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Research Article

IRIS RECOGNITION BASED ON WAVELET TRANSFORM USING SUPPORT VECTOR MACHINE AND DECISION TREE COMBINATION CLASSIFIER

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ABSTRACT
As the digital world grows, using of biometric systems is becoming more important. Biometric identification or authentication is used commonly for the security of places such as universities, airports, ministries and even computer networks. Among the methods of biometric identification, iris recognition systems have gained much attention because of the complex and rich tissue of iris which provides strong biometric measures to identify individuals. In this paper, wavelet transform on three levels was used to extract features from the iris image with some features. With respect to the features extracted from the image of an iris, the feature vector contains 62 features and because of the use of geometric features, the extracted features were rotation invariant. To reduce the effect of very large values in the matrix of features, the extracted features were normalized in interval [0,1]. To reduce the dimensions of the features and speeding up the computation, the matrix of feature extraction was given to a principal component analysis algorithm to separate more important features. Finally, the achieved features are classified by a combination of support vector machine and decision tree classifier. Obtained results indicated the effectiveness of the algorithm on UBIRIS database.

Keywords: *Iris, Wavelet Transform, Support Vector Machine, Decision Tree*

INTRODUCTION
Along with the increasing need for security, biometrics works as a solution for identifying people. This concept is based on structural and behavioral features. Among the structural features are fingerprint, face, and the iris and behavioral features include autograph. The iris biometrics is employed as an important element in the system of identification because of its uniqueness in different people as well as stability of the iris tissue during life. This system increases the detection rate and decreases the false acceptance rate. Thus, the system is reliable and has high security.
Dougman (1993) was the first who provided an iris recognition system based on multi-scale Gabor wavelet transform. Wilds (1997) used the gradient of a binary map of the image edge and Hough transform to determine the boundary of the pupil and the iris. Monroe *et al.*, (2007) presented a new method for the iris coding based on the difference between the Discrete Cosine Transform (DCT) coefficients of angled pieces with an overlap. In another study, Roy *et al.*, (2008) applied Gabor wavelet transform to extract feature as well as the genetic algorithm as a method of feature selection. Chen *et al.*, (2009) used one-dimensional signals and then used one-dimensional energy signals to reduce the complexity of the system and one-dimensional wavelet transform to reduce the feature vector. In another study, Rajan *et al.*, (2010) adopted wavelet transform for the iris tissue feature extraction, and calculated seven features using the co-occurrence matrix on the sub-bands obtained from the analysis of the image by wavelet transform.
In this paper, a method was provided for extracting features from the iris image using 2D wavelet transform in the frequency domain and morphological features in the spatial domain. After feature extraction, the extracted features are normalized. Next, using the principal component analysis (PCA) algorithm the dimensions of the features decrease. Finally, the support vector machine and decision tree combination classifier is employed for classification, which is described in the following.

