FINGER VEIN AUTHENTICATION USING CNN MODEL

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Abstract

One of the main issues of the present is security. In many facets of modern life, identity verification has grown in importance. It has been demonstrated that hand-based bio- metric features are simple to obtain during data collecting. An increasingly reliable approach of automated personal identifi- cation is finger vein biometrics. Due to the physical traits and properties of the vein patterns in the human finger, which are very impossible to forge, finger vein is a special physiological biometric for identifying individuals. Deep hierarchically taught models (like CNN) have recently outperformed other computer vision algorithms in a variety of applications, but biometrics has received less attention up to this point. This is a key concern because there aren't enough examples available in biometrics to effectively train CNN. However, because to the enormous number of parameters that the learning algorithm must optimise, deep learning frequently needs a lot of training data. In this study, we provide a novel method of finger-vein image authentication. In order to support our concept, a publicly available vein image data set has been used as a case study. We found that domain-specific and highly discriminative vascular characteristics are provided by transformations learned from such a network. We use basic convolutional neural network (CNN) with transfer learning. The model has been pre-trained using the VGG16 architecture on a variety of image types from the UCI data world. The input from several biometric features is combined by multimodal systems, which not only improve system performance by making up for the shortcomings of each individual trait but also protect the system against attacks like presentation attacks. Moreover, Vein patterns are a powerful biometric identifier due to the uniqueness of blood vessel networks across individuals and difficulties in their reproduction.

Keywords: Biometrics, Authentication, Finger-vein, Multi- model System, Convolutional Neural Network

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1. Introduction

As we go closer to a globalised information society, crime situations that can happen anywhere in the globe are becoming a threat to the common person's life. Horrors have the capacity to swiftly spread over the globe, raising the risk. One of the Identify applicable funding agency here. If none, delete this. most crucial subjects at the present is security. In many spheres of modern life, identity verification has grown in importance. In the current context, smart human identity recognition for security and control is a big concern. Individuals who have been successfully identified and accepted are entitled to certainrights.

Finger vein biometrics is proving to be the impenetrable form of automated personal identification among the many authentication technologies that have been suggested and put into practise. As the most trustworthy method of au- tomated personal identification, they are quickly displacing other planned and operational authentication methods. In this experiment,The finger veins are used to examine the blood vessel patterns which are visible on the skin surface of the person.The pattern is captured using an observer terminal equipped with a monochrome CCD (charge-coupled device) camera and a near-infrared LED light. Haemoglobin in the blood absorbs light, giving the veins the appearance of a pattern resembling lines. A camera's raw data is transformed to digital form and added to a database of similar images once an image is captured.

The process's initial and most important phase is vein object extraction. The goal is to extract background vein ridges. The extraction approach has a direct impact on the feature extraction and feature matching procedures. As a result, vein object extraction has a significant impact on the system's overall effectiveness. However, using specific preliminaries, we aim to show in this study that our veins are adequate for biometric personal identification in a limited setting.

1. System Architecture

A. Image Acquisition

The finger veins are photographed by the image acquisition module. The image then undergoes preprocessing steps to im- prove and normalise it so that it is simple to extract and make use of the target features. In contrast to fingerprint biometric systems, which employ one type of device to capture the image, finger-vein biometric systems use a different method. Typical finger-vein capture equipment consists of a number of parts. a part of an infrared light source that emits light on the finger's dorsum, or back

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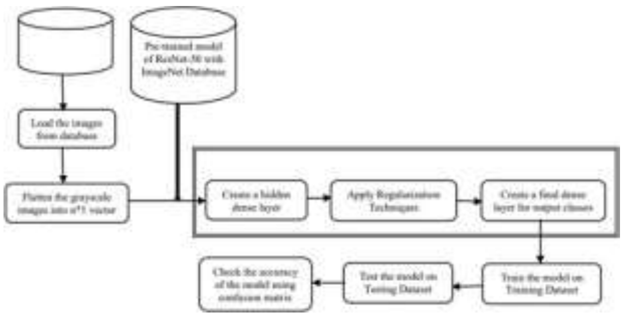


Fig. 1. Architecture Diagram of the proposed Model

B. *Preprocessing*

The most elementary abstraction level of actions on images is referred to as "image pre-processing." By minimising un- desirable distortions or boosting particular visual features that are crucial for later processing and analysis activities, pre- processing seeks to enhance the picture data.

