HYBRID FEATURES BASED MULTIMODAL BIOMETRIC IDENTIFICATION USING CONVOLUTIONAL NEURAL NETWORK AND RANDOM FOREST CLASSIFIER

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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 gray level co-occurrence matrix (GLCM) and wavelet moments. Extracted features are classified by random forest classifier to obtain the simulation results in terms of precision, sensitivity, accuracy, specificity and F-Score.

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 physiological and behavioral characteristics 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 actually a pattern recognition system consisting of the steps of taking biometric data from people, obtaining a feature set from this data set, and comparing this feature set with the template set in the database. 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 recommended one among these features is the finger knuckle surface. The articular surface of the finger knuckle is a congenital skin pattern and expresses a form of the joints on the intra-toe surface. This biometric is rich in tissue information. This richness enables the finger knuckle surface to be used in identification processes even in the presence of low resolution devices.

Systems created using a single biometric such as the finger knuckle surface are reliable, not universal, etc. They face many problems such as due to the necessity of removing these problems, the idea of multimodal-biometric system was put forward [6]. Multimodal biometric systems are systems that are formed by the combination of biometrics obtained from the same sensor or from different 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 for any identification or identity verification application. The fingerprint recognition system is an automatic pattern recognition system consisting of three main stages [7-9]:

- Image Acquisition: The fingerprint is acquired from the database and saved as an image.
- Feature Extraction: Important features which are extracted from images.
- Decision Making: The recorded features are compared with those stored in the database, and a decision is made based on the results of this comparison.

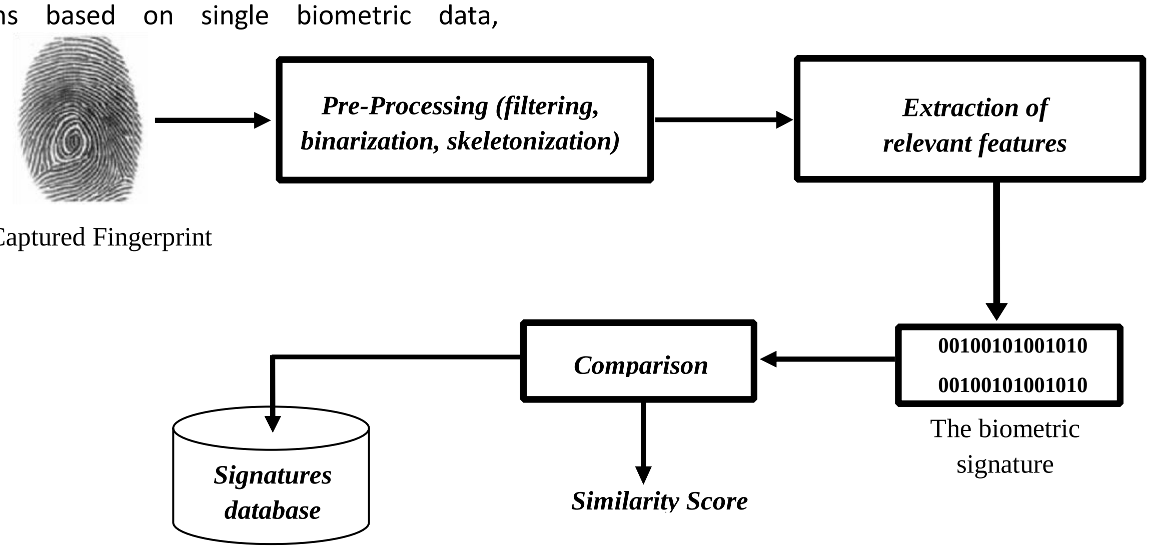

Figure 1: Design of a biometric system based on fingerprints

B. Finger Knuckle Print

Finger knuckle print (FKP) is a new type of biometric mode that has been successfully used to recognize people by the contour and texture of the outer surface of the finger, as shown in Figure 2. These linear structures and textures are very effective in distinguishing between different individuals because they are relatively stable and fixed, does not change during life [10-13].

FKP mode can be used due to some of the advantages of biometric systems. First, acquiring data with low-resolution commercial cameras is relatively easy and inexpensive. Second, FKP based access systems are ideal for both indoor and outdoor use and can perform well in extreme weather and low light conditions. Third, the features of FKP in adults is more stable over time and does not undergo major changes. However, biometric information based on FKP is very reliable and can be successfully used to identify multiple persons [13].

