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A Novel Biometric Authentication System for Blind People Based on Finger Vein and Iris

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For blind persons, a new finger vein and iris-based authentication system using Gray Level Co-occurrence Matrix (GLCM) as a feature extractor and Convolution Neural Network (CNN) as a classifier is presented. In this paper, both the left and right finger vein and iris images of blind people are collected to achieve high-level security. GLCM is preferred to extract the desired features in terms of entropy, energy, dissimilarity, homogeneity and correlation. CNN is used to enhance classification accuracy. In the Python platform, the proposed method is simulated and verified. The performance of the suggested authentication system is superior to the existing systems, according to the experimental analysis. It can achieve Recognition Rate (RR), Equal Error Rate (ERR) and accuracy as 99.92%, 0.26% and 99.8%.
Keywords: Convolutional Neural Network (CNN), Gray Level Co-occurrence Matrix (GLCM), authentication system, Region of Interest (ROI), CNN, Finger vein and Iris.

1. Introduction

Due to the advancement in digital technology, the huge amount of information is stored digitally in computers, mobile phones, internets, government systems, etc [1]. So everyperson needs to protect their personalinformation from others and they preferred knowledge and token-based approaches traditionally to protect their information. The passwords need to be remembered in knowledge-based approaches and key can be stolen in token-based approaches. To mitigate these issues, a biometric authentication system is developed to recognize the personsindividually with the aid of their human biometrics [2].

Personal authentication is vital in today's digital world because it allows security systemsto validate specific people.. The proper andperfect authentication is preferred to manage multiple operations in automobile security, industries, factories, airports, e-commerce, etc [3-5]. This biometric authentication reflects thebehavioral characteristics of the individuals bytaking their samples such as face, iris, fingerprint, palm vein, etc. Anyone of the factors for authentication sometimes generates negative impacts [6] and so multiple factors arecombined in a hybrid manner to frame a highlysecured system.

The authentication system using a fingervein generates high security than other human biometrics. It denotes distinct blood vessels forevery individual and it is more secure in terms of its location. In human beings, the finger veinsare placed beneath the skin of the body which cannot be damaged easily. So it can generatehigh security than authentication systems using fingerprints [7].

The negative impact in fingervein-based authentication systems during weather conditions is lesser than otherbiometric-based authentication systems. This method has some demerits as irregular illuminations conditions, misalignment, etc [8].

An iris-based authentication system is preferred to protect the information in database management applications because of its uniquefeatures. It protects the personal information of individuals from fraudulent activities [9]. The texture features from the iris can be computedby multiple patterns such as circles, zigzag,crypts, furrows, etc. In human beings, the irispattern will never change in their full life and soan iris-based authentication system will easily recognize the individuals. The difficulty of this approach is in the image acquisition part because it acquires eyelashes, eyelids, etc that obstruct the recognition efficiency of the device [10].

In this paper, a novel hybrid biometricauthentication system is proposed for blind people using their left and right finger veins and iris. Image acquisition, pre-processing, segmentation, feature extraction, and classification are the main processes in thisrecognition system. Region of Interest (ROI) selection and canny edge detection algorithms are favoured for the segmentation procedure. Gray Level Co-occurrence Matrix (GLCM) is used to extract the features. The Convolution Neural Network (CNN) is then used to accurately categorise the characteristics. Finally, the matching algorithms SURF andFast Library for Approximate Nearest Neighbours (FLANN) are employed to determine if it is recognised or not.

The following is the remainder of this research paper's part. Section 2 discusses biometric recognition systems, various human biometrics, and their benefits and drawbacks. Section 3 explains the proposed methodology in detail. Section 4 describes the simulation results and performance evaluation. Finally, Section 5has the concluding section.

