traditional finger vein authentication system, there are four steps: Image Acquisition, Pre-processing, feature extraction and matching or verification. To ensure higher accuracy rate of finger vein recognition process training-base methods are more efficient than a non-training-based algorithm. Convolutional neural network (CNN) based network model contains an input layer, several hidden layers, output layer [18, 19]. Generally, a CNN network contains an input layer, several hidden layers, output layer. An architecture of Alexnet is illustrated in Figure 1, where the first layer is the input image 224x224 then several hidden layers and finally the output layer.

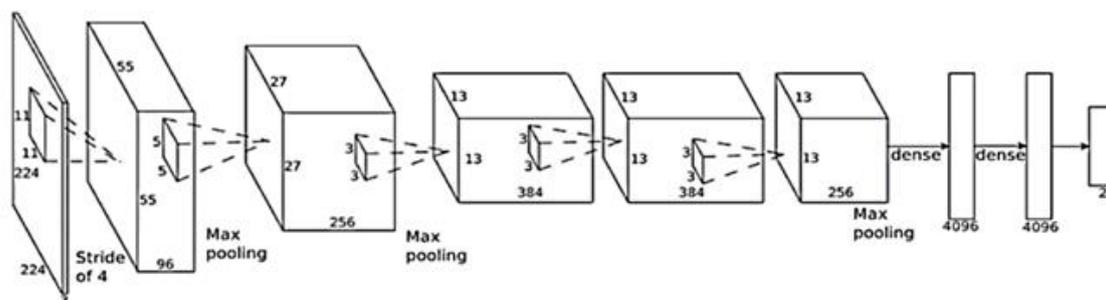


Figure 1. Architecture of Alexnet [20]

Common hidden layers are convolution layer, Rectified Linear Units (ReLu), pooling, normalization etc. Hundreds of images can be modified by this CNN models, for this reason to train a network GPU is needed otherwise difficult to work with complex models. [21] However, more difficult security problem such as, spoofing attacks in finger vein database [22] also getting impressive result. Table 1 shows comparison of related works [23].

Identification accuracy achieved in the research [17] for databases such as HKPU, FV-USM, SDUMLA is 98% while for database UTFVP the rate is 99.4%. A vision-based device was proposed and developed in [8] which is a promising device for phlebotomy procedures. A deep learning-based approach known as LeNet-5 model of CNN which used convolutional neural network for finger vein identification in [24] showcasing a recognition rate of 96% in the Windows-based system and 100% in Linux based system. AlexNet of CNN approach was used in [25] for finger vein recognition which produced an accuracy rate of 99.53%. VGG Net-16 of CNN was used for developing a finger vein identification system in [26] which showcased a recognition rate of 97.7%.

Table 1. Comparison of related works [23]

Author- year	Topic	Method	Strength	Limitation
Rig Das, Emanuele Maiorana, Patrizio Campisi, 2018 [17]	Convolutional Neural Network for Finger-Vein-based Biometric Identification	Applied deep learning method using existence public databases	Used four public databases and establish CNN based finger vein identification system.	Static images used only, didn't created own database for the experiments
Kazi Istiaque Ahmed, Mohamed Hadi Habaebi, Md Rafiqul Islam and Nur Aishah Bt Zainal, 2017 [8]	Enhanced Vision Based Vein Detection System	NIR imaging Technique and contrast limited adaptive equalization to process images	Image quality is better and detecting the vein in real time	Expensive hardware is used to capture images
K. S. Itqan, A. R. Syafeeza, F. G. Gong, N. Mustafa, 2016 [24]	User Identification System based on finger-vein Patterns using convolutional neural network	LeNet-5 network trained finger vein images	Own databased is used and experimental result is pretty acceptable	Image quality is low, recognition is not in real time.
Wenjie Liu, Weijun Li, Linjun Sun, 2017 [25]	Finger Vein Recognition Based on Deep Learning	AlexNet based deep learning method used for finger vein recognition	Result beats expectancy and showed CNN is better than traditional algorithms	Image quality is not pleasing, can be more accurate
Hyung Gil Hong, Min Beom Lee and Kang Ryoung Park, 2017 [26]	Convolutional Neural Network-Based Finger-Vein Recognition Using NIR Image Sensors	Two public databases are used to prove CNN	Non-trained classes can be recognized and reduce complexity	Proposed method is quite more complex than existing methods.

In this research, we are using human finger vein data to acknowledge human identity using our finger vein collector device. However, we assembled more than one copies of a finger and keep as one information which later accommodated for training. In the next section, we illustrated our finger vein recognition approach. In the third section, we explained our experimental results and analysis, and also the last section is about our future vision of this work and conclusion.