Figure 2: Some images of the finger joints fingerprints [11]

The purpose of this article is to develop a hybrid features based multimodal biometric identification system using deep convolutional neural networks. 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 article presents multimodal biometric identification using GLCM and wavelet moments features extraction, followed by hybrid feature classification based on convolutional neural networks with a random forest classifier. There are two input patterns for proposed multimodal biometric identification i.e. fingerprint and finger knuckle images. Figure 3 shows the proposed system modal. The following sections describe the materials and methods used in various stages of experimentation and data processing. Below are the details of each block.

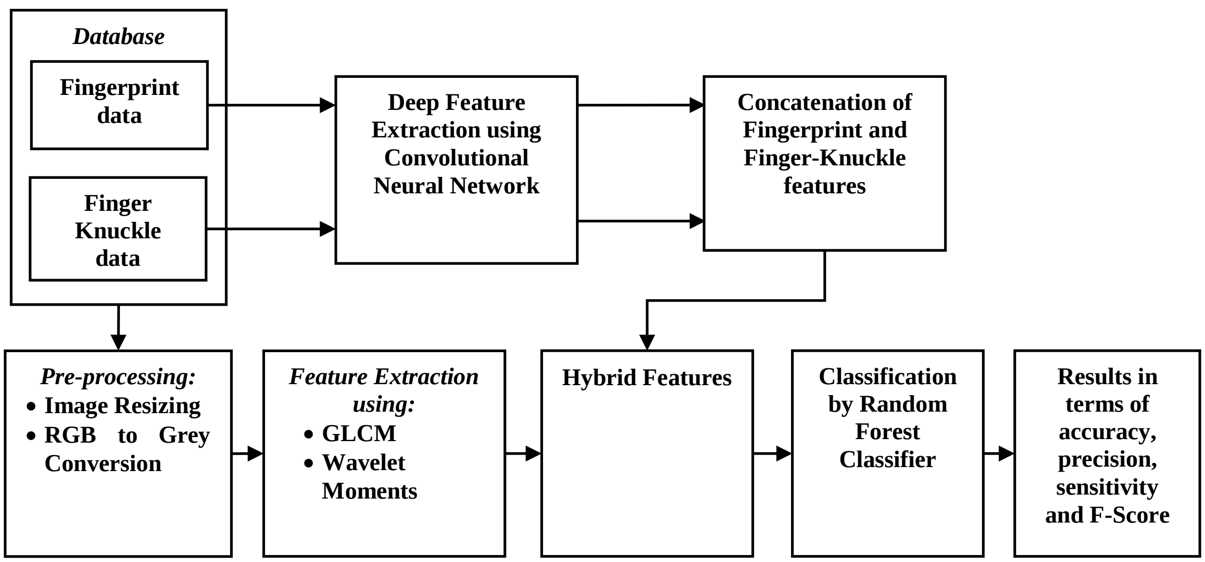

Figure 3: Block diagram of proposed hybrid features based biometric identification

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

The convolutional neural networks or CNNs by its initials are a specialized type of neural networks recommended for the processing of data with a topology in the form of mesh or grid. CNNs have been applied to many tasks with great success. Recently the level of human sight has been surpassed in terms of image recognition thanks to the utilization of a deep convolutional neural network [14].

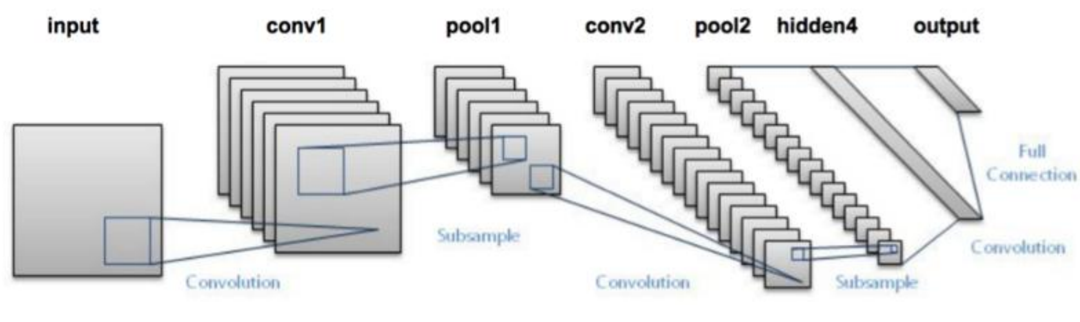

Figure 4: Typical architecture of a deep convolutional neural network [15]