2. Related Works

Different researches are carried out by researchers to mitigate the issues presented in the biometric authentication system. ManishaSapkale et al presented a biometric authentication system using finger veins [11]. In this approach, fractal dimension, lacunae andGabor filter are used for extracting the features.Then the extracted features are classified with the help of a distance classifier. Since it isreliable and low error rate, it consumes more time for the verification process. SubhaFairuz et al designed a CNN-based finger veinrecognition system with high accuracy. It can be attained by using 4 fully connected layers and 5 convolution layers in the classification process [12]. The limitation behind this approach is that it needs to access a massive amount of data for achieving high accuracyleads to more access time.

SamerChantaf et al designed a palm vein- based recognition system suitable for real-time security applications [13]. In this approach, thephotos of the palm veins are taken with the assist of a near-infrared camera. The neuralnetwork is preferred for performing the matching operation with high accuracy. Using the Ridge Energy Direction (RED) method, Hau Ngo et al devised a real-time iris recognition system. The Gaussian kernel is utilised to extract the edge pixels from the iris during the pre-processing procedure. The RED algorithm is used to obtain the rectangular matrix during the feature extraction procedure [14]. Then two directional filters are applied tothe rectangular matrix for generating the binaryvalues: '1' denotes the valid pixel and '0' denotes the noise. Finally, Hamming distance ispreferred for template matching.

The modified version of XOR sum code [15] was proposed by RiteshVyas et al as a feature descriptor for the iris identification procedure. The authors use the IITD and CrossEyed databases to assess the suggested approach's effectiveness. The proposed strategyhas a 37 percent lower equal error rate (EER) than the current method.. But this approach is not applicable for smartphone-based iris recognition. Ismail Boucherit et al presented a merged CNN-based approach and Contrast Limited Adaptive Histogram (CLAH) for finger vein identification [16]. Merged CNN isa combination of multiple CNNs that accepts multiple input images. The limitation of this approach is that it is applicable only for a limited number of training images.

Lu et al [17] presented a finger vein recognition system by combining multiple features to enhance the system performance. It used the CLAHE approach for enhancing the image quality and Gabor filters to extract the Gabor features. Meng et al [18] presented a finger vein recognition system using deformation information. PolyU and SDU- MLA database is preferred to show the performance of the system. Huabin Wang et al presented a finger vein recognition system using weber local descriptors (WLD) and Gabor filter [19]. WLD is used for enhancing the images and Gabor filter is used forextracting the features. Appasamy et al designed a finger vein and iris-based authentication system [20]. In this method, ROIand canny edge detection algorithms are used for segmentation, GLCM is used for feature extraction and Artificial Neural Network (ANN) is used for classification. But the error rate of these approaches is little bit higher.

3. Proposed Method

A novel authentication system is proposedespecially for blind people by exploiting two different approaches as GLCM and CNN. In this research, finger vein and iris are preferred as human biometrics. The biometric authentication system performs its operations intwo phases as enrolment and verification. For the enrolment process, multiple finger vein andiris images of the blind people are collected. The research approach can be divided into five components for the verification process: pre- processing, segmentation, feature extraction, classification, and matching. Figure 1 depicts the suggested authentication system's block diagram.

During the training and testing phases, thisauthentication process is carried out. During the training phase, a large number of blind people'sfinger vein and iris images are collected and stored as a dataset. The finger vein and iris images are acquired in the testing phase, and the features are then matched with the dataset that was saved during the training phase.The noises are removed in the pre-processing stage to obtain the normalised image. After that, the ROI and canny edge detection algorithms are used to segment the data. To obtain the desired characteristics, GLCM is applied to the segmented images. CNN is utilised toaccurately classify the extracted characteristics.Finally, the features are matched using the SURF and FLANN algorithms, and the authentication output is obtained.

