**Multimodal of Ear and Face Biometric Recognition Using AARK Threshold segmentation and Classifier with Score level fusion**

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**Abstract:**
More than one biometric methodology of an individual is utilized by a multimodal biometric system to moderate a portion of the impediments of a unimodal biometric system and upgrade its precision, security, and so forth. In this paper, an incorporated multimodal biometric system has proposed for the identification of people utilizing ear and face as input and pre-preparing, ring projection, data standardization, AARK limit division, extraction of DWT highlights and classifiers are utilized. Afterward, singular matches gathered from the different modalities produce the individual scores. The proposed framework indicated got brings about the investigations than singular ear and face biometrics tried. To certify the individual as genuine or an impostor, the eventual outcomes are then utilized. On the IIT Delhi ear information base and ORL face data set, the proposed framework has checked and indicated an individual exactness of 96.24%

**Keywords:** Ear recognition, Face recognition, multimodal recognition, DWT Feature Extraction, AARK threshold segmentation, ANFIS classifier and CART classifier.

1. **INTRODUCTION:**

Multimodal biometrics dependent on the mix of two separate face and ear biometric modalities offer another way to deal with non-obtrusive biometric validation. To pick face and ear for a multimodal biometric recognition, there are many inspirations. Using traditional cameras, ear and face data can be collected during image acquisition. The processing of data in the face and ear does not require the user's involvement or cooperation. The facial and ear highlights are in close actual nearness to one another. In an image or video taken from the top of an individual, all biometric qualities are mutually present and are both open to a biometric gadget. The combination of face and ear biometrics shows strong outcomes in accuracy and recognition [1, 19, 20] in the earlier writing work.

As other biometrics have been investigated, the utilization of ears as a biometric for human ID has not been concentrated as seriously. Despite the fact that examination here is moderately
restricted, there was a ton of guarantee in utilizing the ear as a biometric for human ID in the exploration that was finished. An obvious piece of the human body that can be utilized in a non-obtrusive biometric method is the neck, much like the face. To be able to hear, humans would most likely have to keep their ears open. In contrast to the face, the ears are not influenced by maturing, truly the ear goes through just minor changes from the earliest stages to adulthood, infarct lengthening because of gravity is the lone modification that happens. As the face does, the ears likewise don't endure the move in appearance by hair development. These are on the whole stars for biometric utilization of the ears [2].

As of late, face recognition has been concentrated a great deal and numerous calculations, work extraction methods and grouping procedures have been produced for this reason, yet everything comes down to the effectiveness of the extraction of the element. Numerous factors, including temperament, well being, beard growth and outward appearances, are inclined to facial qualities. This is a characteristic hindrance to the utilization of the face as a legitimate method of recognizing people. The element extraction strategy utilized should manage the current material, so the condition of the face introduced will determine the end result [3] regardless of how great the element extraction technique utilized is.
The recognition process in this work is separated into two key stages. Each progression is seen as an unmistakable perceived. This implies that if an individual is to be known, it needs to have two pictures of individuals, one is the ear and the other is the face, mirroring each picture to be perceived independently, Fig. 1 shows a proposed work from singular information bases on the ear and face biometric acknowledgment measure. To recognize that individual effectively, each image should be appropriately distinguished to have a place with that individual. The various informational collections utilized with their relating acknowledgment rates are talked about in the development of this work. A strategy for coordinating the consequences of the arrangement of individual pictures to show up at a solitary choice utilizing score level combination is likewise given.

The rest of this paper has contained the following sections. In section 2, related work of ear and face biometric recognition has narrated briefly. The section 3 discussed the proposed system of this work. In section 4, the results and discussion of the proposed system simulation, experimental were shown and discussed. Finally, the section 5 concludes the proposed work.
2. RELATED WORK:
This section discusses the previous work of significant research into the multimodal biometric method. For various sensors, the highlights of the face or different pieces of the person have various properties. Contingent upon the information of the individual obtained for ID purposes, each biometric boundary might be described as better or more terrible. Table 1 sums up the various highlights of multi-modal biometric considers.

