Hybrid Features-Based Multimodal Biometric Identification using Random Forest Classifier and Convolutional Neural Network

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Abstract
In many areas where personal identification is important, security is of great importance. Biometric or multi-biometric systems, which include the physiological and behavioral features of individuals, are more preferred because traditional methods are insufficient and cannot provide security. In the study, a new approach of multimodal biometric identification is proposed consisting of the fingerprint and finger knuckle print (FKP). A deep convolutional neural network (CNN) based hybrid feature extraction technique is utilized along with the GLCM (Gray Level Co-occurrence Matrix) and wavelet moments. Classification of extracted features is achieved by using random forest classifier with simulation results in terms of F-Score, accuracy, sensitivity,precision, and specificity.

Keywords :CNN, FKP, GLCM, Random Forest Classifier, Wavelet Moments.
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I. Introduction

Conventional access control systems used today require various identification tools such as identity documents, passwords, magnetic cards. If these tools are in the hands of other people without the permission of the person, it can cause material and moral losses. Traditional systems in areas such as national security, electronic commerce and banking, where personal identification is extremely important, cannot provide sufficient confidence. For all these reasons, biometric systems have gradually started to replace the traditional systems used for personal identification processes [1].

Biometrics is a scientific discipline that requires automated methods based on the behavioral and physiological features of humans. Biometric features-based personal identification processes are becoming popular day by day, as they have many applications and are more reliable than traditional methods [2]. Biometric systems are basically based on the principle of recognizing one or more physical or behavioral characteristics that only one's own, which cannot be changed by others or himself that serves to prove that the person is himself that distinguishes the person from other people. The fact that biometric systems consist of physical or behavioral features ensures that biometric features are not lost, cannot be used by someone else, cannot be forgotten and cannot be imitated [3] [4].

The purpose of biometric systems is to enable people to use their own features, which are impossible to imitate, without having to memorize information such as passwords and carrying anything with them in order to prove their identity. Thus, the use of these systems ensures the highest level of security [5].

Biometric systems are essentially pattern recognition systems that take biometric data from humans, get a set of features from a database, and compare this feature set to the database's prototype set.Biometric data consists of behavioral features such as gait, voice, keyboard use, signature dynamics, and physical features such as fingerprint, face shape and geometry, iris, DNA, vein structure, palm print, finger knuckle prints [5]. The finger knuckle surface is the most preferred of these qualities. The articular surface of the finger knuckle is a congenital skin pattern that displays the shape of the intra-toe joints.This biometric is rich in tissue information. Because of its richness, the finger knuckle surface may be employed in identification procedures even when poor resolution devices are present.

Systems based on a single biometric, such as the knuckle surface of the finger, are unreliable, not ubiquitous, and so on. They suffer several obstacles, and in order to address these issues, the concept of a multimodal-biometric system was proposed [6]. Multimodal biometric systems are those that combine biometrics received from the same sensor or from other sensors.

In order to avoid the problems encountered in systems based on single biometric data, multiple biometric recognition and verification consisting of finger knuckle surface and fingerprint was performed in this research work.

The two biometric modalities which are used in this paper are:

A. Fingerprint Recognition

Fingerprint recognition is an advanced biometric technology that may be utilised in virtually any identifying or identity verification application. The fingerprint recognition system is a three-stage automated pattern recognition method [7-9]:

- Image Acquisition: The fingerprint is acquired from the database and saved as an image.
- Feature Extraction: Images are used to extract important features.
- Decision Making: The acquired features are compared to those in the database, and a judgement is taken based on the comparison findings.