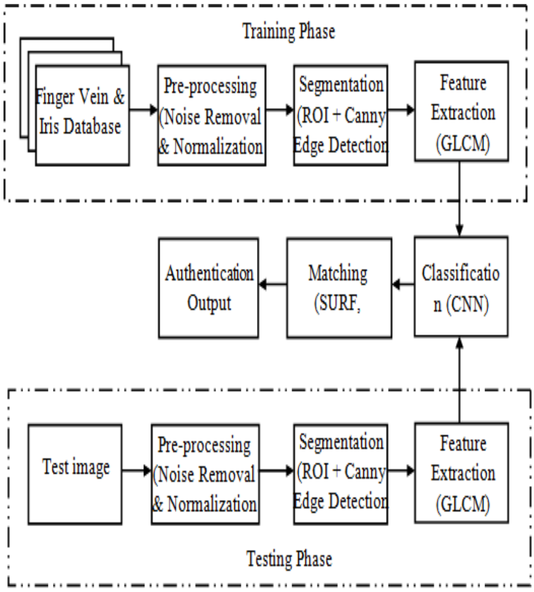

Figure 1. Block Diagram of proposed novelauthentication system

Pre Processing

The images captured from the image acquisition device not only captured the specific iris part and finger vein but also captures some undesired parts. So, pre- processing of images is necessary for further real-time processing. Pre-processing is used foreliminating undesirable distortions and enhancing the feature contents. In this process, the RGB color image is converted into a grayscale image, because edge detection and intensity computations are better in grayscale images than color images

The contrast limited adaptive histogram equalisation (CLAHE) method is desired in this proposed system to improve image visibility. It is a more advanced variant of adaptive histogram equalisation that differs from the contrast limiting aspect of adaptive histogram equalisation. In this approach, the pixels are transformed by applying the enhancement function to the nearby pixels. The processes involved in this approach are image division, mapping over tiles, gray level mapping generation, histogram clipping and enhanced image formation. It enhances the intensity of the images and reduces the noises presented in the finger vein and iris images. Since this process is carried out in the Python ecosystem,the NumPy arrays are used for image reshapingand digital filters are used for further noise reduction.

Segmentation

Segmentation is used for separating the particular iris and finger vein parts from the eyeand finger images of blind people because thesesegmented parts are enough for the authentication process. This process is carried out with the assist of ROI selection and canny edge detection. The undesirable information is removed using ROI selection, and the edges offinger vein and iris images are detected using acanny edge detector.

ROI Selection

ROI is used as the segmentation approach that detects the object within a specific image. In this proposed method, it is used for determining the image fitted within the finger vein and iris. It eliminates the undesirable part of the image and gives the desirable image partwhich is suitable for further process. Here, the computation of image pixels is carried out withthe aid of masking operation. In masking operation, the pixels which are located away from the region point are set as '0' and the remaining pixels are set as '1'. Thus the binarymask is generated and it can easily separate thedesirable features from the background of the iris and finger vein images. The desirable area is segmented in the shape of a circle, oval, rectangle, polygon, etc. The extraction of required features leads to the reduction in computational complexity and enhancement inoverall system performance. The undesirable part elimination in the iris and finger vein images enhanced the reliability as well as accuracy. After completing the ROI selection, the canny edge detection algorithm is used for detecting the edges.

(i) Canny Edge Detection

The features obtained from ROI selection are fed as input to the canny edge detection for detecting the edges effectively in the particularregion. The processes involved in canny edge detection algorithm are noise reduction, gradient computation, non-maximalsuppression and edge thresholding. Initially, toremove the noise in the image region, a Gaussian kernel is utilised. This is done byperforming a convolution operation with the input image, which can be computed using the following expression.

$$g(i,j) = G_\sigma(i,j) * f(i,j) \quad (1)$$

Where $G_\sigma = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left[\frac{-(i^2+j^2)}{2\sigma^2}\right]$, σ denotes the kernel parameter, i and j represent the image pixels. Then gradient computation is carried out in both vertical and horizontal directions. It ismeasured by determining the magnitude and phase and it can be computed by the following mathematical expressions.

$$|Mag(i,j)| = \sqrt{g_x(i,j)^2 + g_y(i,j)^2} \quad (2)$$

$$\theta(i,j) = arctan\left[\frac{g_y(i,j)}{g_x(i,j)}\right] \quad (3)$$

The obtained gradient values determine the edges in thin and thick regions. But, it is in irregular form and so non-maximal suppressionis applied on the gradient intensity values. Thismethod can easily generate the gradient magnitudes in the same direction. Then double threshold approach (high threshold and low threshold) is fed on the gradient magnitudevalues to determine the weak, strong and irrelevant pixel intensity.Strong edge points aredefined as gradient values that are greater than the high threshold value. Non-edge points are those where the gradient value is less than the low threshold value. Weak edge points are defined as gradient values that fall between thelow and high threshold values.