## 2. RESEARCH METHOD

The technology which is revolutionizing the research field of computer vision is CNN and it is continuing to increase the advancement of accurate image classification besides playing a key role in performing feature extraction and recognition tasks such as image retrieval, object detection, semantic segmentation [27]. Due to the fact that the modern era is technologically advanced meaning enhanced computing power and GPU acceleration which makes it possible for the robust and efficient use of CNN. Based on deep CNN a model known as AlexNet [28] which consists of two fully-connected layers, five convolutional layers, and a softmax output layer. This network is coherent, unlike other simplistic networks which include Rectified Linear Units (ReLU), dropout and overlap pooling [29].

### 2.1. Developed a device and construct the database

To create an information and capture finger vein images, we create a tool which can take finger vein pictures by exploitation transmission imaging. There is a space to insert the finger and taking finger vein images, however, the light source illuminates from the underside of the tool as well as images captured from the top. To induce high-quality information, we covered the surroundings, used CMOS camera, take away background noises, NIR light sources, detected the region of interest (ROI) and stored the images in two different folders, one for training and another one for testing.

We collected twice total 12 finger's data and save those according to person's identity for both training and testing purpose. For training, we stored 100 images whereas, 30 images for testing purpose, each folders image are altered furthermore and removed the noises, detected the ROI and kept the data with the support of MATLAB [30].

### 2.2. Training of CNN model

Alexnet can be trained from the initial stage of the network by using random adjustment of weights or it can be trained a pre-train model using transfer learning features, which is faster and also a small number of images needs to train the model. There are five convolutional layers and three fully-connected (FC) layer, in each convolutional layer consist of convolution, Rectified Linear Unit (ReLU) pooling feature detection layers and fully-connected layers connect every neuron of a layer to another layer and provide classification output using softmax function [29].

- a. To proceed with the transfer learning process, we pre-processed our input image from  $747 \times 366 \times 3$  to  $227 \times 227 \times 3$
- b. First convolutional layer's (conv1) filter size is  $11 \times 11 \times 3$  where stride and padding are 4,0 respectively.
- c. ReLu confirms a negative value to zero and keeps it positive
- d. Max pooling reduces the number of parameters by using non-linear downsampling and normalization kernel size is  $3 \times 3$ . When an input image is finished processing then we get an image with the dimension  $55 \times 55 \times 96$
- e. A similar technique is used for other convolutional layers where conv2, conv3, conv4, conv5 generates the following dimensions  $27 \times 27 \times 256$ ,  $13 \times 13 \times 384$ ,  $13 \times 13 \times 384$ ,  $13 \times 13 \times 256$ .
- f. In conv2 filter size is  $5 \times 5$  with stride 1. In the similar manner conv3, conv4, conv5 uses  $3 \times 3$  filter and stride 1. After getting fully-connected layers, we dropout 50%.

## 3. RESULTS AND ANALYSIS

A simple confusion matrix is a table of four types of combinations of actual and predicted value which can measure the performance of a classifier on a test dataset based on that actual values showed in the following Table 2. If the predicted result is the positive and actual result is also positive then it is known as the true positive (TP). Again, If the predicted result is negative but the actual result is positive then it is known as the true negative (TN). Contrarily, If the predicted result is the positive but actual result is negative then that term known as false positive (FP). Furthermore, If the predicted result is the negative and actual result is also negative then it is known as the false negative (FN).

Table 2. Confusion matrix

Confusion Matrix		
	Predicted Positive (P)	Predicted Negative (N)
Actual Positive (P)	True Positive (TP)	False Negative (FN)
Actual Negative (N)	False Positive (FP)	True Negative (TN)

True positive rate (TPR) or, Sensitivity,  $TPR=TP/P=TP/(TP+FN)$ ;  
 True Negative rate (TNR) or, Specificity,  $TNR=TN/N=TN/(TN+FP)$ ;  
 False Positive rate (FPR),  $FPR=1-TNR=FP/(TN+FP)$ , So, Accuracy  
 (ACC)  $= (TP+TN)/(TP+FP+FN+TN)$

True positive rate or sensitivity against False positive rate is known as receiver operating characteristic (ROC) curve which is the curve of probability and it shows the performance of a classification model. Area Under the curve (AUC) indicates the quality of the ROC curve. AUC will be 1 when the ROC curve has an ideal classifier however AUC value zero indicates that the experiment is predicting the false classes [23, 30, 31].

### 3.1. Actual training data and test data

#### 3.1.1. Experiment 1

Using transfer learning on pre-trained Alexnet, we experimented through various type of testing to get a feasible result for our finger vein identification system.

