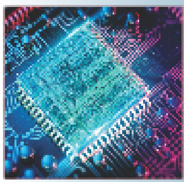
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Identification of Finger Vein Images with Deep Neural Networks

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ABSTRACT:

To establish identification, individuals often utilize biometrics so that their identity cannot be exploited without their consent. Collecting biometric data is getting easier. Existing smartphones and other intelligent technologies can discreetly acquire biometric information. Authentication through finger vein imaging is a biometric identification technique based on a vein pattern visible under finger's skin. Veins are safeguarded by epidermis and cannot be duplicated. This research focuses on the consistent characteristics of veins in fingers. We collected invariant characteristics from several cutting-edge deep learning techniques before classifying them using multiclass SVM. We used publicly available image datasets of finger veins for this purpose. Several assessment criteria and a comparison of different deep learning approaches were used to characterize the performance and efficiency of these models on the SDUMLA-HMT dataset.

KEYWORDS: Finger vein recognition, Deep learning, Biometric, Feature extraction.

1. INTRODUCTION

Every person in the current technological era wants to prevent unauthorized access to their data. Hence, many computer technologies are used to provide data security. Traditional methods [1] and biometric procedures [2] are the two major security mechanisms. Since they may be lost, forgotten, or stolen, passwords, keys, and cards are ineffective as security measures. Biometric procedures replace traditional methods because they give a higher degree of security by leveraging an individual's unique physical characteristics, which cannot be lost or stolen, like their face, fingerprints, a retina scan, iris recognition, voice, signatures, and finger veins. Also, these methods are efficient for identifying people. Each kind of biometric identification has distinct advantages and disadvantages. Iris recognition offers high precision [3], but it needs more cooperation from the user and an expensive apparatus. The benefits of fingerprints [4] include simplicity of use, a low-cost fingerprint scanner, and accuracy; nevertheless, fingerprints are not particularly dependable since they may be readily recorded and replicated. Facial recognition [5] is poor because our faces change as we age, and our traits are not consistent. Table 1 shows comparison of different biometric approaches.

Since it employs a part of the finger that cannot be replicated or stolen, biometric technology of finger vein eliminates restrictions of all other biometric systems. The vein pattern of an individual is stable throughout their lifetime, allowing for reliable identification with a simple device. Biometric to fingerprint recognition, the accuracy of finger vein biometric identification stands out. Surfaces are unmarred by the vein structure, which is resistant to the effects of time and weather [6]. This technology may be used in several settings, including government agencies, banks, passport agencies, hospitals, and more.

As we are all aware, AI has taken over the globe in the past few years. Many advances in AI and the proliferation of dexterous strategies are in evidence. The smarts of the system are improving automatically [7]. Deep learning is a branch of AI that automatically generates such systems so that they may learn from data without being trained each time and swiftly accept situations based on the context in which they are used [8]. Deep learning techniques are used to tackle challenges in a variety of fields, from medical diagnostics to engineering to business [9]. In today's technological world, biometric identification is a promising new method for keeping our electronics safe. By using deep learning techniques, biometric systems can detect picture spoofing with high accuracy and little computational expense.

Incorrect identification of finger-vein lines affects the precision of finger-vein characteristics. To get more precise results during feature extraction, the optical filter must be chosen. To correctly identify an impostor, it is necessary to derive discriminant features based on these factors {Formatting Citation}. Using deep learning and image preprocessing, we were able to extract invariant characteristics from NIR images of finger veins that illustrate our problem statement.

Table 1: Popular Biometrics - Comparison

	Face	Iris	Voice	Fingerprints	Veins
Secure	●	●			●
Low cost			●	●	●
Accuracy	●	●	●	●	●
Easy to use			●	●	●

Using image preprocessing and deep learning methods, near-infrared images of finger veins can be used to find properties that don't change [11]. The system will incorporate consistent features from a variety of ways before making a prediction. Our research focuses on the following:

- We used a publicly available dataset of finger veins for our investigations.
- Various DL methods were used to extract finger vein pattern features.
- The extracted vein properties have been classified for identification purposes.

2. LITERATURE REVIEW

Different authentication mechanisms are utilized for finger vein biometrics. According to [12], the first strategy is a traditional method that employs matching algorithms after feature extraction and image preprocessing. It requires robust image preprocessing; biometric features necessitate a costly and compact model. Mou et al. [13] provide a highly recommended deep learning solution for complicated pattern detection. It can extract complicated biometric features without requiring a costly mathematical model. This biometric authentication method works well. Neural Networks based on Support vector machine (SVM) are commonly employed as classifiers, according to J. Kim et al. [14]. Liu, Y., et al. [15] describe the application of deep learning - DL for identification through biometrics, which demonstrates the best accuracy and precision. It is a multilayered architecture which properties of data having automatically extracted without human intervention.