Feature Extraction

The segmented images are fed as input to the GLCM which is one of the most effective feature extraction methods. It extracts the features by determining the textural relationship between the pixels. Based on the brightness of the pixels, it determines the frequency of the pixels of segmented finger vein and iris images. It represents the image asa matrix that contains the gray level values equal to the number of rows and columns. In this approach, 0^o, 45^o, 90^o and 135^o are used to construct the co-occurrence matrix which playsa significant role in extracting the statistical features.

Let NxN be the matrix size, Pij be the co- occurrence matrix, (i,j) be the element indicating the frequency of pixel values in relation to grey level values, i be the neighbourhood pixel value, and j be thereference pixel value. Gray level image and GLCM are illustrated with an example is shownin Figure 2. The input image taken here as an example contains 8 gray level values is shown in Figure 2a. The relationship between the reference and neighbour pixels with respect to the horizontal orientation is shown as the GLCM matrix in Figure 2b.

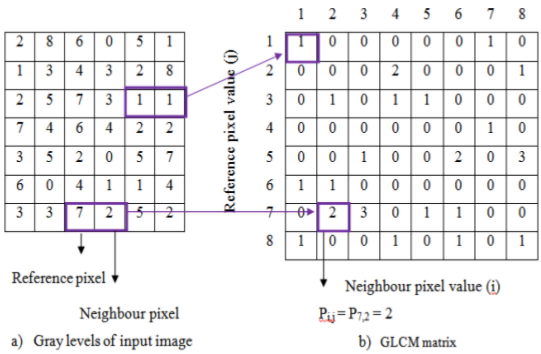

Figure 2 Gray levels of the input image and GLCMmatrix

Based on its statistical characteristics, GLCM computes different texture features such as mean, variance, standard deviation, entropy, energy, contrast, dissimilarity, correlation, homogeneity, cluster shade, etc. In this proposed research work, entropy, energy, homogeneity, correlation and dissimilarity are derived as features from finger vein and iris images of blind people. These features can be computed by the following expressions

$$Entropy = \sum_{i,j=0}^{N-1} P_{i,j}\left(-ln\ P_{i,j}\right) \quad (4)$$

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

$$Homogeneity = \sum_{i,j=0}^{N-1} \frac{P_{i,j}}{1+(i-j)^2} \quad (6)$$

$$Correlation = \sum_{i,j=0}^{N-1} P_{i,j} \left[\frac{(i-\mu_i)(j-\mu_j)}{\sqrt{(\sigma_i^2)(\sigma_j^2)}} \right] \quad (7)$$

$$Dissimilarity = \sum_{i,j=0}^{N-1} P_{i,j} |i-j| \quad (8)$$

Classification

In this proposed authentication system, CNN is used as a classifier to classify the extracted features obtained from GLCM. The efficacy of CNN relies on the properties ofextracted features. Here, the extracted features from the finger vein and iris are fed to CNN for classification. CNN is termed as a supervised learning module and training classifier suitable for image authentication applications. This learning approach exploits multiple layers for processing their parameters. The CNN used in the proposed authentication consists of the following layers: (1) 5 convolution layers, (2) 3max-pooling layers and (3) 3 Rectified Linear Unit (ReLU).