MATERIALS AND METHODS

Method

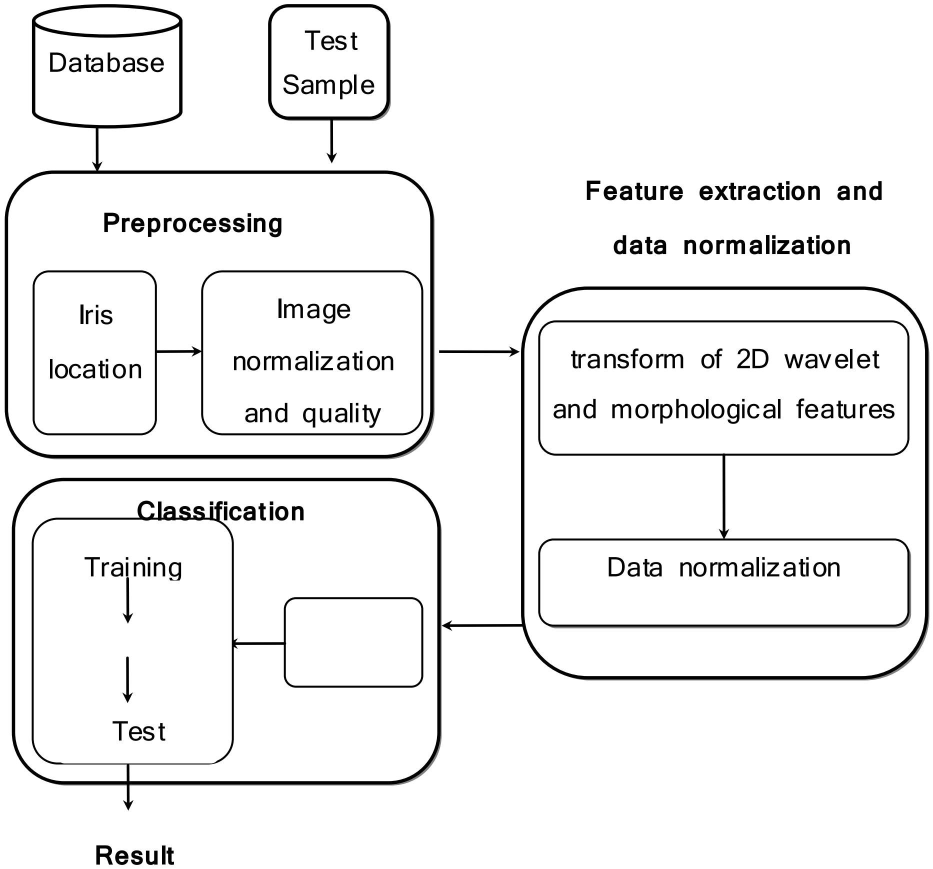

Figure 1: The Structure of the System

The proposed the iris recognition system includes 3 key steps: 1) preprocessing, 2) feature extraction and data normalization, and 3) feature selection and classification. Figure 1 shows the structure of the proposed system.

Preprocessing

The image taken from the iris does not only include the desired area, but also unhelpful areas such as eyelid and the pupil. Therefore, it cannot be directly used. In addition, the position of the eye and the camera can affect its quality. For example, if the distance of the person with the camera becomes smaller or larger, the size of the iris changes. In addition, the noises in the environment also have a great impact on image quality. For this purpose, a primary processing of the iris should be performed on the iris location, the iris normalization and improving the image quality.

*The iris location and identification of the affected areas***:** The iris is located between the pupil and sclera. Thus, at this point the internal borders (the iris/the pupil) and external borders (the iris/sclera) should be determined. To specify the borders of the pupil, given that the pupil is darker than other areas; the image becomes binary by choosing an appropriate threshold. The threshold value equals the maximum value between 0 and 100 on the image histogram. Noise caused by cilia removed by the morphology operator and finally the coordinates of the center and radius of the pupil is calculated through the following equation (1):

$$X_p = (x_{max} + x_{min})/2 \qquad (1)$$
$$Y_p = (y_{max} + y_{min})/2$$

Where, X_p and Y_p are coordinates of the center of the pupil and x_{max}, x_{min}, y_{max} and y_{min} are the maximum and minimum values of Y and X axes. Finally, the radius of the pupil is calculated by relation (2):

$$\begin{aligned} R_1 &= x_{max} - x_{min} \\ R_2 &= y_{max} - y_{min} \end{aligned} \qquad (2)$$

R_1 and R_2 are estimation of the pupil radius. Here, the greater values are considered as the pupil radius.
Before specifying the external border, gamma correction (Masek, 2003) is employed to improve the image contrast. Non-maxima suppression is used to zero pixel values proportional to weak edges, so that only the dominant edges are produced. Finally, having the center of the pupil, the coordinates of the iris center and radius is obtained by Hough transform.
In the past, many methods have been provided, in which only the upper or lower part of the iris containing no important information are used to remove noise caused by the eyelid and eyelashes. In the proposed method, to access more valuable information, the iris is divided into four effective areas:

1. Corner right area with a sector between -π/4 and π/4 and a radius equal to the radius of the iris.
2. Upper area with a sector between π/4 and 4π/5 and a radius equal to 1/3 of the iris radius.
3. Corner left area with a sector between 4π/5 and 4π/3 and a radius equal to the radius of the iris.
4. Lower area with a sector between 4π/3 and -π/5 and a radius equal to 1/2 of the iris radius.