W. D. et al. [16] provide matching based on distance, which compares a newly taken photo to previously saved images using a technique that is based on distance between the two sets of images. Two histograms which are normalized, representing the region of interest (ROI) in a image having veins of finger can be compared using the Euclidean distance, as shown by I. Dokmanic et al. [16]. M. A. Ali et al. [17] utilized a fusion-based method to combine two separate histograms to generate a histogram of magnitudes (HCOM) and competitive orientations. A histogram of a local binary pattern histogram (HCMLBP) and competitive orientations (HCO) derived from a competitive magnitude image was combined (M. Abdullah et al.). [18]. Here, we display the Euclidean distance between two histograms by comparing them to their nearest neighbor and calculating the similarity between them. Additionally, the Euclidean distance is used to calculate the space separating the four corners of a processed image and the four corners of a saved image. An approach for the effective extraction of corner points as features was suggested by G. Wu and colleagues [19]. After the effective extraction of corner points as features was suggested by G. Wu and colleagues [19]. After the use of morphological and Gaussian blur preprocessing methods to the picture, the Harris Corner method was used to locate corners, each of which was then given a unique identifier and label before being saved in the database. It was determined, with the help of the Euclidean distance, how far off the four corners of the processed picture were from those of the database. The verification is considered to have been successful if the computed distance is smaller than the predetermined threshold value. This strategy had a success rate of 99.96% when it was implemented.

3. PROPOSED METHODOLOGY

This section of the research provides detailed information about the methods employed for this study. The first phase of our suggested technique is to acquire pictures of the finger veins of the user. Deep learning algorithms are used to get the vein's characteristics, which are then used for classification after being preprocessed.

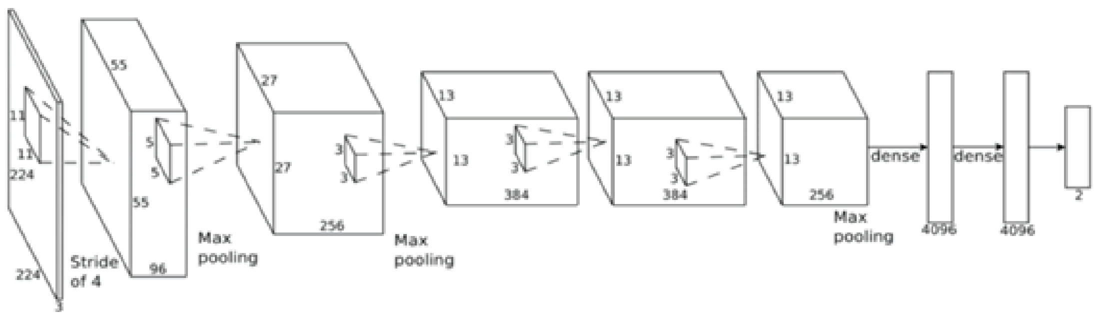

Figure 1: AlexNet Network Architecture

Classification is the final step in a biometric identification system and determines whether or not an image is authentic. Classification follows feature extraction to expose fakes [20].

Therefore, the finger vein patterns must be correctly extracted from a picture of the finger veins for a biometric identification system to work, and the entire extraction process must be quick so that the user can easily employ the system.

3.1. AlexNet

Convolutional neural networks, like AlexNet, need to be trained before they can be utilized in a practical setting. The architecture of AlexNet is more complicated than other similar systems since it adds additional filters to each succeeding layer. Figure 1 [21] demonstrates that in addition to its five convolutional layers, AlexNet has three completely linked layers.

The network that was employed for this research requires photos to have a resolution of 227 by 227 by 3 pixels [22]. Since the photos in the dataset are all varying dimensions, this network modifies the dimensions of the images that are used for training and testing automatically. This network will be learned by analyzing training photos and identifying characteristics within those images. The first layers only include low-level features, whereas succeeding layers build higher-level features up from the lower-level ones they already contain. To train a multiclass SVM with these characteristics, multiclass SVMs that have been trained using Deep Learning and Fitcecoc functions in Matlab are used.

3.2. VGGNet

Having 3x3 convolutions, 16 total convolutional layers, and a variety of filters with a larger kernel size [23], VGGNet is very similar to AlexNet. Adding a convolution layer with a size of 3x3 on top of each preceding layer is one way to increase the network's depth.