TABLE 1: REVIEW OF MULTI - MODAL BIOMETRIC USING EAR AND FACE

| Authors                  | Datasets               | Biometrics | Technique Used | Performance of Classification in Percentage | Total Subjects were used |
|--------------------------|------------------------|------------|----------------|----------------------------------------------|--------------------------|
| Darwish et al. [4]       | Yale and MIT          | Ear + Face | PCA            | Accuracy of 92.24%                           | 15                       |
| S.M.S. Islam et al. [5]  | UWA                    | Ear + Face | 2D Iterative storeroom point | Accuracy of 93.8%                            | 56                       |
| Zengxi Huang et al. [6]  | USTB and Yale         | Ear + Face | SRC            | Accuracy of 95.732%                           | 79                       |
| Xu Xiaona et al. [7]     | USTB                   | Ear + Face | KPCA, Kernel Fisher Discrimant Analysis (KFDA) | Accuracy of 94.52%                           | 79                       |
| M.H. Mahoor et al. [8]   | West Virginia University database | Face + Ear | Weighted sum technique | Accuracy of 95%,                             | 402                      |

A multi-biometric framework is presented by A.A. Using face and ear. [4]. Darwish et al. In finding the covariance matrix’s own vectors, PCA decorrelates results. For usage, MIT, ORL and Yale information bases are utilized. The individual pictures of the face and ear are standardized and preprocessed, at that point converted into the space of the PCA. The proficiency of the technique is 92.24%. It inferred that face and ear combination is a fruitful procedure in view of its high exactness and security.

S.M.S. Islam et al.[5] gave the timetable extraction of neighborhood 2D highlights from ear and face biometrics and their course of action at the component and score levels for distinguishing proof. 2D features removed from the ear are fused at the feature level with frontal facial details. By a weighted sum law, L3DF scores and the iterative closest point algorithm were merged at
the matching stage. With non-neutral face, this device achieved accuracy rate recognition and verification of 93.8%.

Sparse Representation (SR) proposes the multimodal strategy for face and ear at include level combination by Zengxi Huang et al. [6]. Scanty Representation based Classification (SRC) and Robust Sparse Coding were the SR-based characterization strategies utilized in the arrangement cycle (RSC). At last, along with Multimodal SRC with highlight weighting (MSRCW) and Multimodal RSC with include weighting, they have acquired a gathering of multimodal acknowledgment strategies dependent on SR (MRSCW).

Xu Xiaona et al.[7] propose a novel bit based component combination calculation approach in the mix of face and ear. The component combination approach was acquainted and applied multimodal biometrics dependent on the ear and profile face biometrics combination, in blend with the KPCA or KFDA calculation. This plan decides the normal law, the item rule, the weighted-total principle in the piece based combination technique and the examination of the USTB information base. The investigation shows that the exact rate was 94.52 percent, and that strategy is proficient for includes combination level.

H. Mahoor et al.[8] proposed utilizing a weighted total methodology with 2D face and 2D ear combination at the degree of match scores. To determine an assortment of facial tourist spots from frontal facial pictures, the Active Shape Model is utilized. An assortment of edges is extricated from a video cut for ear acknowledgment, and the ear territory is rebuilt in 2D in each edge utilizing the Form from Shading (SFS) calculation. By methods for the iterative nearest point (ICP) calculation, the subsequent 2D ear models are adjusted. The framework's effectiveness was expanded up to 95%.

3. PROPOSED METHODOLOGY:
The proposed strategy of the work included is recorded in this part. To improve the exactness of the acknowledgment framework, multimodal biometrics [21-25] of the ear and face are incorporated. The example ear and face picture perceived in the proposed framework appear in figure 1. Two diverse facial and ear modalities are applied here. The acknowledgment stage comprises of preprocessing, division, extraction of highlights and orders. To limit or eliminate a portion of the distinctions in the information picture, the info face and ear pictures are preprocessed. It upgrades the picture to improve the framework's acknowledgment proficiency. From the info, image, structure and surface highlights are removed. A shape work is the utilization of the changed territory, expanding calculations to remove the state of the face and ear. At long last, the class has been utilized to survey the precision of recognition.