Iris image normalization and quality improvement: The irises of different people may vary in size and even the size of the iris of the same eye may vary based on the changes in the distance from the camera as well as in the light.
These changes have a considerable effect on the adjustment. To get accurate results, compensation caused by these changes are required. Thus, the image is mapped using "Daugman Rubber Sheet" model from the Cartesian coordinates to polar coordinates (Daugman, 1993).
Since the act of identification is performed using the patterns in the iris tissue, the captured image must be of good contrast quality. Depending on the shooting conditions and the location of the light source, the ambient light may not be uniformly distributed across the iris surface. Therefore, in the proposed method, first the histogram equalization is normalized on the image of the iris and then the linear wiener filter is applied on the output of the histogram equalization as shown in Figure 2.

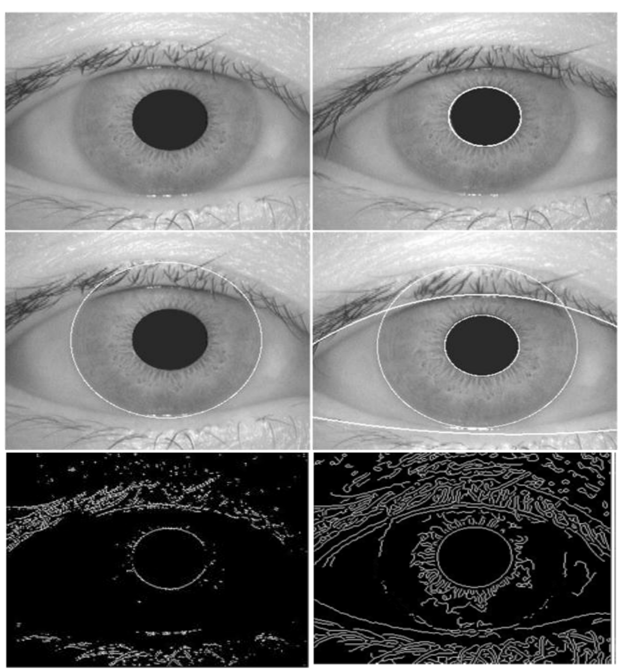

Figure 2: Output of Wiener Filter

Feature Extraction and Data Normalization:
Feature extraction is among the important steps in identification systems. Thus, the extracted features must be invariant toward issues such as scale and rotation. The iris patterns will be Scale invariant (resistant) through opening the iris area and its mapping to a rectangular region with a fixed size. In addition, in the proposed method, the iris patterns will be rotation invariant due to the use of morphological features. The extracted features will be explained in the following.
Wavelet transform: Recently wavelet transform has been extensively used in signal processing. An important advantage is providing high time Resolution in high frequencies and good frequency resolution in low frequencies. Because of the excellent local ability in time and frequency, wavelet transform can reveal local characteristics of the input signal. The multi-scale characteristics by wavelet transform decomposes a pattern to different scales, each displaying a specific coarseness of the signal (Scholl, 1999). Wavelet transform has different bases that each produces different results in different applications. The results of several bases are discussed in the experimental results section.
The multistage decomposition process of the wavelet from signal X[n] is shown in Figure 3. As seen in Figure 3 is a high-pass filter g[n] and a low-pass filter h[n] are employed in the decomposition process (Haralick, 1973).

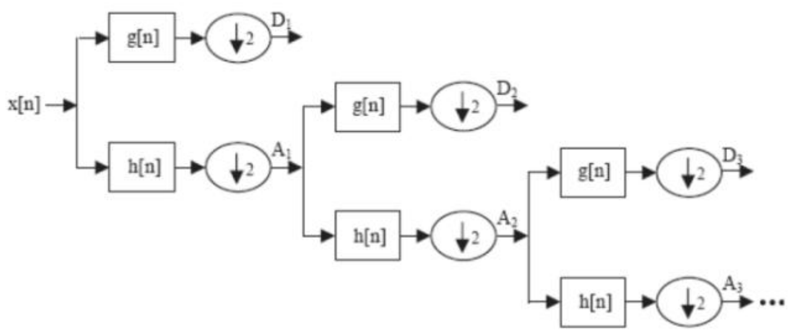

Figure 3: The Process of Multi-Level Wavelet Decomposition of the Signal x[n]

After applying the two-dimensional wavelet transform to two levels, the Approximation coefficient of the final level is used as the feature vector.
Morphological features: The 1st level histogram of gray surfaces shows the probability of a gray area occurrence in the image as shown in Figure 4. The 2nd tilevelme histogram is denoted by $H(y_q, y_r, d)$, also known in some references as the co-occurrence matrix. The co-occurrence matrix is one of known methods in tissue analysis. This matrix shows the probability distribution of a pair of gray surfaces occurrence which the displacement vector d specifies their relative position. Although the co-occurrence matrix extracts some features of the tissues but it cannot analyze the tissue. Therefore, the number of features that can be provide important information from the tissue are calculated offer by the occurrence matrix in different directions (Soh and Tsatsoulis, 1999; Clausi, 2002; Becq *et al.*, 2005).