VGGNet comes under VGG16 and VGG19. The VGG network is described as having weight layers of 16 and 19, respectively. The functionality of the VGG16 may be understood by comparing it to that of the AlexNet. Since VGGNet's accuracy improves with greater network depth, it is the most recommended Convolutional Neural Network (CNN) for feature extraction [24]. Figure 2 depicts the structure of the VGG16 network.

3.3. Residual Neural Network (ResNet)

The network becomes deeper as the number of layers increases, and a problem of degradation arises as the accuracy decreases and depth increases. ResNet was developed to address this problem; it explicitly operates on modules and places layers in residual mapping [16]. ResNets are simple to optimize and can achieve greater accuracy with a larger network depth. ResNets consist of two or three layers of nodes. ResNet 18 and 34 are tiny networks with two layers, whereas ResNet 50, 101, and 152 have three layers [25]. The experiment utilizes ResNets 18, 50, and 101. ResNet 18, 50, and 101 have, respectively, 72, 177, and 347 layers.

Most ResNet's CNN layers are located in the network's core. It contains a collection of rectified linear units, max pooling layers, and convolutional layers. The network's final layer is the classification layer. This network required an input image size of 224 by 224 pixels. The initial layer extracts fundamental characteristics such as clumps and edges. These characteristics are processed and transformed into high-level characteristics by the network's deeper layers. These characteristics are used to train multiclass SVMs with the fitcecoc function of Statistics and Deep Learning Toolbox [25]. Test features are used to evaluate the accuracy of a trained classifier.

4. EXPERIMENTAL DETAILS

4.1. Data Collection

Venous pattern recognition is the most important area in biometric identification now. For the development of novel algorithms for feature extraction and classification, a benchmarking dataset is required so that results may be compared.

layer name	output size	18-layer	34-layer	50-layer	101-layer	152-layer
conv1	112×112	7×7, 64, stride 2				
conv2_x	56×56	3×3 max pool, stride 2				
		$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$
conv3_x	28×28	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times8$
conv4_x	14×14	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix}\times6$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times6$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times23$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times36$
conv5_x	7×7	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$
	1×1	average pool, 1000-d fc, softmax				
FLOPs		1.8×10^9	3.6×10^9	3.8×10^9	7.6×10^9	11.3×10^9

Figure 2: VGGNet Network Architecture

Figure 3 depicts one of the online-accessible datasets used in this investigation, SDUMLA-HMT [26].

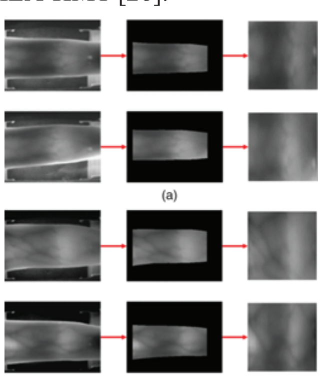

Figure 3 (a), (b): Infrared image of a finger

In 2010, researchers at Shandong University working on deep learning and its applications compiled this dataset [18]. Figure 4 shows a finger vein capturing device developed by the Joint Institute for Intelligent Computing and Intelligent Systems at Wuhan University.

Figure 4: Finger vein image capturing device

The images of 106 people's ring, middle, and index fingers from both hands are shown in Table 2. Each fingertip was photographed six times to create these six images of finger veins.

Table 2: Explanation of a Dataset

# of Fingers	3-right hand, 3-left hand
# of Classes	106
# of Images	3,816
# of Person	106
# of captures - Images	6
Testing Images	1,272
Training Images	2,544

A total of 3816 images, or 0.85G bytes, were collected. Each bmp image has a resolution of 320 pixels by 240 pixels. Detailed below is an explanation of the dataset, which consists of files separated into left- and right-hand subfolders according to the names of the people involved. For ease of use, I renamed the picture "001 Lindex (1)." Figure 4 depicts what is claimed to be the first ever image of the ring device worn by 001's right index finger.

4.2. Evaluation Metrics

Classification accuracy, ROC curve, F1-score, and training time are used for comparing the performance of ML algorithms, and feature importance is used for the extraction of highly valued features [27].

4.2.1. Classification Accuracy

Accuracy defines the fraction of true estimated predictions to the overall number of predictions. The only use of classification accuracy is not effective because of the unbalanced dataset possibility. Comparing [28][29], the accuracy is manipulated by using the formula.