The process of max-pooling layers and ReLU can be computed by the mathematical expressions (9) and (10).

$$Y = \sum_{i=1}^{N-1} z_i k_{n-i} \quad (9)$$

Here, x denotes input map, Y denotes output map, k denotes filter and N denotes the elements count in z.

$$f(z) = \max(0, z) \quad (10)$$

Here z denotes the input which is fed to the neuron.

The softmax function is used to get fully convolution layer output, and it may becomputed using the following expression.

$$S(r,i) = -log\left(\frac{e^{z_i}}{\sum_{i=1}^{N} e^{z_j}}\right), \text{ i} = 1,2,.. \text{ j} \quad (11)$$

Here, r denotes the output neurons.The detailedarchitecture of the CNN classifier can be described as follows.

- L1: It is the input layer having the size of [88x88] is same as the size of iris and finger vein images. The single-channel formation in this process omits the unnecessary computations.
- L1M1: It is the first hidden layer and consists of 64 convolution filters which have the size of [3x3x1]. In this stage, the size of the max pooling layer is [2x2] and the ReLU activation function is [2x2]. In this layer, the input data is converted into CL1M1 which is

composed of [42x42x64]features.

- L2M2: It is a second hidden layer and the number of convolutional filters in this stage is 128. Every convolutional filterhaving the size of [3x3x1], max pooling layer having the size of [2x2] and ReLU activation function having the size of [2x2]. In this layer, the input data is converted into CL2M2 which is composedof [19x19x128] features.

- L3M3: It is a third hidden layer and the number of convolutional filters in this stage is 128. Every convolutional filterhaving the size of [3x3x128], max poolinglayer having the size of [2x2] and ReLU activation function having the size of [2x2]. In this layer, 20% probability ispreferred to avoid the interconnection between the first and second layers. In thislayer, the input data is converted into CL3M3 which is composed of [9x9x256] features.

- L4M4: It is a fourth hidden layer termed asa fully connected layer and its process in a flattening manner that means it transformsthe 2D array into a linear vector. Here, thesize of the feature is [1x1x20,736].

- L5M5: It is the last hidden layer that acts as the feature descriptor for the features get from finger vein and iris images. Finally, the label prediction is carried out by the softmax function.

Matching

SURF and FLANN algorithm is used for matching the feature descriptors obtained from CNN process. SURF uses box filters for findingthe Gaussian difference and to perform the approximation. The matching operation using SURF is faster because it computes the convolution in parallel rather than Gaussianaverage computation. In this matching algorithm, the points are detected with the assistof a Hessian matrix-based blob detector. Wavelets are applied in both directions to predict the orientation of feature descriptors. Inthis matching operation, the same contrast features increase the speed of the matchingprocess. It also equipped the hamming distance to match the descriptors and it can be computed by the following expression.

$$HD = \frac{1}{N - \sum_{k=1}^{N} Xn_k + Yn_k} \sum_{j=1}^{N} (X_j \oplus Y_j).Xn'_j.Yn'_j \quad (12)$$

Here X_j, Y_j denotes the bit-wise elements takenfor comparison; Xn_j, Yn_j denotes the noise mask representation of bit-wise elements and Ndenotes the number of elements.

For further improvement in the accurate matching process, FLANN algorithm-based matcher is preferred. In this proposedauthentication system, FLANN is preferred because it is suitable for applications that haveamassive amount of data set and high order features. It is a collection of multiple optimization approaches applicable for matching the feature descriptors faster.

4. Results and Discussions

In this research work, the biometric authentication system is designed for blind people and it uses their finger veins and iris forthe recognition process. For experimental analysis, 3816 left and right finger vein imagesand 460 left and right iris images are collected as a dataset. The iris images are taken in Near Infra-Red (NIR) range to get highly rich features. The proposed authentication system suitable for blind people is verified in the Python platform which contains the OpenCV library.

The images captured from the image acquisition process are fed to pre-processing which gives the normalized image feasible for further process. It includes the operation of grayscale conversion, noise removal and normalization. The pre-processing process carried out for the right and left iris images is shown in Figure 3.Since this research focused on two different human biometrics, the pre- processing is also carried out for left and right finger veins and it is shown in Figure 4.