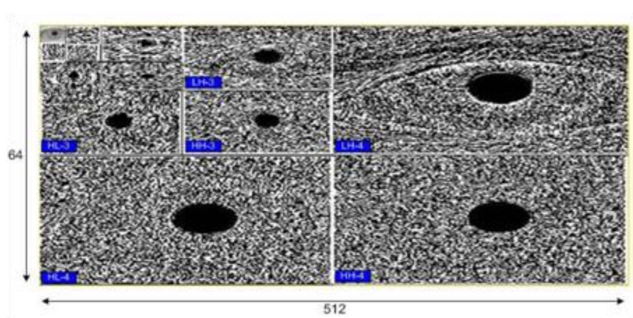

Figure 4: Histogram of Gray Surface

Geometric features (Veluchamy, Perumal and Morgan Ponuchamy, 2012, p. 616): Geometric features are as follows: area, perimeter, form factor, roundness, the ratio of the large diameter to the small diameter of the iris, convexity (curvature of the iris inside or outside), area of the smallest bounding box to the iris, solidity, eccentricity, difference area, elongatedness. In order to have a better recognition system some of these features related to the border of iris are used (Yun *et al*., 2007).

Features associated with the iris border: Features which are selected to be sent are as follows: (average NRL, Radial distance criteria SD, roughness index, zero crossing, sub-borders).

Features associated with Fourier transform: From border related features, the following features are created: (average Fourier, Fourier variance, Fourier energy, Fourier irregularity, energy for bending).

Statistical properties of tissue (Veluchamy, Perumal and Morgan Ponuchamy, 2012, p. 616): It is better to separate statistical properties of feature for better recognition and concatenate them to the other features. They are histogram average, histogram variance, histogram skewness, histogram kurtosis, histogram energy, histogram irregularity (Yun *et al*., 2007).

Wavelet transfer tissue features: Features that come up after apply wavelet are energy and entropy of low frequency components, horizontal high frequency components, vertical high-frequency components, diagonal high-frequency components and range of frequency components of the image (in the horizontal and vertical alignment).

In the proposed method, each of the iris patterns is extracted in the location and frequency domains of 62 features. These features obtained from db2-base wavelet transform of Iris images. Therefore, by combining the features of location and frequency domains, the feature vector is obtained as follows:

$F= [f_1\ f_2\ f_3 \dots f_{18}\ f_{19}\ f_{20}\ A_2]$ (3)

Data normalization: To reduce the effect of infinite values, to prevent features with large values from overcoming those with small values and to fix problems in the feature selection process (Peng *et al*., 2005) each value of the feature matrix are normalized in interval [1, 0]. To perform the operation, many methods were investigated among which $\bar{\chi}_{ij} = \chi_{ij} / (max(\boldsymbol{\chi}_j) - min(\boldsymbol{\chi}_j))$ increased the efficiency of the system. Here, $\boldsymbol{\chi}_j$ is a vector of independent features.

Reducing the dimensions of features: In training and testing artificial intelligence systems, data or features extracted from the data is important. Magnitude of the feature vector dimensions increases the complexity of the classification, and sometimes the system precision is reduced because of waste features. Through some examination, the PCA algorithm was selected to reduce the dimensions of the features. Given the specific vector resulting from the features extracted from the training data and labels related to these data, the PCA algorithm combines the components of the feature vector so that the training data could be retained with lower number of features. In the proposed method, with regard to the precision of 95% the important features were retained and other combined features were removed, i.e. considering the measures taken, only 12 of the 62 features were retained as the combined effective features and the rest was removed.