Accuracy = (TP + TN) / (TP+FP+TN+FN) (1)

Table 3: Results of Experiments

Classification Models	**DenseNet**	**KNN + DNN**	**CNN (Resnet18)**	**CNN (Resnet50)**	**CNN (Resnet101)**	**CNN (Alexnet)**	**CNN (VGG19)**
Testing images	2544/ 1272	2544/ 1272	2544/ 1272	2544/ 1272	2544/ 1272	2544/ 1272	2544/ 1272
Classes	106	106	106	106	106	106	106
Total no. of images	3816	3816	3816	3816	3816	3816	3816
Accuracy (%)	96.72	97.64	93.15	80.25	92.92	92.84	91.82

4.2.2. F1-Score

It is used for calculating the harmonic average of recall and precision. It is considered a more effective testing metric because it studies false negative and false positive predictions too because of precision and recall usage. Precision is used for calculating the number of true positive values from all the positive predicted values, while recall is used to calculate the positive values that are predicted correctly from all the values. If the value of the F1-score is high, then it shows that the values of recall and precision are also high, and vice versa [30]. Formulations for F1-score, precision, and recall are given below.

Precision = TP / (TP+FP) (2)

Recall = TP / (TP+FN) (3)

F1-Score = (2 Precision * Recall) / (Precision + Recall)* (4)

4.2.3. ROC Curve

The ROC Curve ("Receiver Operating Characteristic Curve") is used for testing a classification-based model's performance based on false positive predictions and false negative predictions ratio through a graph. It plots the TPR and FPR at different classification points.

True Positive Rate (TPR) =TP / (TP+FN) (5)

False Positive Rate (FPR) = FP / (FP+TN) (6)

4.2.4. Time for Training

A model's speed and agility are measured through this metric.

4.2.5. Feature Importance

It is then used to compute the correlation between every feature and their predicted labels.

4.3. Implementation Details

The suggested approach is executed sequentially to attain the desired outcomes. MATLAB R2018a is used for all experiments. Classifiers' efficacy is assessed using performance evaluators after the classification process is complete.

MATLAB was used to train deep learning classifiers on the dataset, and a multiclass classifier was used to attain the best result.

5. RESULTS AND DISCUSSIONS

Multiple experiments were run to determine the best methods for extracting features from CNNs. Features are generated using Alex Net, VGG, Resnet, and classes are assigned using the SVM-supporting Fit multiclass model fitcecoc. There is a separation between the dataset's training and testing sets. There are 2,544 images in the training set and 1,274 in the testing set. The multiclass model fitcecoc is used to categorize the features extracted by CNN.

The accuracy is determined by comparing the predicted labels to the actual labels. Table 3 displays the outcomes of the experiment. Based on the results of the investigation, we can conclude that VGG16 is superior to other CNNs at generating its own features (93.31%). Figure 5 illustrates the accuracy of each method.

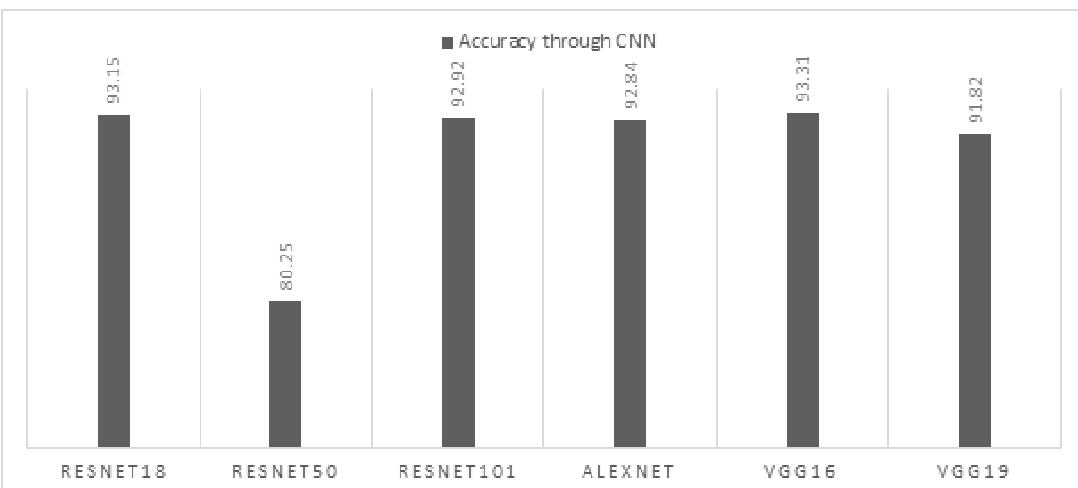

Figure 5: Comparison of accuracies of CNNs

6. CONCLUSION

93.31% of the time, the proposed procedure can be used to detect fakes, based on the experiments and results. Additionally, preprocessing is an integral component of the system's overall functionality. Various levels of accuracy resulted from the removal of various features. ResNet15 and ResNet101 outperformed the other models, but VGG16 was the most precise of all. Thus, with various CNN-based features, an accuracy of 93.31 percent was attained.

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