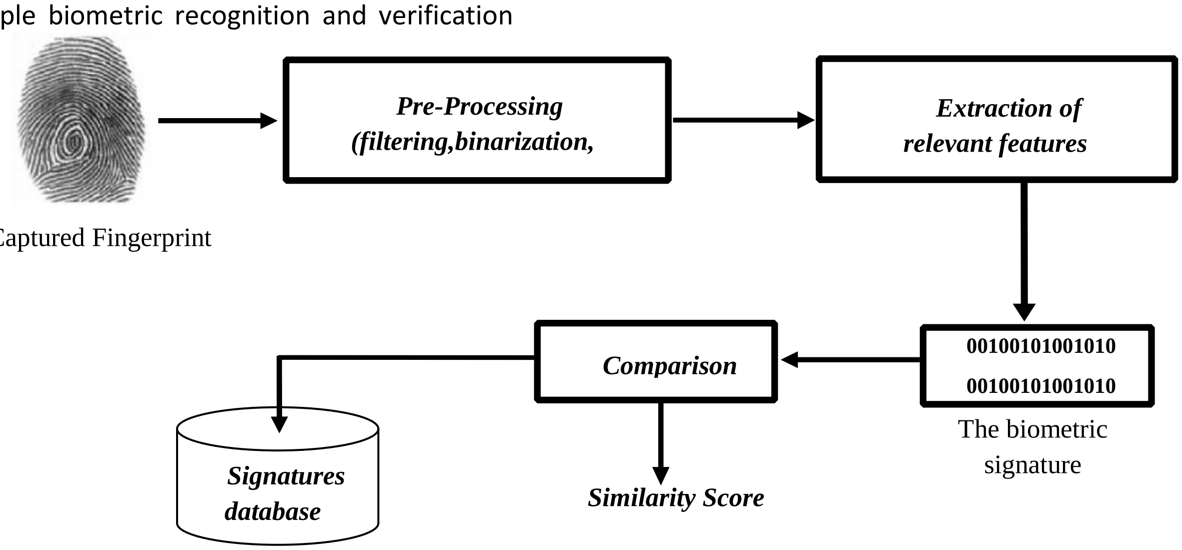

Figure 1: Fingerprint recognition basedbiometric identification system

B. Finger Knuckle Print

As demonstrated in Figure 2, finger knuckle print (FKP) is aninnovative form of biometric mode that has been effectively utilized to detect persons by the contour and texture of the outer surface of the finger. Because they are very permanent and fixed, these linear patterns and textures are particularly useful in discriminating between various individuals [10-13].

Because of the benefits of biometric systems, FKP mode may be employed. To begin, capturing data with low-resolution commercial cameras is simple and affordable. Second, FKP-based access systems are suitable for both outdoor and indoor use, and they can operate successfully in inclement weather and low-light conditions. Third, the features of FKP in adults are more stable throughout time and do not change much. Biometric data based on FKP, on the other hand, is quite reliable and may be used to successfully identify many persons [13].

Figure 2: Sample images of finger joints infingerprints [11]

The primary goal of this study is to create a multimodal biometric identification system using deep convolutional neural networks and hybrid features. The second part presents the proposed methodology, and the third presents the simulation results, and the fourth part contains the concluding comments.

II. Proposed Methodology

This paper discusses multimodal biometric identification with GLCM and Wavelet Moments features extraction followed by hybrid feature classification based on convolutional neural networks with a random forest classifier. The proposed multimodal biometric identification comprises of two input patterns i.e. finger knuckle and fingerprint images. The developed system model is depicted in Figure 3.The following sections describe the materials and methods used in various stages of experimentation and data processing. Below are the details of each block.