C. *Feature extraction*

The technique of feature extraction transforms unprocessed data into controllable numerical features while maintainingthe details of the initial data set. The target features are extracted from the images taken during the previous stage of image acquisition by the feature extractor module. Numerous research papers have recommended one or more of the desired qualities that can be retrieved from finger veins for inclusionin finger-vein biometric recognition systems.

D. *Classification*

In order to get a matching score and establish whether the template data agree, the classification or matching modulecompares a sample template or query with the template contained in the database. The similarity of the templates increases with the matching score. Researchers have proposed a variety of classifiers for finger-vein identification systems to match the query with the stored template data.

2. Processing

Typically, in order to improve the image quality for use as an input image and to ensure that relevant information can be detected, a number of pre-processing tasks are needed in image-based biometric systems (such as finger vein biometric). These tasks include enhancing contrast, brightness, edge in- formation, noise removal, sharpening, etc. In our experiment, we very specifically and thoroughly specify each and every preprocessing approach.

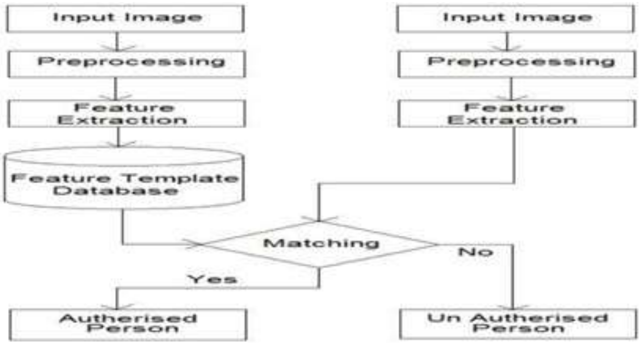


Fig. 2. Flow Diagram of proposed Model

A. Image sharpening

Digital images can be given the image sharpening effect to make them appear sharper. The definition of edges in an image is improved through sharpening. The photographs with bad edges are the dull ones. The contrast between the background and the edges is minimal. Here, The database includes several pictures of the veins in our fingers. Then, when each image has been loaded from the dataset, it has been sharpened to emphasise the image's small details.The image is shown in fig.3