3.1. Preprocessing
Binarization is the basic preprocessing form. If images are converted to binary images, they are used for different procedures, such as reducing noise, filling or eliminating possible holes, improving the test area and protecting against disconnection [9].

3.2. Ring Projection

For the translation of 2D images into 1D vectors, ring projection is carried out [10]. Let \( M \) and \( N \) denote \( T(c, d) \), and the origin of the denotes of the template \((x_0, y_0)\) is transformed into polar synchronization from the Cartesian organization \( T(c, d) \). As a ring projection rate, \( PT(r) \) denotes 'T' as a template and 'r' as a radius.

\[
P_T(r) = \frac{1}{S} \sum_{\theta=0}^{2\pi} T(r, \theta) \quad 0 \leq r \leq R \quad (1)
\]

Where, \( r \in [0, R] \), \( r = \text{(int)}\sqrt{(c - x_0)^2 + (d - y_0)^2} \) \( R = \min(m, n) \). \( T(r, \theta) \) denoted as the pixel value point in \((r, \theta)\). The pixel intensity in the formula based on \( PT \) is defined in fig.3 by the centered circle of template \( T(r) \). Due to the unchanged value of \( PT(r) \) expressed by any pixel of an image as a concentric rotation, \( PT(r) \) is rotation invariant.

![Figure 2: Ring Projection](image)

With the use of the look up table, template size is tailored based on changed width, it is easy to define a circle concentric by useful outcomes. Depending on the search table, approximate integer size values are generated. As a vector in the ring projection, the concentric circle with the pixel values is concluded in the template.

\[
P_T = [P_T(0), P_T(1) \ldots \ldots P_T(R)] \quad (2)
\]

Respectively, the ring projection vector of sub image are assigned as,

\[
P_T = [P_T(r_1), P_T(r_2) \ldots \ldots P_T(r_N)] \quad (3)
\]

The normalized ring projection with correlation among \( P_T \) and \( P_S \) is given as,

\[
< P_T, P_S > = \frac{\sum_{r}^{R} [P_T(r) - P_T] \times [P_S(x, y) - P_S(x, y)]}{\sqrt{\sum_{r}^{R} [P_T(r) - P_T]^2} \sqrt{\sum_{r}^{R} [P_S(x, y) - P_S(x, y)]^2}} \quad (4)
\]

3.3. Information Normalization

The non-linear approximation is used in a gray scale image to vary or normalize the pixels [11]. For changing the pixels, two different methods are used. Translation will be the first approach. The pixel is located at \((l, k)\) with the pixel value \( y_{orig} \), which is used to test the normalized pixel values through linear translation:

\[
y_{new} = y_{orig} - y_{back} + c \quad (5)
\]

\[
y_{new} = \frac{y_{original}}{y_{back}} \cdot C \quad (6)
\]
C will be adjusted to the value 255, for creating the white color background to ensure that the pixel rate does not exceed 255.

3.4 AARK Segmentation
For mathematically determining the basic problems, the AARK segmentation algorithm is used. Using the RK equation with the 4th order method, using the method of lines, a numerical differential equation was originally solved. Using a scheme of linear equations with a completely different pattern based on the 4th order equation system, the Adaptive Approach Runge-Kutta (AARK) algorithm solved the fundamental problem. By applying the RK 4th order method [12], the precise threshold value for the ear contour of the face image was obtained. In threshold segmentation, the value obtained from the above method could be used to evaluate the value of the threshold in the image. The threshold value computation involves the following equations:

\[ P_{i+1} = q_i + \frac{1}{6} (s_1 + 2s_2 + 2s_3 + s_4) \]  
(7)

\[ s_1 = f(p_i, q_i) \]  
(8)

\[ s_2 = f(p_i + \frac{1}{2} h, q_i + \frac{1}{2} s_1 h) \]  
(9)

\[ s_3 = f(p_i + \frac{1}{2} h, q_i + \frac{1}{2} s_2 h) \]  
(10)

\[ s_4 = f(p_i + h, q_i + s_3 h) \]  
(11)