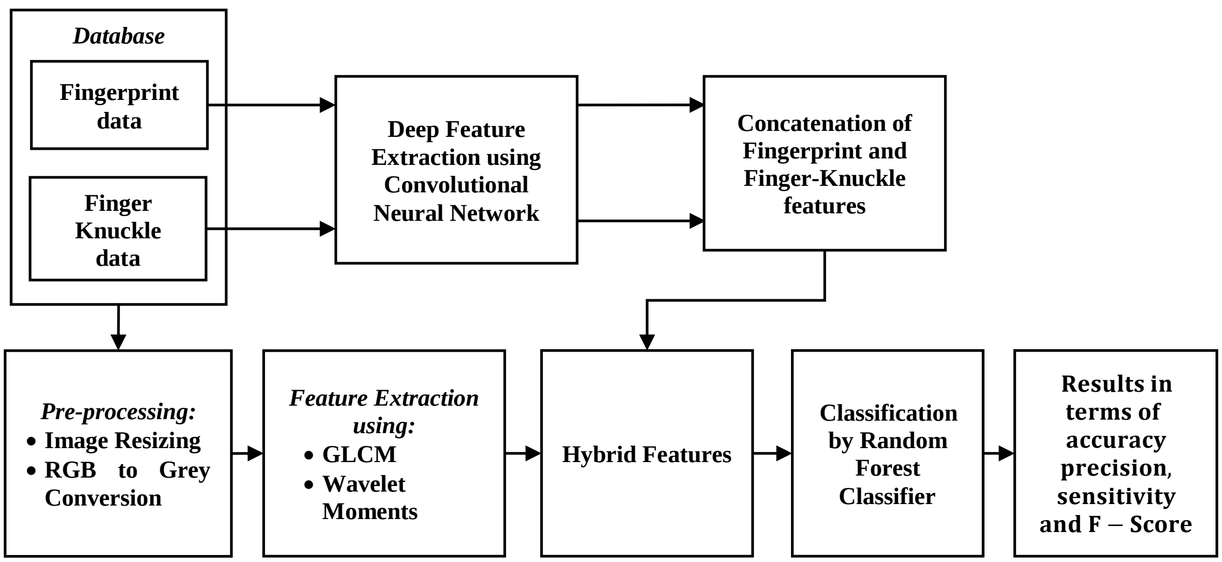

Figure 3: Block diagram of proposed hybrid features based biometric identification

A. Deep Features Extraction using Convolutional Neural Network (CNN)

The idea of CNN is to pass the image through a succession of convolutional filters providing a reduced and relevant description of the image. These attributes are then transferred to a multilayer perceptron, which is made up of hidden layers and a fully linked output layer, allowing categorization of the figure in the image. Convolution filters and fully connected layers are learned simultaneously.

We present here the different modules used in CNNs:

The Convolution: The centerpiece of the CNN is the convolutional layer. The resulting output is called a feature map. A convolutional layer consists of several convolution filters (or kernels) to be applied on an input matrix (an image or a previous feature map).

Let I be an input of size $W \times H \times C$ and a convolution kernel G of size $K \times K \times C$.The output of the convolution of I by G is written $I^{'}$ and the size W. The value of $I^{'}$ at position (i, j) is calculated as follows:

$$I'_{i,j} = \sum_{k_1=0}^{K-1} \sum_{k_2=0}^{K-1} \sum_{c=0}^{C-1} G_{k_1,k_2,c} I_i \left(\frac{K-1}{2} + k_1, j\right)\left(\frac{K-1}{2} + k_2, c\right) \quad (1)$$

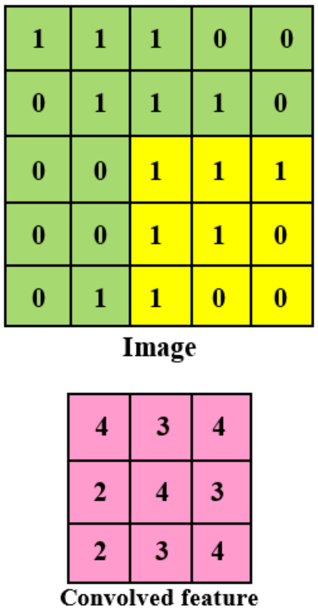

Figure 4: The operation of convolution [15]

Figure 4 recalls how convolution works. In practice, a value (called bias) associated with the convolution filter is added at each position of the filter output. During learning, the values of the weights and biases of the neurons making up these filters are learned. These filters make it possible to extract local characteristics unlike the multilayer perceptron where the responses resulting from a hidden layer are extracted on the globality of the data (due to the completely connected layers). A filter of a convolutional layer is applied to all the positions of the input matrix; this is why we speak of shared weights. The underlying idea is that similar features can be found at different places in the image.