The Operation of Convolution: In its most general form, a convolution is an operation applied to two functions with real numbers as arguments. The operation of convolution is defined by the following mathematical expression [16]:

$$s(t) = \int x(a)w(t-a)da \tag{1}$$

Commonly the convolution operation is symbolized by:

$$s(t) = (x * w)(t) \tag{2}$$

Using the terminology associated with convolutional neural networks, the first term (in this case (x)) of the convolution operation is often referred to as input, while the second argument (in our case w) it's called kernel. The output or result of the operation or convolution is usually called a feature map. When working with a computer, discrete data will be available, so that what used to be an integral function of logical functions, will have to become a sum of "discrete" functions also continuous, of the following shape:

$$S(t) = (x * w)(t) = \sum_{a=-\infty}^{\infty} x(a)w(t-a) \tag{3}$$

In deep learning applications, the input is usually a vector of several dimensions (tensor), and the kernel is often a multidimensional vector of parameters that are modified by the learning algorithm. For example, if it is used as input data, an image I, the most frequent is that a two-dimensional kernel is used, which in this case we will denote as K:

$$S(i,j) = (I * K)(i,j) = \sum_m \sum_n I(i-m, j-n)K(m,n) \tag{4}$$

B. Pre-Processing for Second Phase

The previous subsection detailed about the first part of methodology and the second phase starts from this section.

1. Initially, the input image is resized to 224×224 pixels using the built-in resizing function available in MATLAB.
2. After resizing, the face image in RGB format is converted to grayscale using the rgb2gray function if the input image is colored.

C. Feature Extraction

The goal of extracting feature in image processing field is to express the feature in numerical or symbolic form called encoding. Depending on the case, the values of these features can be real, integer or binary. The vector composed of n features represent a point in the new space of n dimensions. The steps involved in feature extraction are shown in the block diagram in Figure 3 using two feature extraction methods explained in following subheadings.

1. Gray Level Co-Occurrence Matrix (GLCM)

Gray level co-occurrence matrices are constructed from the analysis of pairs of pixels for a distance and orientations given between them.

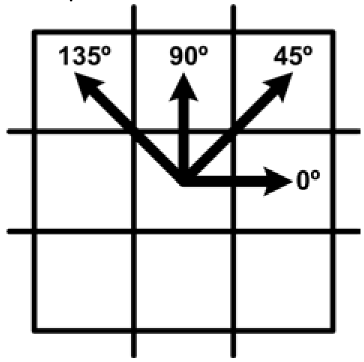

Figure 5: GLCM distribution [17]

Below are some measures of detection of texture features [18]:

- Angular Second Moment (ASM): It is also called uniformity. The higher the ASM, the greater uniformity (less variation in gray levels), if the ASM is 1, the image is completely uniform.

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

- Contrast: It is the amount of local variations in the shades of gray in the image. The greater the variation in shades of gray, the greater the contrast.

$$\sum_{i,j=0}^{N-1} P_{i,j}(i-j)^2 \tag{6}$$

  If the contrast is 0, the gray levels are constant throughout the image.
- Correlation: It is the linear dependence of the shades of gray in the image:

$$\sum_{i,j=0}^{N-1} P_{i,j} \frac{(i-\mu_i)(j-\mu_j)}{\sqrt{(\sigma_i \sigma_j)}} \tag{7}$$

  If the correlation is 0, there is no linear correlation between the gray levels.
- Entropy: It is a measure of the complexity of the image. The greater the entropy, the greater the complexity.

$$\sum_{i,j=0}^{N-1} P_{i,j}\left(-LnP_{i,j}\right) \tag{8}$$

- Inverse Difference Moment (IDM): It is also called homogeneity. The IDM increases when the contrast between the pixel pairs decreases.

$$\sum_{i,j=0}^{N-1} \frac{P_{i,j}}{1+(i-j)^2} \tag{9}$$

Each one at three distances (1, 5 and 10 pixels) and four orientations (0º, 45º, 90º and 135º), and their corresponding mean values as shown in Figure 5.