Where: \( t = t_0 + i h \), ‘h’ represented as time step size. Here \( s_1, s_2, s_3, s_4 \) refers to the slopes and \( p_i, q_i \) denote the point of arguments. The RK with adaptive segment method is an efficient practice for removing the over segmented areas. From the input image each pixel incorporates the shifting and adding technique along with segmented image. Any single pixel could make use of the adding and shifting method. By evaluating the total number of cubes through adding and shifting each cube the unnecessary components are extracted from the Pixel Cube. The Adaptive coefficients p and q are also evaluated. Finally the consolidated value is found by calculating the sum of each pixel values. It eliminates the unnecessary Pixel components.

3.5 DWT feature extraction
Discrete Wavelet Transform (DWT) gives an efficient localization for space-frequency when computed with Fourier’s conventional analysis[13].

\[ W_\phi(j_0, k) = \frac{1}{\sqrt{M}} \sum_x f(x) \phi_{j_0, k}(x) \]  
(12)

\[ W_\psi(j, k) = \frac{1}{\sqrt{M}} \sum_x f(x) \psi_{j, k}(x) \]  
(13)

Here \((t)\) the mother wavelet might be commonly denoted. ‘b’ is called translation of factor and as a factor is represented ‘a’. In its first step, the suggested method uses specially built LL sub-bands. HH/HL/LH represents the image of the low-dimensional real ear and also protects valuable image details.

3.6 Classifier
Two different forms of classifiers, namely CART and ANFIS, are being sued. The tree of classification and regression is the classification in pattern recognition of the nonparametric process. In order to find the precise classification accuracy, it requires the creation and
identification of the decision tree using training data. The high volume of data can be classified by the classification and regression tree. When further division is applied, the decision tree increases continuous division in the calculation of impurity [18]. There can be two types of subsets, i.e. start point and end point of the feature space, binary decision tree organized rules. To define the vectors acquired by extracting features, the ANFIS classifier is primarily used. Classifiers assume a significant job in estimating the exactness of the activity. The ANFIS classifier is utilized here to consolidate the ANN and Fuzzy arrangement calculations [14]. The calculation keeps on being performed until the normal blunder is gotten. Among the six layers present in the ANFIS design, five are covered. The classifier model has an information grid which aggregates all the highlights got. In view of the attributes got from the DWT, the Fuzzy shows are produced. Two participation positions here are utilized as high and low.

3.7. Score Level fusion
For each methodology, highlight vectors are created independently. For each biometric attribute to deliver coordinated evaluations, removed component vectors contrasted and the layouts living in the information base exclusively. The yield assortment of match scores that are joined to make a composite coordinating score relies upon the accuracy of and biometric channel. For example, the match score of the face and hand modalities can be consolidated by utilizing the straightforward whole principle to get another match score that is then shipped off the choice module [15].

4. RESULTS AND DISCUSSION:
Test results that were acquired from the proposed face and ear recognition system are given. From the start level face and ear calculations are tried independently. At this level the individual outcomes are processed.

4.1. Compared with existing classification outputs with the proposed work classification outputs

Figure.3 illustrates the comparison resultant images with existing classification methods and a proposed classification method.

