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Finger Vein Based Authentication using Deep Learning Techniques

Madhusudhan M V, Udayarani V, Chetana Hegde

Abstract*: Security is one of the major concerns of current times. Biometric based methods are found to be more reliable and accurate in authenticating an individual. Hand-based biometric traits are proved to be easily accessible during data collection. Collecting, storing and processing biometric trait images of all the employees is always a challenge for larger organizations. Deep learning techniques come to rescue from such situations. In this paper, we propose a novel approach for authentication using finger-vein images. We use basic convolutional neural network (CNN) with transfer learning. The model has been pre-trained on various types of images available on ImageNet database through ResNet – 50 architecture. This pre-trained model has been then run through CNN model with appropriate number of hidden layers and activation functions. The optimizers and loss functions are used to achieve appropriate classification among the images. The simulation results of proposed model has shown 99.06% of accuracy in classifying an individual.

Keywords* : Adam Optimizer, Categorical Cross Entropy Loss Function, Convolutional Neural Network, Deep Learning, Dropout, Early Stopping, Relu Activation Function, ResNet–50, Softmax Activation Function.

I. INTRODUCTION

Functionality of human identification and authentication exists from the ancient days. As the crime rate increases, security is essential [1]. Hence, authentication of an individual was much required. Human identification and authentication can be done in two ways, viz. by using behavioral characteristics and by using physiological characteristics [2]. Behavioral characteristics such as voice, keystrokes, signature, gait, etc. are easy to forge and replace, hence such biometric systems can be easily getting spoofed. There are various physiological characteristics in use today such as finger print, knuckle print, palm veins, finger veins, face recognition and iris recognition. To achieve higher level efficiency, two or more traits also be combined. Pros and cons of various biometric traits are mentioned in the Table 1 [3].

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* Correspondence Author
Madhusudhan M V*, Computer Science Engineering, Presidency University, Bengaluru, India. Email: mv.madhu@gmail.com
Udayarani V, School of Computing and IT, Reva University, Bengaluru, India. Email: udayaraniv@reva.edu.in
Chetana Hegde, Senior Faculty of Data Science, Manipal ProLearn, Bangalore, India. Email: chetanahegde@ieee.org

Hand based biometrics such as palm veins and finger veins are attracting researchers in more numbers from past decades as they are easy to access, highly accurate and impossible to replicate [5]. From the medical research it is proved that:

1) Every individual has a unique finger vein pattern,
2) For the same person, finger veins vary among his/her fingers, and
3) As the individual grows, their finger vein pattern will not change [3,4].

There are many outstanding advantages of finger vein features:

1)As every individual having unique finger vein pattern, it provides excellent clear cut dissimilarities between individuals.
2) Finger vein patterns are alive.
3) Finger vein pattern remains same and does not change with time.
4) It is almost impossible to forge, obfuscate or mutilate the finger vein pattern [3].

Despite advantages, there are some challenges and improvements to be done to attain elevated performance in the image acquisition device and efficient preprocessing techniques [3].

Biometric system based on finger vein works in four stages: image acquisition, image preprocessing, feature extraction and feature matching. Image acquisition can be done with help of near infrared light in two ways, light reflection method and light refraction method [6]. Usage of efficient image acquisition device is very crucial otherwise there will be too much of preprocessing to be done. Many existing finger vein recognition systems work well with neat and clean image. So, improvements are required even if image is not clear and if finger's position is perverted or depraved. Once vein image is obtained, it is necessary to preprocess it to enhance the image for better performance [7]. In finger vein biometric systems, feature extraction plays an important and critical role. Feature extraction methods are classified into three categories 1) dimensionality based 2) local binary based and 3) vein structure based. Extracted feature should be matched with the stored template. For this efficient matching algorithm is required.

Since it is easy and efficient to make deep learning networks to learn the patterns, we are incorporating the concept of deep learning in the finger vein biometric system. There are many GPU accelerated deep learning frameworks to train the convolutional neutral networks [8]. From the past several years, striking advances in the field of deep learning and artificial intelligence results in exceptional high performance in image processing particularly by using deep convolutional neural network.

Major innovation is that, it operates directly on the raw image extracting the features from the acquired image, thus improves the time efficiency [9].