2. Wavelet Moments

Wavelet transform is used to decompose low frequency images in order to distinguish high frequency components, 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 the M image results in a subset shown as [1]:

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

To further reduce the size of the input, DWT can be applied N times to obtain a level N decomposition. Thus, the drawing at the end of the four-step DWT can be represented as follows:

$$M = M_a^4 + \sum_{i=1}^{4}\{\{M_h^i + M_v^i + M_d^i\}\} \tag{11}$$

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 applies Fourier transforms to change the image from the time domain to the frequency domain. The DWT mathematical expression is defined as follows:

$$DWT_{x(n)} = \begin{cases} dd_{j,k} = \sum img(n)hh^*{}_s(n - 2^s r) \\ ap_{j,k} = \sum img(n)ll^*{}_s(n - 2^s r) \end{cases} \tag{12}$$

Here $ap_{j,k}$ resembles the approximate coefficients and $dd_{j,k}$ represents the detailed coefficient of DWT. The functions $ll(n)$ and $hh(n)$ are low-pass and high-pass filters, respectively. The r and s parameters are the translation ratio and wavelet scale, respectively.
We should be interested in images or areas with a uniform texture so that the mean and standard deviation are expressed as follows:
Mean: for a vector of random variables A, consisting of N scalar observations, the mean is determined as [1]:

$$\mu_{mn} = \frac{1}{N}\sum_{i,j=1}^{N} ap_{ij} \tag{13}$$

Where the approximation coefficient ap_{ij}, N of scalar observations, μ_{mn} is the mean of the wavelets.

$$\sigma_{mn} = \sqrt{\frac{\sum_{i=1}^{m}\sum_{j=1}^{n}(|I_{mn}(i,j)| - \mu_{mn})^2}{N-1}} \tag{14}$$

Here, $I_{mn}(i,j)$ represents the observed values of the items in the sample, μ_{mn} is the mean of those observations, and N is the number of observations in the sample. σ_{mn} is the standard deviation of the wavelet value.
The wavelet moments is generated with σ_{mn} and μ_{mn} as feature components:

$$f_g = (\mu_{00}, \sigma_{00}, \mu_{01}, \sigma_{01} \dots \dots . \mu_{45}, \sigma_{45}) \tag{15}$$

D. Classification by Random Forest Classifier

Breiman (2001) presented a random forest with the following very general definition [20]:
"A random forest is a classifier consisting of a set of basic decision tree type classifiers, which are defined as":

$$\{h(x, \Theta_k),\ k = 1, \dots L\} \tag{16}$$

Let $\left(\hat{h}(\Theta_1), \dots, \hat{h}(\Theta_q)\right)$ be a set of predictive trees with $\Theta_1, \dots, \Theta_q$ independent random variables $\mathcal{L}_n$. The $\hat{h}_{RF}$ random forest predictor was obtained by adding this set of random trees as follows:

- $\hat{h}_{RF}(x) = \frac{1}{q}\sum_{l=1}^{q} \hat{h}(x, \Theta_l)$, the mean of the predictions of individual trees in the regression.
- $\hat{h}_{RF}(x) = \operatorname{argmax}_{1 \le k \le K} \sum_{l=1}^{q} 1_{\hat{h}(x,\Theta_l)=k}$, the majority of votes of individual forecast trees in the classification.

The term random forest comes from the fact that individual predictors are explicit here for predictors for each tree, and each tree depends on an additional random variable (i.e., different from $\mathcal{L}_n$).
The classification process followed by the random forest method consists of [20]:

1. Assignment to a node if it is terminal, deciding whether a node will be labeled as a sheet or it will carry a test.
2. If the node is not terminal, then we have to select a test to assign it.
3. If the node is terminal, then we must give it a class.

The general algorithm for decision trees is as follows:
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 decision tree A is obtained
Exit: decision 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