Pooling: The pooling layer (or agglomeration) makes it possible to add spatial invariance during the extraction of characteristics while reducing the dimension of inputs. It can be of different natures but the most used types of pooling are Max Pooling (illustrated in Figure 5) and Average pooling. Max Pooling returns the maximum element over a calculation window. Average pooling is used to return the average of the elements over a calculation window.

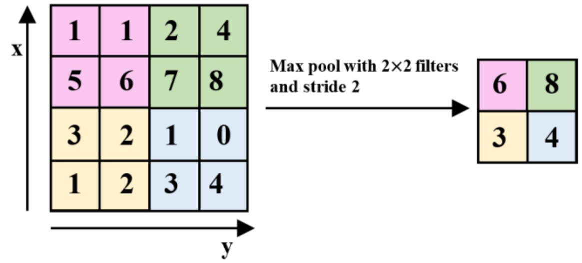

Figure 5: Illustration of Max Pooling

*Activation Functions:*Different activation functions enable nonlinearity at different layers of CNNs.Among the best-known are:

- The sigmoid function, which was originally utilized in the multilayer perceptron:

$$f(x) = \frac{1}{1+e^x} \quad (2)$$

- The hyperbolic tangent:

$$f(x) = \frac{e^x e^x}{e^x + e^x} \quad (2)$$

- The Rectified Linear Unit (ReLU):

$$f(x) = \max(0, x) \quad (3)$$

This is perhaps the most common in deep CNNs since it facilitates optimization. It has the benefit of offering sparse replies and reducing gradient vanishing difficulties. This is because sigmoid and hyperbolic tangents produce very small gradients when the absolute magnitude of the input is substantial.

B. Pre-Processing for Second Phase

The preceding paragraph described the first step of technique, and this section begins the second phase.

1. The supplied image is first enlarged to 224×224 pixels using MATLAB's built-in resizing tool.
2. If the input image is coloured, the rgb2gray function converts the face image in RGB format to grayscale after scaling.

C. Feature Extraction

In image processing, the purpose of feature extraction is to mathematically or symbolically encapsulate the feature, which is known as encoding. Depending on the context, the values of these properties can be binary, integer, or real. A point in the new n-dimensional space is represented by the vector of n attributes.Figure 3 depicts the stages involved in feature extraction utilizing two feature extraction approaches that are detailed in the subheadings below.

1. Gray Level Co-Occurrence Matrix (GLCM)

GLCM are built by analysing pairs of pixels for a distance and orientation specified between them.

The following are various texture detecting techniques. [17]:

- *Angular Second Moment (ASM):*It is also known as consistency. The greater the uniformity (less fluctuation in grey levels), the higher the ASM; if the ASM is 1, the image is fully uniform.

$$\sum_{i,j=0}^{N-1} P_{i,j}^2 \tag{4}$$

- *Contrast:*It is the number of local differences in the image's grayscale hues. The larger the variance in grey tones, the higher the contrast.

$$\sum_{i,j=0}^{N-1} P_{i,j}(i-j)^2 \tag{5}$$

  When the contrast is set to zero, grey levels remain consistent across the image.

- *Correlation:*It is the image's linear dependency of grayscale shades:

$$\sum_{i,j=0}^{N-1} P_{i,j}\frac{(i-\mu_i)(j-\mu_j)}{\sqrt{(\sigma_i\sigma_j)}} \tag{6}$$

  There is no linear link between the grey levels if the correlation is 0.