Table 1. Pros and Cons of various biometric systems characteristics

Biometric Trait	Major advantage	Major limitation	Level of security	Device	Cost	Ease of use
Finger print	Wide application	Skin peeling, sweating	Good	Contact	Low	High
Iris	Highly accurate	Glasses, contact lens	Very Good	Contactless	High	Medium
Face	Remote capture	Lighting conditions	Medium	Contactless	Low	High
Knuckle print	Highly accurate	Rich in lines and creases	High	Contact	High	medium
Palm veins	Highly accurate	Skin peeling, sweating	Very good	Contactless	High	High
Finger vein	Highly accurate	Few	Very Good	Contactless	Medium	High

This paper is organized as follows: related work is presented in Section II. Architecture and modelling is provided in Section III. In Section IV, implementation and performance analysis is discussed and finally conclusion is presented in Section V.

II. RELATED WORK

Generally, biometric systems involve four major steps viz image acquisition, image preprocessing, feature extraction and matching. In image preprocessing stage, many tasks are performed to enhance the quality of the image by doing noise removal, resizing, sharpening, identifying the region of interest, image enhancement, blurring, deblurring, etc. in feature extraction stage, image segmentation is done in order to get the finger vein information. Finally, extracted finger vein feature is matched against the stored template in order to authenticate.

Syafeeza Ahmad Radzi et al [3] proposed finger vein biometric based on convolutional neural network which focused more on preprocessing and developing a CNN model. Segmentation is done by using local dynamic thresholding which results in lower computation complexity. CNN architecture is developed based on fused convolutional and subsampling layers. The proposed method tested on the samples from 50 and 81 subjects which is not sufficient to decide the robustness, efficiency and accuracy of the system.

Hyung Gil Hong et al, [6] proposed finger vein recognition using convolutional neural networks in which ROI is identified based on upper and lower finger boundaries. Recognition of finger vein is done by pre-trained CNN model. This method requires much preprocessing tasks as it captures the finger vein image by using only six 850 nm near infrared LEDs.

Rig Das et al [10] uses convolutional neural network for biometrical identification with the help of finger vein. They performed comprehensive set of experimental tests over four publicly available and commonly used databases. But requires improvement in the identification accuracy if finger vein images are not captured with the same illumination intensity and environmental lighting conditions.

Mansur Mohamed Ali et al [11] proposed a finger vein recognition system with gray level co-occurrence matrix which works based on the discrete wavelet transform. The proposed method provides higher accuracy right if there is no flexibility in the distance between the finger and the camera and if there is no flexibility to rotate and translate.

Iram Malik et al [12] uses repeated line tracking and gabor filter methods for human identification using finger vein pattern. Even though these two features are used to extract the features, they are combined these two approaches to increase the effectivity and reliability. By combining finger vein biometric with some other biometric techniques, higher accuracy can be achieved which are much essential for the security concerns in the sensitive areas.

Huafeng Qin et al [13] uses deep learning model for finger vein verification. They segmented the vein pixels from the background pixels and recovers the missing vein patterns by predicting the probability of a pixel to belong to a vein pattern. For this, they used ample statistics on non linear pixel correlations, through a hierarchical feature representation using deep neural network. Also, CNN based scheme is used to instinctively learn features from the tender pixels in order to achieve finger vein verification. The trained CNN model will not be able to identify the vein pixel if it is characterized by the poor illumination.

Wenjie Liu et al [14], proposed finger vein recognition system with the help of deep learning. In order to extract the region of interest, width and length of the finger vein is extracted by using compass operator. Five convolutional layers and two fully connected layers are used in the network architecture of CNN Model. Accuracy should be checked by running on the public database with a large quantity of data.

K S Itqan et al [15] proposed a user identification system based on finger vein with the help of convolutional neural network. They emphasize more on the preprocessing and the CNN design.

Four-layer CNN model is used which is derived by Lenet-5 architecture having smaller sized neural network. Subsampling layer and convolutional layers are fused and two fully connected lone nodes are used as a classifier. The proposed methodology has to be tested against the ginger vein real time system to know the accuracy.