Classification

The classifier discussed in this article, is a support vector machine and decision tree combination classifier. First the support vector machine classifier is applied on the training data and the results will be analyzed. The flaw that can be taken for this method is the low-speed classification. To improve and expedite the classification, the data that are sufficiently distant from the support vector machine classifier are classified using C4.5 decision tree classifier. The steps are shown in Figure 5 (Kumar and Gopal, 2010). As seen in Figure 5, the classification steps are as follows:

1. Classification of training data using the support vector machine classifier
2. Determining the threshold to specify the proximity of the separator vector
3. Construction of the decision tree with training data; data that are distant enough from the dividing line take their own label and data that are located near the dividing line take separate label (0).
4. Applying the decision tree algorithm on the test data
5. Applying the support vector machine on data which are labeled (0) by the decision tree.

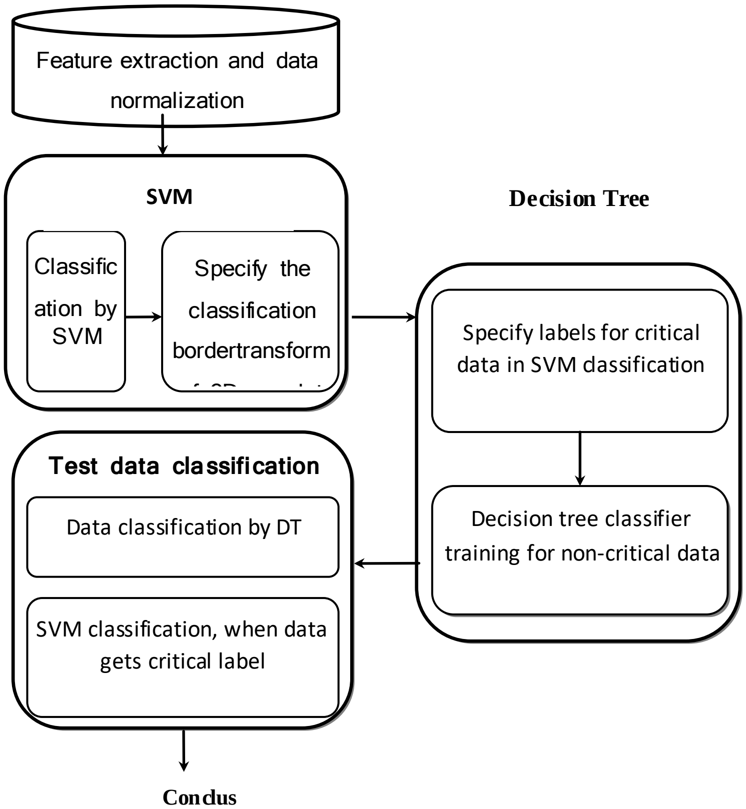

Figure 5: Classification Approach in the Proposed Method

RESULTS AND DISCUSSION

Experimental Results

In this paper, the performance of the system was tested by the UBIRIS database (2015). The database contains 756 image of 108 people, i.e. each person has 7 images each taken within an interval of a month. Three images are taken in the first month and next fourth image are taken in the second month.

The features extracted from the pattern of the iris contain two features in the location and frequency domains. To achieve the frequency domain features the db2-base wavelet transform was used and each of the four areas are normalized so as to decompose 2 effective levels and only the second level features estimate coefficient obtained in the frequency domain are used. As described in the previous section, 62 features is extracted from each the iris images and after applying the PCA technique, only 12 features are used. Then the support vector machine and decision tree combination classifier is used for classification. Considering the value of 0.2 for the threshold parameter, the best results will be obtained. Experiments are performed on all images in the database, i.e. 756 images of 108 people and 7 per person. The K-fold method is used to estimate the precision of the system and k = 5, i.e. 20% of the data is considered for the test and 80% for training. The precision of the system should equal the average precision of the whole process.

To extract feature of wavelet transform based on tests conducted (Figure 6), the type of wavelet used has a significant effect on the precision of the system so that the comparison of precisions of different bases indicate wavelet transform with different feature (Figure 6). The results of this comparison showed that db2 with an average precision of 99.20% for 488 features will have the best performance while db5 with the highest average precision of 98.41% for 550 features will have the minimum performance.