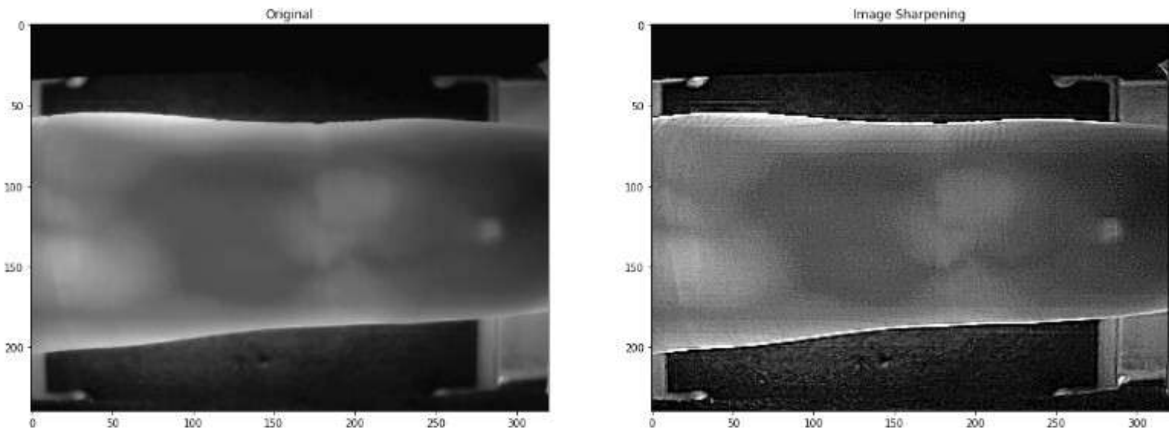


Fig. 3. Image-Sharpening

B. Image shape and feature extraction

The Otsu Threshold method, an adaptive thresholding tech- nique, is used to extract the image's features. It may choose the best threshold value for the input image by taking into account every possible threshold value (from 0 to 255). In Otsu thresholding, statistical data of an image is used. This method is a picture thresholding based on clustering. When the histogram is bimodal, it functions. The strategy essentiallyaims to maximise the between class variation while simulta- neously minimising the within class variance.

Total variance=Within class variance +Between Class Vari-ance.

C. Processing of image

Dilation and erosion are the two most fundamental morpho- logical processes. Dilation in a picture refers to the addition of pixels to object boundaries, whereas erosion refers to the removal of pixels from object boundaries. The morphological dilation and erosion processes describe the state of any given pixel in the output image. Here, morphological approaches are used to process photos of finger veins before the images are transmitted for noise removal.

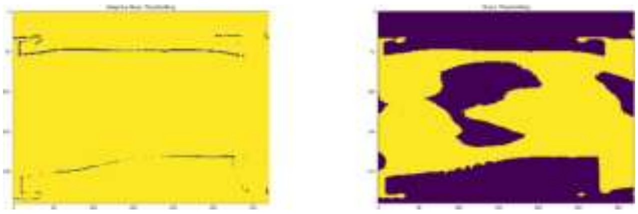


Fig. 4. Otsu’s Thresholding image

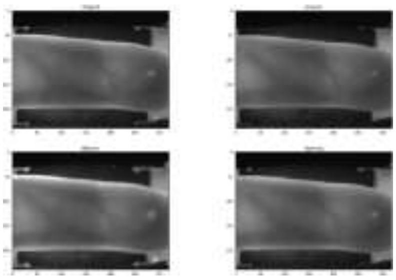


Fig. 5. Erosion and Dilation image

D. Vein extraction

The Sobel filter is used for edge detection. To work, it calculates the gradient of picture intensity at each pixel inthe image. It determines the highest ascent from light to dark and the direction and pace of change. The Sobel filter makes use of two 3 x 3 kernels. There are two for changes in the horizontal and vertical directions, respectively. To compute the approximate derivatives, the two kernels are convolved with the original image Sobelx and Sobely are two imagesthat, respectively, contain the horizontal and vertical derivativeapproximations.

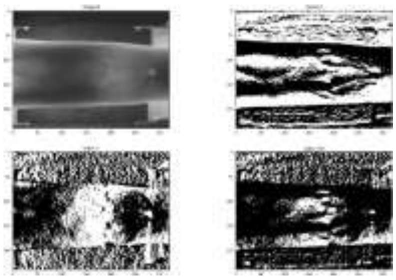
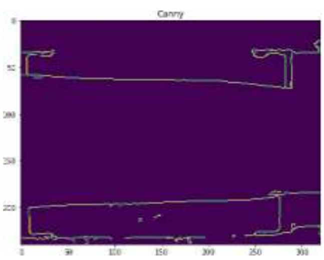


Fig. 6. Extraction of vein features

CANNY EDGE:

- Canny edge detection is a technique for image processing that finds edges in an image while reducing noise. Theimage is initially smoothed using the clever edge detec- tion to lower noise. The gradient is then located in the image to draw attention to the regions with high spatial derivatives.The programme suppresses any pixels outside of these zones that are not at their maximum value.



- In our experiment, we applied the Sobel and Canny edge detection techniques to various images of finger veins in an effort to determine the most effective method of vein detection. This experiment including the application of several techniques to the images has allowed us to draw the conclusion that the Canny edge detectors performance is much better than the Sobel edge detector in terms of producing smooth and thin edges.