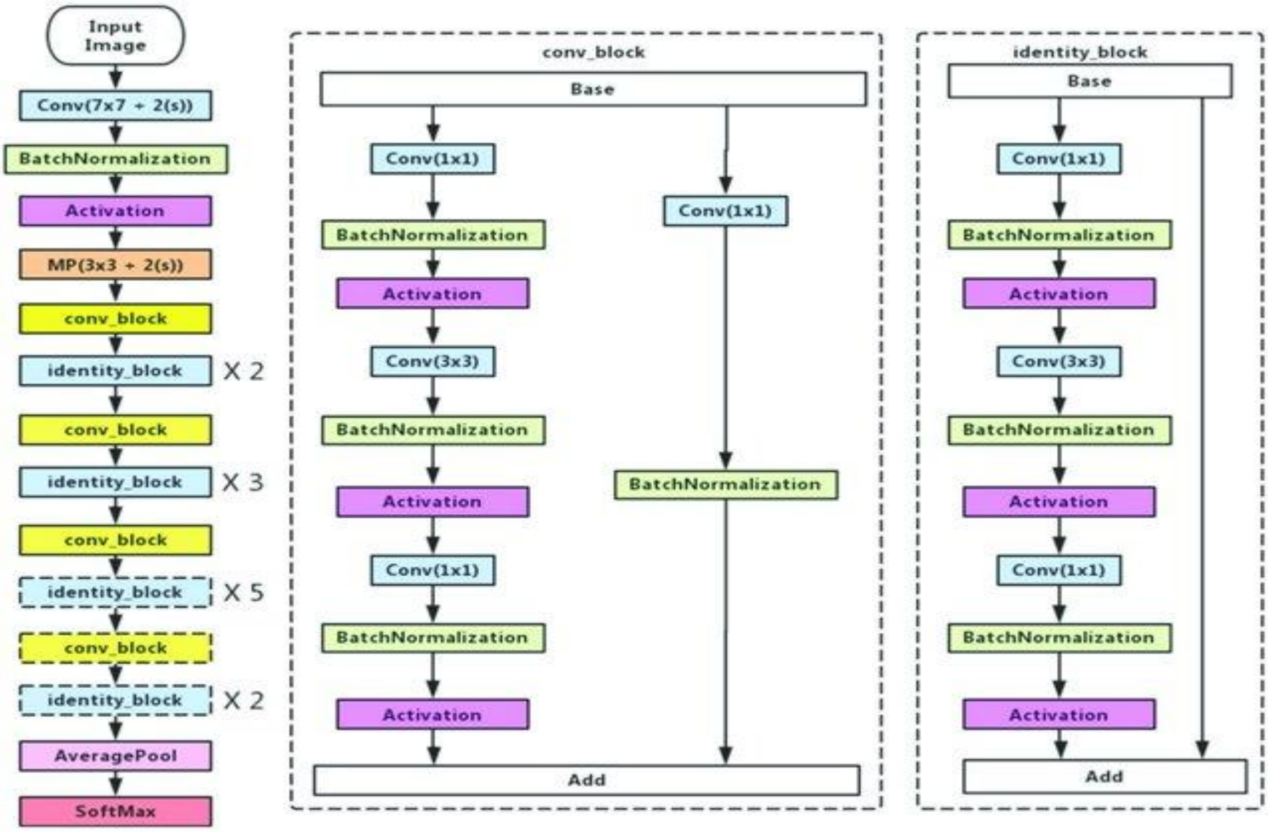


Figure 1: ResNet-50 Architecture for Transfer Learning

Huafeng Qin and Peng Wang [16] proposed an finger vein verification system based on the LSTM recurrent neural networks. Seven baselines were used to label the pixels in a validation set and the training set. For different orientations, different sequences were created for each labelled pixel. In order to predict the probability of occurrence of pixel belonging to the vein pattern, every sequence is forwarded to SCNN-LSTM, which results in enhancement of the image. To perform verification, enhanced image is encoded by supervised coding scheme.

III. METHODOLOGY

As discussed, most of the researchers worked on neural networks approach for finger-vein authentication and/or identification have followed traditional CNN model. Basically, a CNN model requires a huge dataset so as to learn from the training dataset. The finger-vein database used in the proposed work is SDUMLA-FV built by Shandong University [17], which has finger-vein images of just 106 individuals. Hence, the proposed work has been implemented based on transfer learning model [18]. The transfer learning is an approach where the model is pre-trained on a huge database of images and the knowledge gained by the model through those images is used for training another set of images. One of the major transfer learning models is ResNet-50 [19] and the architecture of this model is shown in Figure 1.