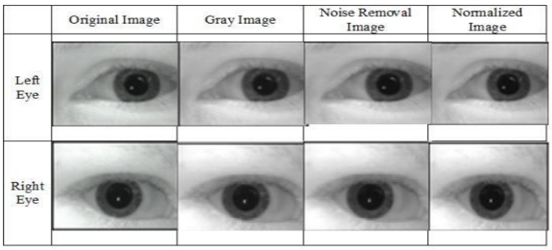

Figure 3. Pre-processing stages of left and right eyeimages

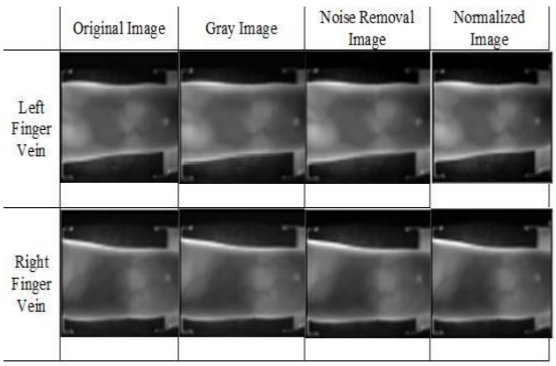

Figure 4. Pre-processing stages of left and rightFinger vein images

After completing the pre-processing operation,a ROI selection canny edge detector is used to segment the pre-processed finger vein and iris pictures. Figure 5 shows the ROI selection and segmentation output of the left and right iris images, while Figure 6 shows finger vein images.

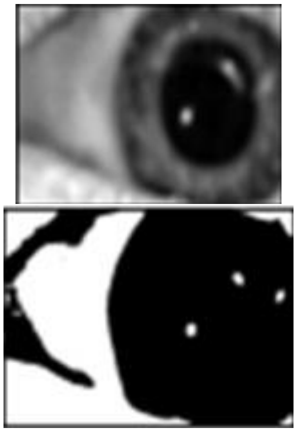

Figure (5a.) ROI and Segmented output of left eye

Figure (5b.) ROI and Segmented output of right eye

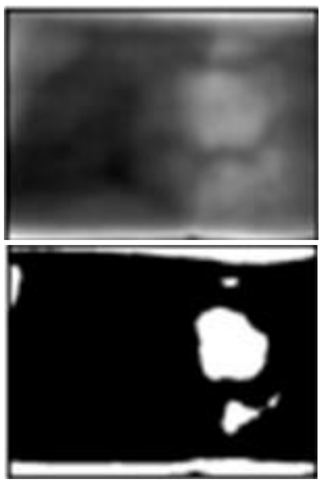

Figure (6a.) ROI and Segmented output of left Fingervein

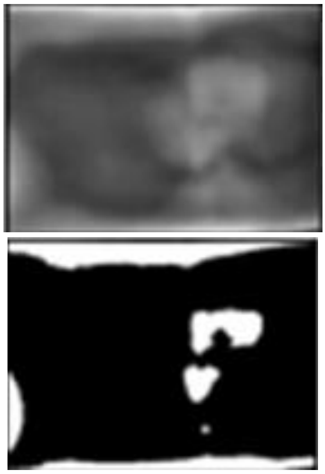

Figure (6b.) ROI and Segmented output of RightFinger vein

The segmented image outputs are fed as input to the GLCM for extracting the features such as energy, entropy, correlation, dissimilarity and homogeneity. These features are classified using CNN and finally matching is performed using SURF and FLANN. The feature descriptors in the iris image are matchedwith the finger vein image and it is shown in Figure 7.