Fig. 7. Canny edge Detection

E. Oriented filter enhancement

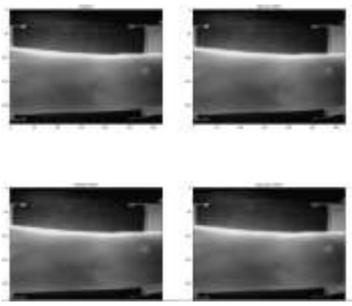


Fig. 8. Applying various filters

From Fig.8 you can see that,we have added different filters to the images to know which method is best for modifying and enhancing the image. In order to enhance or identify edges in a picture, filters are mostly employed to suppress either the high frequencies or the low frequencies present in the image. Eithera spatial or a frequency filter can be applied to an image.

3. Experimental Results

A. Plotting sample finger images

We ran extensive experiments on our finger-vein database to evaluate the effectiveness of the suggested strategies.The training data and testing data datasets were created from the images of the finger veins used in this investigation. Then, as we have seen, these images travel through several processing procedures. This dataset contains approximately 20 distinct images of each fingervein for experimentation. These are depicted in Fig. 9. Following the loading and classification of the images from the finger vein database, each image of a finger vein is given a name and additional pixels are added before being subjected to various preprocessing procedures to identify its largest contourand largest extreme points.

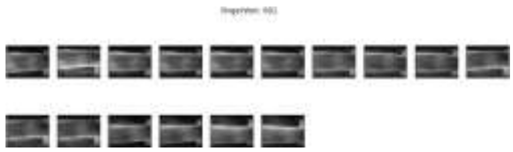


Fig. 9. Collection of Fingervein images

B. Implementing the key algorithm for finger vein patternrecognition

We employed VGG16, a top-notch vision model architec- ture, in this experimentation. We attempt to anticipate theresult using this architecture. When categorising 1000 pictures into 1000 different categories, the object identification and classification method VGG16 has a 92.7 accuracy rate.

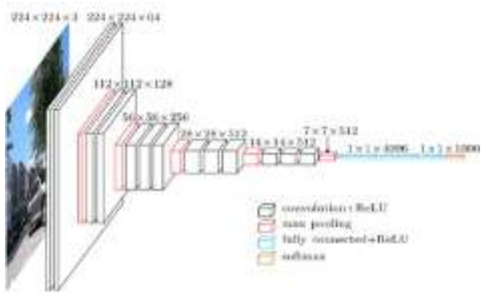


Fig. 10. VGG16 Architecture

The most noticeable feature of VGG16 is that it prioritised having convolution layers of 3x3 filters with a stride 1 and always utilised the same padding and maxpool layer of 2x2 filters with a stride 2. Its conclusion uses two fully connected layers (FC) and a softmax for output. In VGG16, the number 16 refers to the 16 layers with weights.

- Here, we import all the necessary libraries before be- ginning to implement VGG16. Since we are developing a sequential model,we will be employing the sequential method. Here we have imported ImageDataGenerator from keras.preprocessing. Then, we are creating an ImageDataGenerator object for both training, testing and validation data and sending the folder containing the training data to the object train-datagen and the folder containing the test data to the object test-datagen in a similar manner, the folder containing the validation data to the object val-datagen.