- *Entropy:*It measures the image's complexity. The greater the entropy, the greater the complexity.

$$\sum_{i,j=0}^{N-1} P_{i,j}\left(-LnP_{i,j}\right) \tag{7}$$

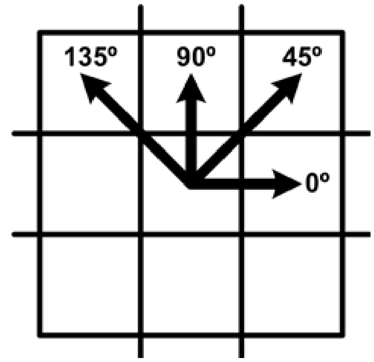

Figure 6: GLCM distribution [18]

- *Inverse Difference Moment (IDM):*It is also known as homogeneity. The IDM grows when the contrast between pixel pairs decreases.

$$\sum_{i,j=0}^{N-1} \frac{P_{i,j}}{1+(i-j)^2} \tag{8}$$

Each one at four diverse orientations (0º, 45º, 90º and 135º) and three diverse distances (1, 5, and 10 pixels), with the corresponding mean values displayed in Figure 6.

2. Wavelet Moments

In order to distinguish high frequency components, the wavelet transform is utilized to decompose low frequency images, since they can obtain certain transform information from the extracted image

Multi-resolution frequency data arrays allow the use of frequency segments with eigenvalues because an expression or extraneous component is limited to multiple sub-bands. These methods describe these individual sub-bands and focus on the sub-band containing the most relevant data [19].

For a set of images, a 4-level DWT decomposition was used. This gives 4 subgroups in the form of detailed scores and ratios. The zoom factor is a match (A), which is the same input image, but at a reduced size. In this case, the detail ratios are horizontal (h), vertical (v) and diagonal (d). Applying DWT to a single layer in M image results in a subset shown as [1]:

$$M = M_a^1 + \{M_h^1 + M_v^1 + M_d^1\} \tag{9}$$

DWT can be used N times to get an N-leveldecomposition to further reduce the amount of input. Thus, at the completion of the four-step DWT, the drawing may be characterized as:

$$M = M_a^4 + \sum_{i=1}^{4}\{\{M_h^i + M_v^i + M_d^i\}\} \tag{10}$$

At the end of the two-stage DWT, the input image is enlarged from $m \times n$ to $\frac{m}{2} \times \frac{n}{2}$.

DWT employs Fourier transforms to translate images from the time domain to the frequency domain. The mathematical expression for DWT is as follows:

$$DWT_{x(n)} = \begin{cases} dd_{j,k} = \sum img(n) hh^*{}_s(n - 2^s r) \\ ap_{j,k} = \sum img(n) ll^*{}_s(n - 2^s r) \end{cases} \tag{11}$$

Here $ap_{j,k}$ resembles the approximate coefficients and $dd_{j,k}$represents the detailed coefficient of DWT.The functions $ll(n)$ and $hh(n)$ represent low-pass and high-pass filters, respectively. The r and s parameters reflect the translation ratio and wavelet scale, respectively. We should be looking for images or regions with a consistent texture, with the mean and standard deviation represented as follows:

Mean: The mean of a vector of random variables A with N scalar observations is calculated as [1]:

$$\mu_{mn} = \frac{1}{N}\sum_{i,j=1}^{N} ap_{ij} \tag{12}$$

Where the approximation coefficient is symbolized by ap_{ij}. Nrepresents scalar observations andμ_{mn} symbolizes the mean of the wavelets.

$$\sigma_{mn} = \sqrt{\frac{\sum_{i=1}^{m}\sum_{j=1}^{n}(|I_{mn}(i,j)| - \mu_{mn})^2}{N-1}} \tag{13}$$

Here, $I_{mn}(i,j)$symbolizes the perceived values of the items in the sample, μ_{mn} is the observations' mean, and N denotes the number of observations in the model. σ_{mn} is the wavelet value's standard deviation.

The wavelet moments is generated with σ_{mn} and μ_{mn} as feature components:

$$f_g = (\mu_{00}, \sigma_{00}, \mu_{01}, \sigma_{01} \ldots\ldots.\mu_{45}, \sigma_{45}) \tag{14}$$

D. Classification by Random Forest Classifier

The random forest approach combines the bagging and random subspace methods [20]:

"A random forest is a classifier consisting of a set of basic decision tree type classifiers", represented as:

$$\{h(x, \Theta_k), \qquad k = 1, \ldots L\} \tag{15}$$

With $\Theta_1, \ldots, \Theta_q$ random variables that are unrelated to $\mathcal{L}_n$, consider $\left(\hat{h}(\Theta_1), \ldots, \hat{h}(\Theta_q)\right)$ as a group of tree predictors. The predictor of random forests $\hat{h}_{RF}$ is created by mixing this collection of random trees in the way indicated below.