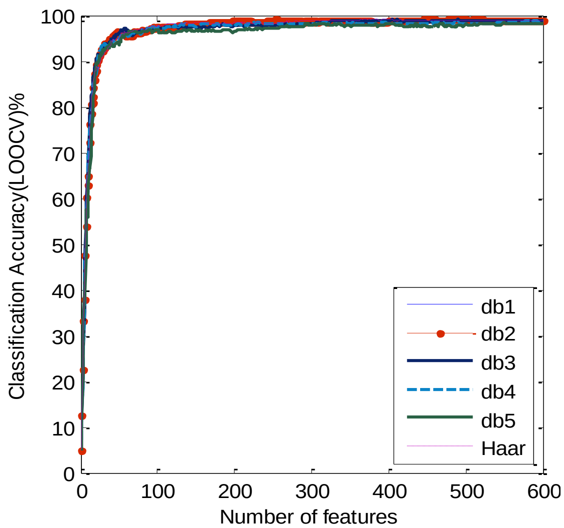

Figure 6: Comparison of Average Precision of Different Wavelet Bases Transformation with Different Numbers of Features

Table 1 shows the features extracted from the iris in the location and frequency domains. A total of 62 features are calculated. After normalizing the feature matrix, the output is given to the PCA algorithm. Select 12 features, the best average precision can be achieved. The results of applying the PCA algorithm on the features listed in the Table 1, shows that the use of only 12 features can provide precision higher than 95% and at the same time the complexity of the algorithm sufficiently decreases.

Table 1: Calculated Features in the Spatial and Frequency Domain

Covered Features (%)	Features Number
90.41	10
95.36	12
95.45	20
97.73	30
98.82	40

Table 2 depicts the percentage covered for a number of features intended in the PCA method. The best coverage percentage seems to be achieved by 12 features, which covers 95% of the information. As the table clearly shows, changes are tangible before the value of 12, but then the coverage slowly increases.

Table 2: Accuracy Evaluation Achieved from Smoothing Parameters

Accuracy of Algorithm (%)	Methods
100	Daugman[J.G. Daugman,1993]
99.81	Roy *et al.*,[K.Roy,2008]
99.35	Chen *et al.*,[C.H.Chen.2009]
99.31	Poursaberi *et al.*,[A.Poursaberi,2007]
99.20	Proposed method (average precision)
100	Proposed method (maximum precision)
99.34	Proposed method without SVM
99.87	Proposed method without DT

In Table 3, comparison is made between different methods and the results of the proposed algorithm are presented.

Table 3: Comparison between Different Methods

Feature	Feature Name
f1	Auto-correlation [D.A. Clausi ,2002]
f2	Contrast [L.Soh,1999], [D.A. Clausi ,2002]
f3	Correlation [L.Soh,1999], [D.A. Clausi ,2002]
f4	Cluster Prominence [D.A. Clausi ,2002]
f5	Cluster Shade[D.A. Clausi ,2002]
f6	Dissimilarity[D.A. Clausi ,2002]
f7	Energy [L.Soh,1999], [D.A. Clausi ,2002]
f8	Entropy [D.A. Clausi ,2002]
f9	Homogeneity [D.A. Clausi ,2002]
f10	Maximum Probability [D.A. Clausi ,2002]
f11	Sum of Squares Variance [L.Soh,1999]
f12	Sum average [L.Soh,1999]
f13	Sum Variance [L.Soh,1999]
f14	Sum Entropy [G.Becq,2005]
f15	Difference Variance [L.Soh,1999]
f16	Difference Entropy [L.Soh,1999]
f17	Information Measure of Correlation1 [L.Soh,1999]
f18	Information Measure of Correlation2 [L.Soh,1999]
f19	Inverse Different Normalized [G.Becq,2005]
f20	Inverse Different Moment Normalized [G.Becq,2005]
A2	Approximation coefficient in levele2

Conclusion

In this paper, a new method was proposed for classifying the features extracted from the iris image using combination of support vector machine and decision tree classifier. The advantages of this method are as follows: First, the SVM classifier precision is higher than other classifiers in AI issues. Second, the speed of the decision tree classifier is higher than other classification algorithms. Third, with the combination of these two classification algorithms it was proved that not only the precision diminished but it enhanced. Fourth, PCA could be employed as a powerful way to reduce the dimensions of the features and finally, using K-Fold, the precision of the system is estimated. Average and maximum precisions are 99.20% and 100% respectively. These results show the effectiveness and reliability of the proposed system.

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