For the first experiment, we used 50 images from each of the four classes to train our network where the highest number of the epoch was 8 and the mini-batch size was 20 shown in Figure 2(a) which took a total time of 37.5s for the test to run while the predictive ability is 91% and AUC is 0.942. As we can see in the first experiment performance is really pleasant. A better model means lower the losses, the loss value indicates how strong or poorly a specific model is performing after each iteration, However, one would assume that the reduction of loss after each, or several, iteration(s). From Figure 2(b), we can see that training loss going downward from around 1.4 to 1.

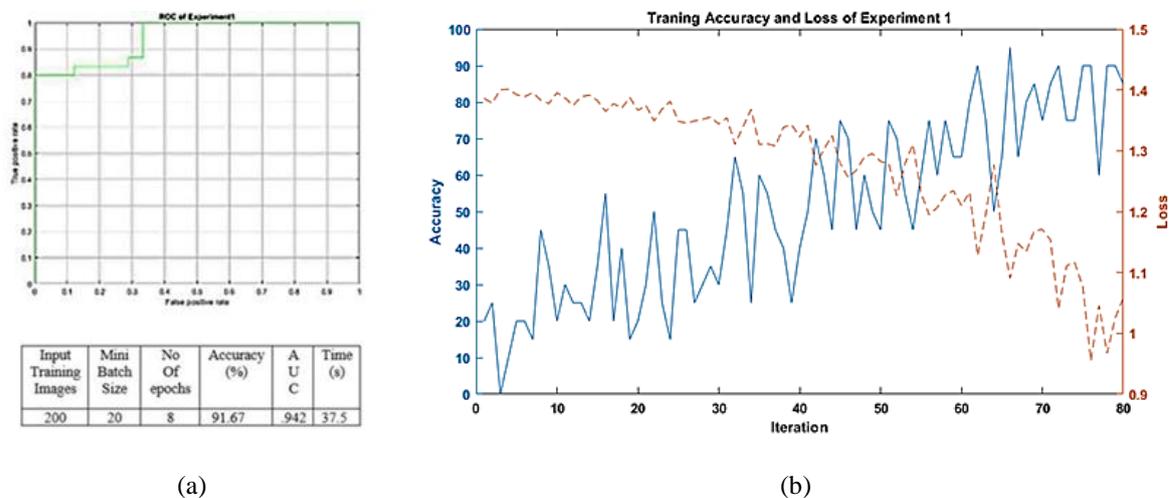


Figure 2. (a)ROC curve of Experiment 1, (b) Training accuracy (%) and loss of Experiment 1

#### 3.1.2. Experiment 2

On the other hand, for the second experiment we used 50 images per finger to train the network which took an execution time of 178s which is higher than the previous experiment. Although the second test took a slightly higher time for processing the data, the predictive efficiency is 100% and AUC is 1 which is an excellent in terms of performance. It is also notable that, the number of epochs is 90 and minibatch size was 32 according to Figure 3(a), which is better in comparison to the first experiment still, this experiment delivered a better result. In this experiment from Figure 3(a), we can see that AUC is in ideal situation and predictability is 100% while Figure 3(b) showcases training loss drop to 0.

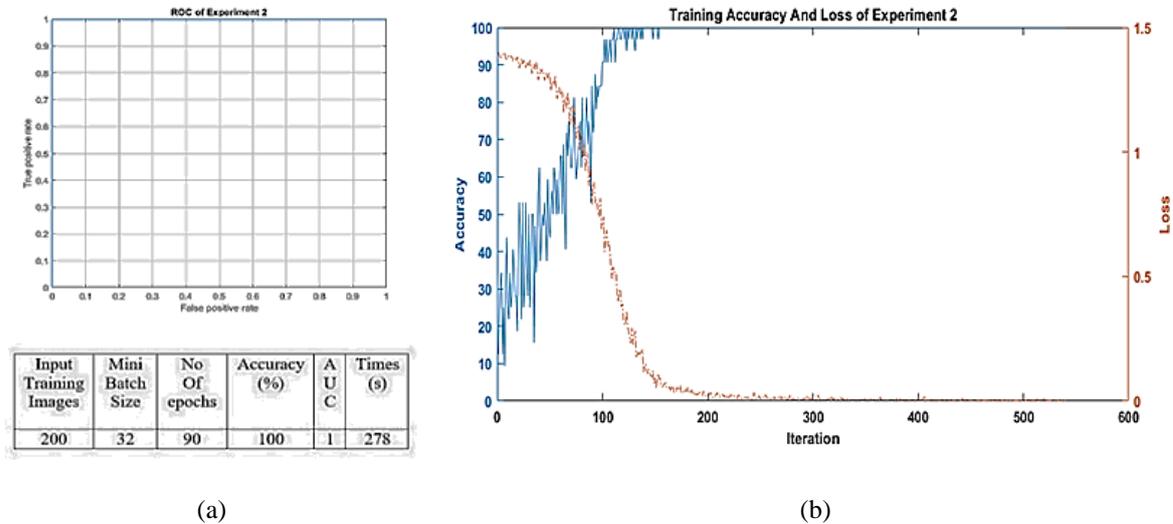


Figure 3. (a) ROC curve of experiment 2, (b) Training accuracy (%) and loss of experiment 2