- $\hat{h}_{RF}(x) = \frac{1}{q}\sum_{l=1}^{q}\hat{h}(x, \Theta_l)$, which is the average of the predictions made by individual trees in the regression.
- $\hat{h}_{RF}(x) = arg\,max_{1 \le k \le K}\sum_{l=1}^{q} 1_{\hat{h}(x,\theta_l)=k}$, which is the classification's majority of individual prediction trees' votes.

The phrase "random forest" refers to a system where each tree is dependent on a separate random variable (in addition to $\mathcal{L}_n$) and where each individual predictor is explicitly predicted for each tree.

The random forest method's classification procedure consists of the following steps [20]:

1. *When a node is determined to be terminal, it is chosen whether it will be marked as a sheet or carry a test.*
2. *If the node is not terminal, we must attach a test to it.*
3. *If the node is terminal, it must be allocated a class.*

A generalized algorithm for RF is stated below:

$$Input: sample\ S$$

Initialize the current tree to the empty tree;
The root designates the current node
Repeat
See if the current node is terminal
If the node is terminal, then
Assign it a class
If not
Select a test and generate as many new child nodes as there are answers to this test
End if
Explore another node if there is one
Until a tree A is obtained
Exit: tree A

III. Simulation Results

Table 1: Simulation results

Evaluation Parameters	Values
Accuracy	98.33%
Error	1.67%
Sensitivity	98.46%
Specificity	99.59%
Precision	98.33%
False Positive Rate	0.41%
F − Score	98.33%
Matthews Correlation Coefficient	0.9797
Kappa	0.9479

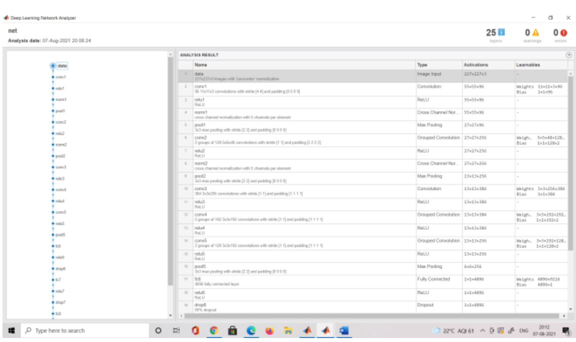

Figure 7: Convolutional neural networkanalysis - 1

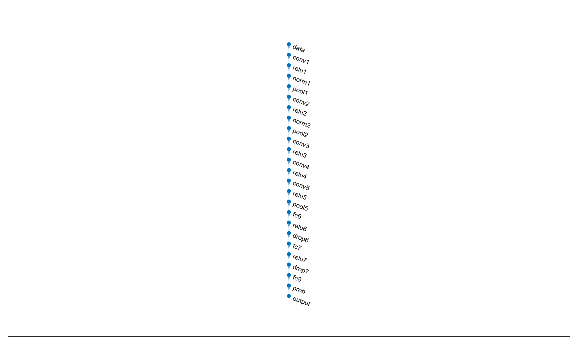

Figure 8: Convolutional neural networkanalysis - 2

IV. Conclusion

This study allowed us to validate the feasibility of a multimodal biometric system by concatenating two biometric modalities: fingerprint and finger knuckle. It has been observed that convolutional neural networks as feature extractor is a very powerful alternative. GLCM, wavelet moments, and deep features are used to generate hybrid features. The Random Forest classifier is utilized in the classification step. The most essential thing to remember is to select an appropriate training dataset for the data environment in which the testing is planned. Experiments were used to validate the developed approach. When the three different feature extraction procedures are assessed, successful results are produced with a maximum accuracy of 98.33%.

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