The proposed work aims to implement classification algorithm to classify 106 individuals based on their finger-vein images. Hence, this will be a multi-class classification problem with 106 different classes. The SDUMLA – FV database constituted with six images of each of index, middle and ring fingers of both left and right hands of an individual. Hence, there are totally 36 images for every person. The total number of images in the database would be 36*106 = 3816. The initial task is to put all these images into a single folder, without any distinction. This whole data set must be divided two parts: training set and testing set. Each of these sets must be again bifurcated as input and target. Here, the inputs are the images themselves and the target is the name of the class (0 to 105). With this initial setup, we must proceed for building the model. The architecture of the proposed work is shown in Figure 2. The proposed work follows various steps like flattening the image, model building etc. as discussed in the following sub-sections.

A. Flattening the Image

The sample input grayscale images are shown in Figure 3. These images are of two-dimensional array (of m x n pixels) to a one-dimensional array (of mn x 1 pixels). Think of this layer as unstacking rows of pixels in the image and lining them up. This layer has no parameters to learn; it only reformats the data.

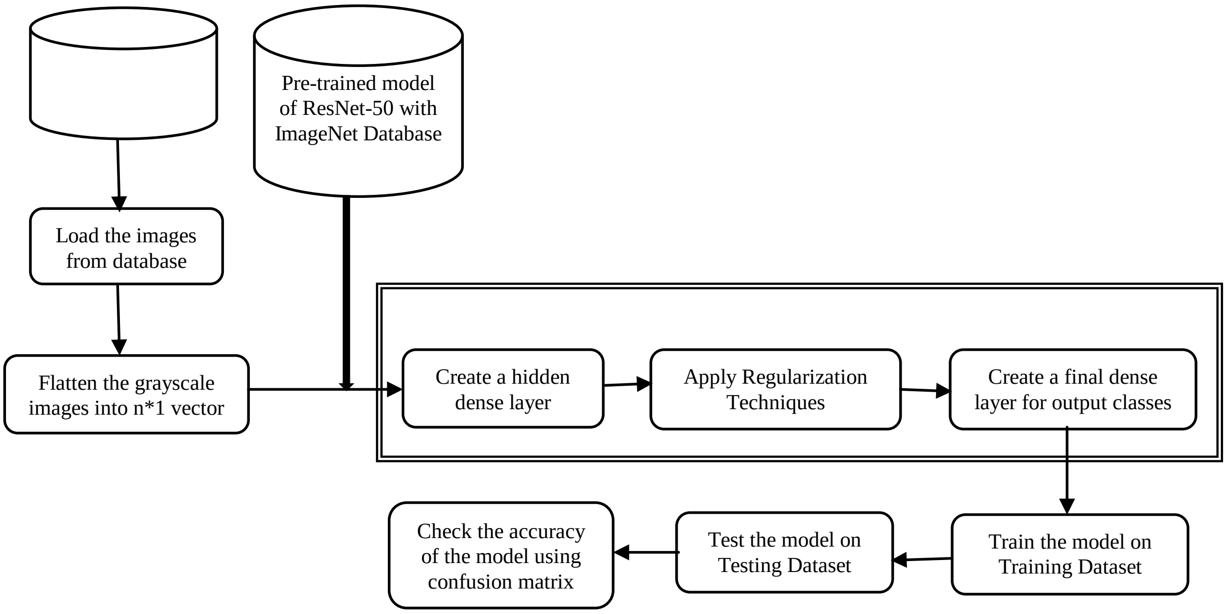
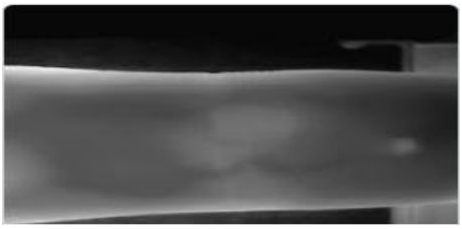
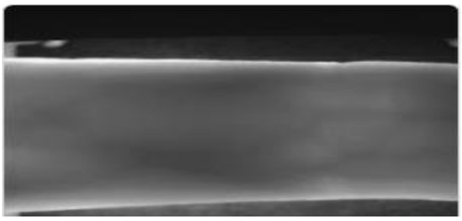