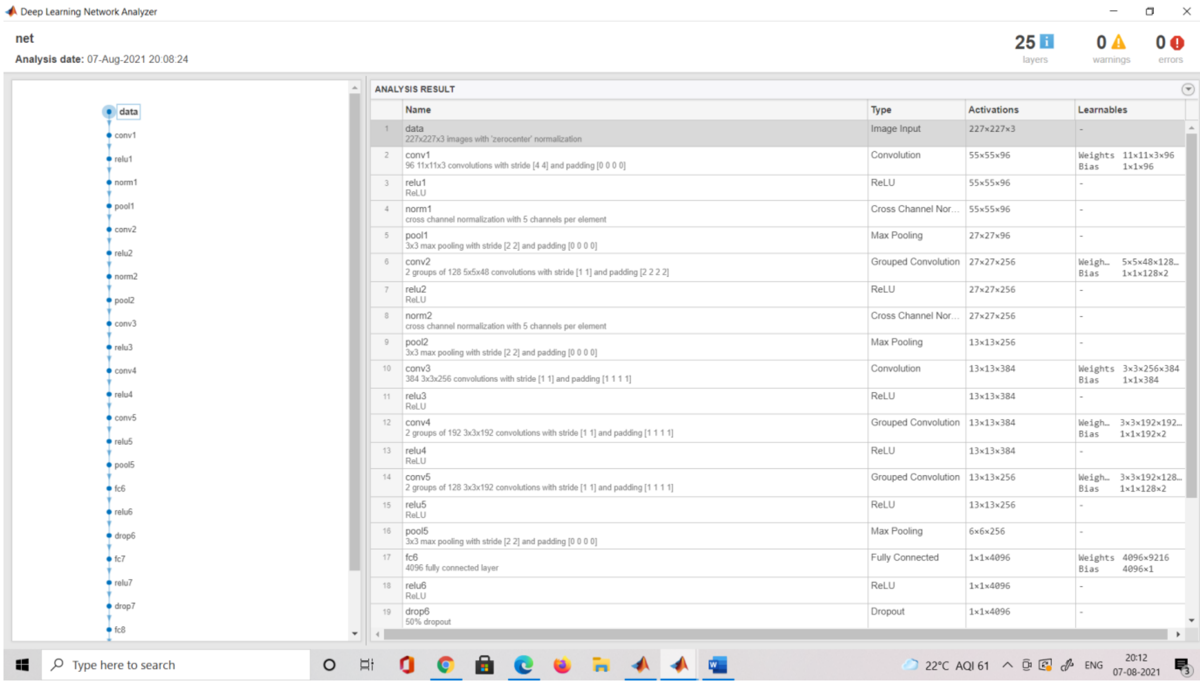

Figure 6: Convolutional neural network analysis -1

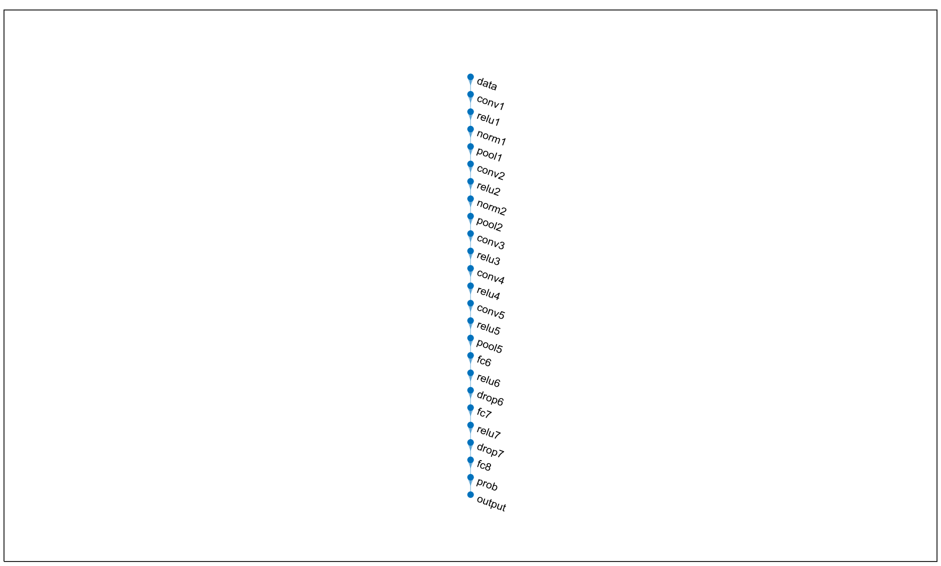

Figure 7: Convolutional neural network analysis -2

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. Hybrid features are obtained using GLCM, wavelet moments and deep features. For the classification stage, Random Forest classifier is used. The important thing is to choose well a specific training dataset for the data environment with which you later want to test. The performance of the proposed method has been tested in the experimental studies carried out. When the three different feature extraction methods are considered, it is seen that successful results are achieved with a maximum accuracy of 98.33%.

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