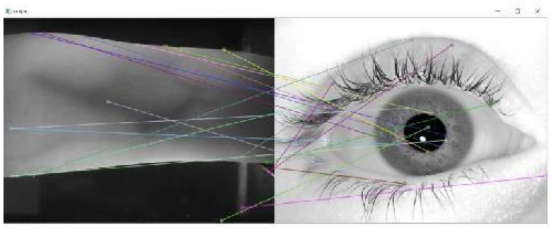

Figure 7. Matching output

The performances of the proposed biometric authentication system are evaluated in terms of recognition rate (RR), equal error rate (ERR) and accuracy. The RR and ERR of the proposed authentication system are compared with the existing authentication system and it is tabulated in Table 1

Table 1. RR comparison of authentication systems

Authentication system	Biometrics used	Methods used	RR (%)
Lu et al [17]	Finger vein	CLAHE, Gabor filters	98.79
Meng et al [18]	Finger vein	Dense SIFT	94.01
Dat Tien Nguyen et al [1]	Iris	CNN, SVM	96.15
H. Wang et al [19]	Finger Vein	DCG WLD	99.42
Ahmed A Mustafa et al [8]	Finger vein	CLBP, POC	98.95
K. Appasamy et al [20]	Finger vein and iris	GLCM, ANN	99.21
Proposed authentication system	Finger vein and iris	GLCM, CNN	99.92

From the tabulated results, it is observed that the RR of the proposed authentication system is better than existing authentication systems. TheRR of proposed authentication system is increased by 1.13%, 5.91%, 3.77%, 0.5%, 0.9% and 0.7% when compared with the existing authentication system mentioned in [17], [18], [1], [19], [8] and [20] respectively. The ERR ofthe proposed authentication system is comparedwith the existing techniques and it is shown viacomparison graph in Figure 8.

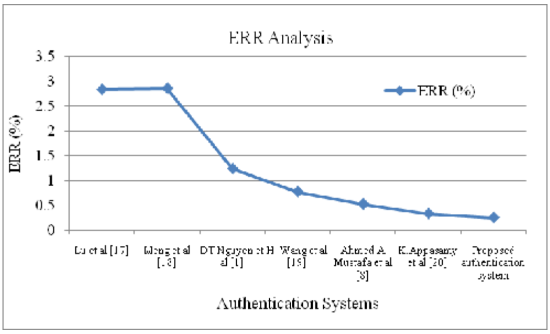

Figure 8. ERR comparison of authenicationsystems

The ERR of proposed authentication system is lesser than existing authentication systems is shown in Figure 8. The proposed authenticationsystem designed for blind people has lesser ERR by 90.84%, 90.90%, 79.03%, 66.66%, 50.94% and 30.76% when compared with the authentication systems cited as [17], [18], [1], [19], [8] and [20] respectively. The accuracy of the proposed authentication system is compared with the existing approaches is tabulated in Table 2. Theaccuracy can be computed by the following expression

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \times 100 \quad (13)$$

Where TP denotes true positive, TN denotes true negative, FP denotes false positive and FN denotes false negative.

Table 2. Accuracy comparison of authenticationsystems

Authentication system	Accuracy (%)
Lu et al [17]	96.3
Meng et al [18]	96.9
Dat Tien Nguyen et al [1]	98.1
H. Wang et al [19]	97.4
Ahmed A Mustafa et al [8]	96.5
K. Appasamy et al [20]	98.4
Proposed authentication system	99.8

From the tabulated results, it is observed that the accuracy of the proposed authentication system is increased by 3.50%, 2.90%, 1.70%, 2.40%, 3.30% and 1.40% when compared with the existing techniques such as [17], [18], [1], [19], [8] and [20] respectively.

5. Conclusion

An effective finger vein and iris-based authentication system is designed for blind people. It enhanced the security by utilizing twodifferent biometrics as iris and finger vein. Thissystem used CLAHE for enhancing the qualityof images, ROI selection and canny edge detection approach for segmenting the images without distorting any desired features. It used GLCM for extracting the desired features and CNN for classifying the features. It can attain high accuracy of 99.8% due to the utilization ofCNN. The error rate of the proposed authentication system is low as 0.26%.

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