**3.1.3. Experiment 3**

Lastly, in the third experiment, we trained the network with a minimal number of images which was 80 in total, taking 20 images from each class. Furthermore, epoch count was 20 and mini-batch size was 16 in Figure 4(a) and the total predictive ability is 100% which is better than the first and second experiment because this experiment, number of epoch and minibatch size is less than experiment 1 and 2. AUC is high which is 1 and took less time than previous experiments and accuracy 100% according to Figure 4(b) where loss value dropped to ~0. Thus, if we do comparison between these three experiments, third experiment's results are better than first and second experiments.

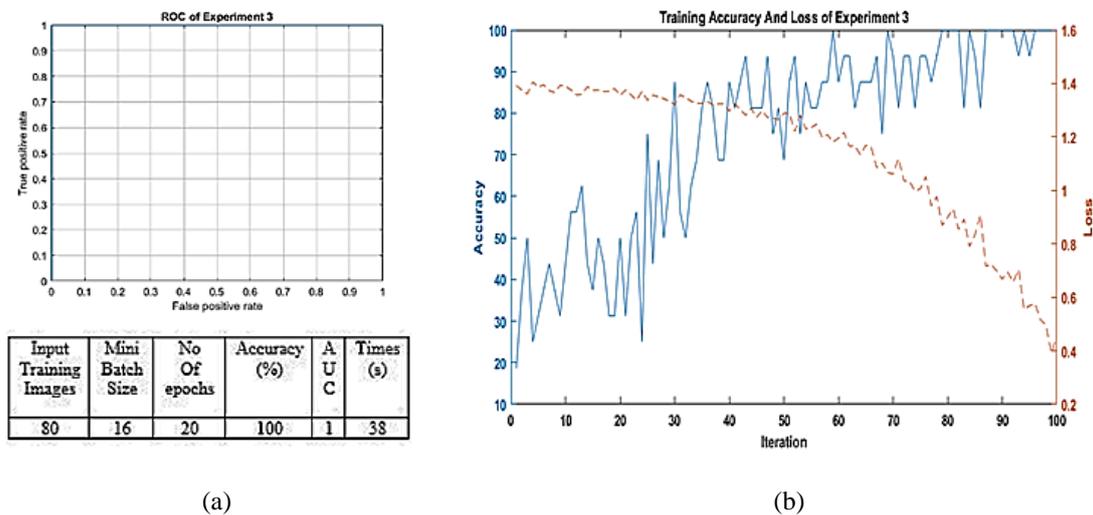


Figure 4. (a) ROC curve of experiment 3, (b) Training accuracy (%) and loss of experiment 3

**3.2. Actual training data but erroneous test data**

Now, to confirm that our experiments are working perfectly, we replaced erroneous finger vein images to test data and check the validity of the experiments. To analyze furthermore the experimental data are given below.

### 3.2.1. Experiment 1

In this experiment 1, we trained the Alexnet as previously but replaced the four categories with several erroneous test data. This experiment 1 as shown in Figure 5 displays the training accuracy is 50% and AUC is 0.6. We know that 50% accuracy is not decent enough for recognition as well as the AUC is 0.6 which indicates a poor model and from ROC curve 5(a), we can state that it not a perfect model which is in fact true. In 5(b), training loss did not cross 1 but dropping the values which specifies that the model is working according but not with proper data.