Figure 2: Architectural Diagram of the Proposed Work



(a)



(b)

Figure 3 (a) and (b): Sample images of finger vein

B. Dense Layer

The flattened array of image pixels is provided as input to a fully connected feed forward neural network, and this layer is known as dense layer. The proposed work is implemented with 250 neurons in the hidden dense layer. The Relu activation function used for the training is as given in Eq (1).

$$y = \begin{cases} 0, & x \leq 0 \\ x, & x > 0 \end{cases} \tag{1}$$

It is a non-linear activation function and makes sure that the output from each neuron results in a positive value.

C. Regularization

One of the common problems faced in deep learning algorithms is overfitting. When the model performs very well on the training set but underperforms on the testing set, then such situation is known as overfitting. There are several regularization techniques [20] available that can perform well into different situations. One of the popularly used regularization technique in neural networks is dropout [21]. Dropout is a technique where randomly selected neurons are ignored during training. They are "dropped-out" randomly. For example, if the dropout rate is defined as 0.2, then 20% of the neurons in each layer are dropped during an epoch. The whole process is done during training. The dropout rate in the proposed work is 25%. Since, the dropout is done during training, one need to multiply the activation of each of the unit where dropout is applied by the factor of dropout during the prediction process, as a compensation.

D. Output Layer

The output layer consists of 106 neurons representing each of the classes or persons. This is also a dense layer with softmax activation function. The softmax activation takes input a vector of K real numbers, and normalizes it into a probability distribution consisting of K probabilities proportional to the exponentials of the input numbers. The function is as given in Eq. (2).

$$P(y = j \mid \theta^{(i)}) = \frac{e^{\theta^{(i)}}}{\sum_{j=0}^{k} e^{\theta^{(i)}}} \tag{2}$$

where,

$$\theta = w_0 x_0 + w_1 x_1 + \ldots + w_k x_k = W^T X$$

The class which is having highest probability is the predicted class for that image.

E. Training the Data

Once the model has been built as discussed in the previous section, the model must be trained to learn the weights. To train a deep neural network, one must use an optimization algorithm. The proposed algorithm uses adaptive learning rate optimization algorithm viz. Adam [22]. It is an algorithm for first-order gradient-based optimization of stochastic objective functions, based on adaptive estimates of lower-order moments. An optimization technique generally requires a loss function to map an event or values of variables onto a real number representing the cost associated with the event. The loss function viz.

Categorical cross Entropy [23] is used in the proposed model. The mathematical representation of this loss function is as given in Eq. (3) below –

$$L(y,\hat{y}) = -\sum_{j=0}^{M}\sum_{i=0}^{N}(y_{ij} * \log(\hat{y}_{ij})) \quad (3)$$

Here, $\hat{y}$ is the predicted value. This loss function is used for single label categorization, where only one category/class is applicable for each data value. As any given finger-vein image can belong to only one person, usage of this loss function makes sense here.

The model has been trained for 100 epochs with early stopping approach [24]. It is also one of the regularization techniques to prevent overtraining. If validation error is not improving after few iterations, we stop the training. This is an automated way.

IV. RESULT

The proposed algorithm is implemented using TensorFlow 2.0 with Keras [25]. The programming language used is Python 3.7. The GPU available with Google Colab [26] is used as the CNN requires a high RAM for execution.

As discussed before, the image dataset has been divided into training and testing set with 3052 and 764 images respectively. When the model is trained and tested on these images, it stopped after 19 epochs. The values for training loss, training accuracy, validation loss and validation accuracy are briefed in Table 2.

As the number of epochs increases, the accuracy increases and the loss decreases. But, the rate at which increase in accuracy and decrease in loss for training set and testing set will be different. The generalization performance of both sets with respect to accuracy and loss are given in Figure 4 and Figure 5.