- A softmax layer is then established; this layer will pro- duce a value between 0 and 1 depending on the model's confidence in the class to which the images belong. The softmax layer has been created, and now the model is ready.We can check the summary of the model we have created.

```
Model: "model"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         [(None, 320, 240, 3)]     0
_________________________________________________________________
block1_conv1 (Conv2D)        (None, 320, 240, 64)      1792
_________________________________________________________________
block1_conv2 (Conv2D)        (None, 320, 240, 64)      36928
_________________________________________________________________
block1_pool (MaxPooling2D)   (None, 160, 120, 64)      0
_________________________________________________________________
block2_conv1 (Conv2D)        (None, 160, 120, 128)     73856
_________________________________________________________________
block2_conv2 (Conv2D)        (None, 160, 120, 128)     147584
_________________________________________________________________
block2_pool (MaxPooling2D)   (None, 80, 60, 128)       0
_________________________________________________________________
block3_conv1 (Conv2D)        (None, 80, 60, 256)       295168
_________________________________________________________________
block3_conv2 (Conv2D)        (None, 80, 60, 256)       590080
_________________________________________________________________
block3_conv3 (Conv2D)        (None, 80, 60, 256)       590080
_________________________________________________________________
block3_pool (MaxPooling2D)   (None, 40, 30, 256)       0
_________________________________________________________________
block4_conv1 (Conv2D)        (None, 40, 30, 512)       1180160
_________________________________________________________________
block4_conv2 (Conv2D)        (None, 40, 30, 512)       2359808
_________________________________________________________________
block4_conv3 (Conv2D)        (None, 40, 30, 512)       2359808
_________________________________________________________________
block4_pool (MaxPooling2D)   (None, 20, 15, 512)       0
_________________________________________________________________
block5_conv1 (Conv2D)        (None, 20, 15, 512)       2359808
_________________________________________________________________
block5_conv2 (Conv2D)        (None, 20, 15, 512)       2359808
_________________________________________________________________
block5_conv3 (Conv2D)        (None, 20, 15, 512)       2359808
_________________________________________________________________
block5_pool (MaxPooling2D)   (None, 10, 7, 512)        0
_________________________________________________________________
flatten (Flatten)            (None, 35840)             0
_________________________________________________________________
dense (Dense)                (None, 5)                 179205
=================================================================
Total params: 14,893,893
Trainable params: 179,205
Non-trainable params: 14,714,688
```

Fig. 11. Implementation of VGG16 algorithm

- As we use ImageDataGenerator to feed input to the model, we are using model.fit generator. We will provide fit generator with train and test data. The batch size for training data is set in fit generator steps per epoch, while the batch size for test data is set in validation steps.Then the model will start to train and we can see the training/validation accuracy and loss.

Fig. 12. Epochs

- After the training of the model, you can see the accuracy and loss of training and validation. You may have noticedthat we are giving the hist variable the output of themode.fit generator. we will visualise it all using the training/validation accuracy and loss data that is kept in hist.

C. Model prediction

Predictive modelling is a prominent statistical technique forbehaviour predictions. The predictive modelling helps to build a model which uses the past and present data to anticipate the future outcomes.

In this case, we used the model.predict class to forecast the result. With the help of trained data, this model may be built, fitted, and applied to provide predictions. Finally, the values of the prediction list and the true list are matched. Based on this matching, inferences are then made, and the findings are shown through a confusion matrix between the true labels and predicted labels which is shown in fig.x

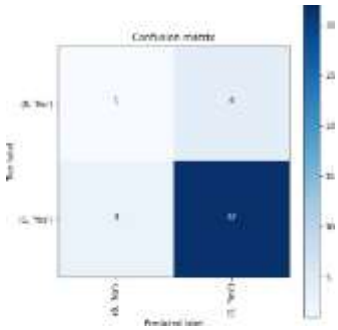


Fig. 13. Confusion Matrix

4. Conclusion

In only a few years, finger vein pattern recognition has as- sumed a significant role in the second generation of biometrics. This research suggested a finger vein recognition method to increase the speed of finger vein registration and recognition based on the design of VGG16 characteristics.

For VGG16 implementation, adequate feature extraction and matching recognition were used, along with simulation testing and analysis to confirm the system's efficacy. On VGG16, some important algorithms for extracting finger vein fea- ture and matching recognition are implemented. By utilising constrained surroundings, we offer a personal identification system based on finger vein patterns. We can infer from our experimental findings that the strategies discussed in this paperprovide positive outcomes.

5. References

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