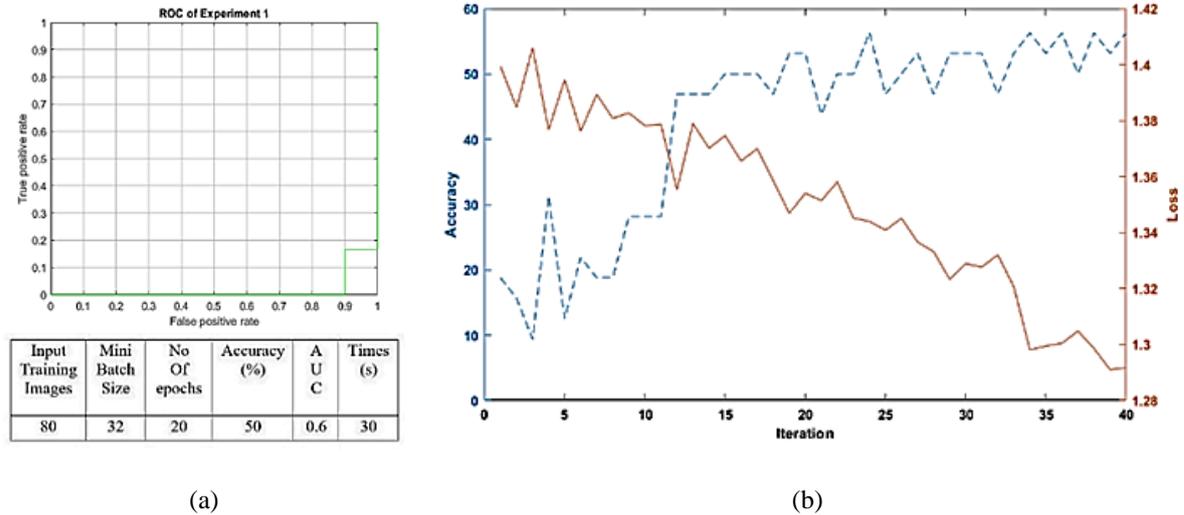


Figure 5. (a) ROC curve of Experiment 1, (b) Training Accuracy (%) and loss of Experiment 1

### 3.2.2. Experiment 2

In the same way this experience is completed where in Figure 6(a) number of epochs and mini batch size is 32, but this time the training accuracy is zero percent and AUC is zero which directs that this model is not decent. Besides in Figure 6(b) the training loss goes downward and lands at 0. Thus, we can say that our erroneous data has been testified that our model is working appropriately.

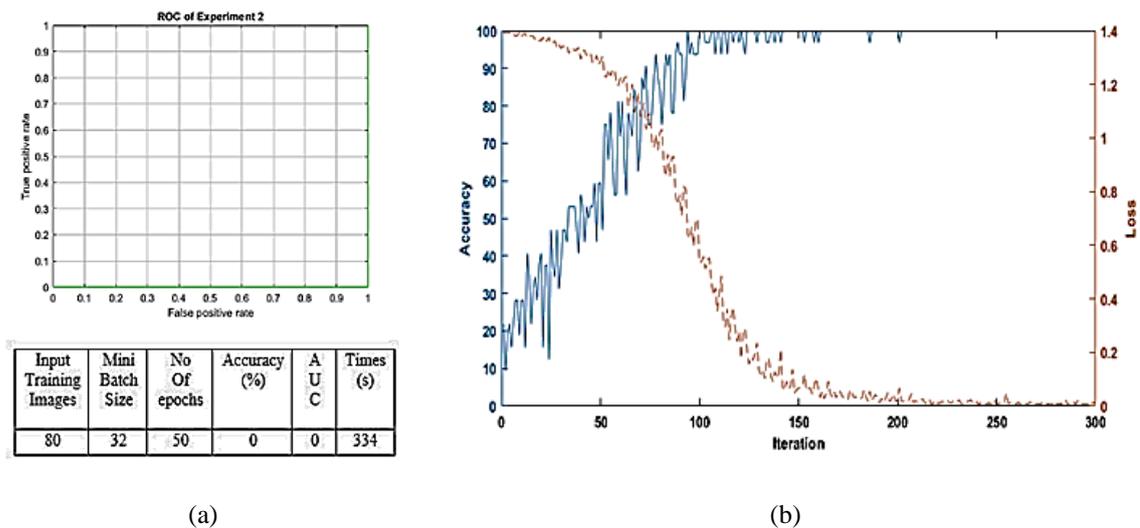


Figure 6. (a) ROC curve of experiment 2, (b) Training accuracy (%) and loss of experiment 2

#### 4. CONCLUSION

In this paper, we introduced a transfer learning base CNN model which can recognize a finger vein with pre-trained test data. However, we analyzed and verified that the model is giving precise results by using both correct and erroneous test data. Further, we visualized the ROC curve and found experiment 3 in the previous section as a supreme model where used 20 epochs, 16 minibatch sizes and attained 100% training accuracy and AUC=1 and in experiment 2 of section 3.2.2, was the worst example where accuracy 0% and AUC=0 which means, this example predicted false classes. The outcome was satisfactory and, in the future, we would like to develop a real-time system based on these experimental results which will have the ability to identify finger veins in real time.

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