It is a customary to draw a confusion matrix for any classification problem. Here, we are dealing with 106 classes and hence the confusion matrix will be of order 106 * 106. As the representation of such a big matrix is almost impossible on a paper, it is not being included here. But, it is found that only one misclassification is resulted – the finger-vein image of person number 72 has been wrongly classified as person number 14. Thus, the proposed model has shown 99.06% of accuracy in authenticating the person.

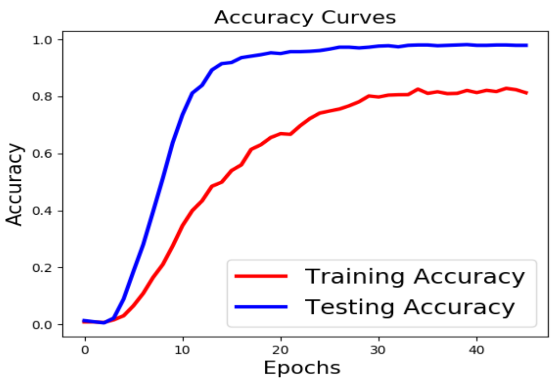


Figure 4: Accuracy curves for training and testing set

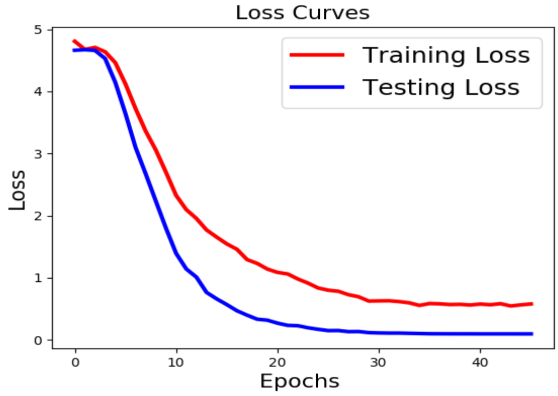


Figure 5: Loss curves for training and testing set

V. CONCLUSION

In this paper, we have presented a novel approach to authenticate an individual based on his/her finger-vein images. The deep learning technique of convolutional neural networks is applied along with transfer learning. The usage of transfer learning with ResNet–50 helped to achieve higher accuracy, as the learning is backed by the pre-trained model with millions of images from ImageNet database. We have used just one hidden layer with 250 neurons, and to have lower complexity, the dropout regularization is used. Appropriate optimization functions and loss functions are used to handle overfitting. As the algorithm resulted in 99.06% of accuracy in person authentication, we can conclude that the CNN model designed is found to be reasonably good.

Table 2: Performance Analysis of the proposed model

Epoch #	Time Taken	Training Loss	Training Accuracy	Validation Loss	Validation Accuracy
1	315s 103ms	4.7671	0.0236	4.6133	0.0380
5	290s 95ms	1.1645	0.6707	1.0166	0.7212
10	289s 95ms	0.1488	0.9528	0.4019	0.8861
15	289s 95ms	0.0250	0.9928	0.0061	0.9987
19	290s 95ms	0.0191	0.9944	0.0058	0.9987

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AUTHORS PROFILE

Mr. Madhusudhan M V received B.E from Mysore University in the department of Electronics and Communication from PES Mandya, in the year 2001 and received M.Tech degree from Visveswaraya Technological University (VTU), in the department of Computer Science Engineering, from JNNCE shivamogga in the year 2007. He is currently a research scholar in REVA University, Bengaluru in the field of Digital Image processing. Currently working as an Assistant Professor in the department of Computer science engineering, in Presidency University, Bengaluru. Presented six national level conference paper, one international Conference paper and one journal. Digital Image processing, biometrics, Design and analysis of algorithms, Digital electronics, and networks are the interested areas.

Dr. Udaya Rani V(Vinayakamurthy) received her PhD in Computer Science from the Mother Teresa University, Kodaikanal, Tamil Nadu, India, in 2014. She has published one patent and more than 20 journal papers in Conferences,National and International Journals of High Impact Factor. Her research area includes Data Mining, machine Learning, Big data Analytics, Genetic Algorithms.

Dr.Chetana Hegde, has completed PhD in Biometrics from Bangalore University in 2013. She is a senior member of IEEE and has published 35+ papers in refereed international journals and conferences like IEEE, ACM, Springer-Verlag and Elsevier. Her works have gained 220+ citations (Google Scholar) from fellow researchers.