| Ear Input Images | CNN [17] | PCA [18] | SVM [18] | Proposed CART | Proposed ANFIS |
Table 2: Comparison results for Accuracy of using Ear images

| Sl:No | CNN [14] | PCA [16] | SVM [16] | Proposed CART | Proposed ANFIS |
|-------|----------|----------|----------|---------------|---------------|
| Ear1  | 0.266    | 0.455    | 0.824    | 0.851         | 0.916         |
| Ear2  | 0.348    | 0.668    | 0.733    | 0.851         | 0.973         |
| Ear3  | 0.339    | 0.772    | 0.835    | 0.873         | 0.984         |
| Ear4  | 0.497    | 0.795    | 0.815    | 0.881         | 0.935         |
| Ear5  | 0.389    | 0.764    | 0.895    | 0.882         | 0.980         |
| Ear6  | 0.478    | 0.717    | 0.753    | 0.856         | 0.948         |
| Ear7  | 0.467    | 0.758    | 0.863    | 0.858         | 0.987         |
| Ear8  | 0.475    | 0.682    | 0.852    | 0.810         | 0.971         |
| Ear9  | 0.394    | 0.691    | 0.818    | 0.844         | 0.972         |
| Ear10 | 0.485    | 0.795    | 0.748    | 0.850         | 0.985         |
| Ear11 | 0.498    | 0.796    | 0.842    | 0.877         | 0.980         |
| Ear12 | 0.478    | 0.597    | 0.712    | 0.850         | 0.965         |
| Ear13 | 0.497    | 0.764    | 0.833    | 0.834         | 0.951         |
| Ear14 | 0.498    | 0.587    | 0.850    | 0.826         | 0.964         |
| Ear15 | 0.388    | 0.595    | 0.845    | 0.842         | 0.960         |
| Ear16 | 0.499    | 0.598    | 0.817    | 0.792         | 0.987         |
| Ear17 | 0.486    | 0.799    | 0.828    | 0.862         | 0.968         |
| Sl:No: | CNN [14] | PCA [16] | SVM [16] | Proposed CART | Proposed ANFIS |
|-------|----------|----------|----------|---------------|---------------|
| Ear1  | 0.468    | 0.896    | 0.6486   | 0.874         | 1.0000        |
| Ear2  | 0.498    | 0.878    | 0.713    | 0.874         | 1.0000        |
| Ear3  | 0.609    | 0.953    | 0.704    | 0.941         | 1.0000        |
| Ear4  | 0.688    | 0.936    | 0.832    | 0.959         | 1.0000        |
| Ear5  | 0.598    | 0.954    | 0.812    | 0.956         | 1.0000        |
| Ear6  | 0.445    | 0.822    | 0.724    | 0.899         | 0.986         |
| Ear7  | 0.566    | 0.722    | 0.888    | 0.880         | 0.978         |
| Ear8  | 0.450    | 0.746    | 0.734    | 0.950         | 0.989         |
| Ear9  | 0.482    | 0.850    | 0.739    | 0.089         | 0.897         |
| Ear10 | 0.429    | 0.759    | 0.702    | 0.938         | 0.889         |
| Ear11 | 0.466    | 0.765    | 0.852    | 0.954         | 0.878         |
| Ear12 | 0.455    | 0.750    | 0.831    | 0.895         | 0.967         |
| Ear13 | 0.412    | 0.743    | 0.700    | 0.908         | 0.975         |
| Ear14 | 0.429    | 0.767    | 0.882    | 0.952         | 0.894         |
| Ear15 | 0.568    | 0.856    | 0.752    | 0.833         | 0.985         |
| Ear16 | 0.459    | 0.759    | 0.763    | 0.846         | 0.898         |
| Ear17 | 0.418    | 0.741    | 0.820    | 0.916         | 0.978         |
| Ear18 | 0.442    | 0.774    | 0.851    | 0.969         | 0.897         |
| Ear19 | 0.568    | 0.874    | 0.816    | 0.808         | 0.898         |
| Ear20 | 0.494    | 0.771    | 0.843    | 0.940         | 0.988         |
| Sl:No| CNN [14] | PCA [16] | SVM [16] | Proposed CART | Proposed ANFIS |
|-----|---------|---------|---------|--------------|--------------|
| Ear1| 0.0054  | 0.0017  | 0.0052  | 0.0025       | 0.0042       |
| Ear2| 0.0018  | 0.0028  | 0.0051  | 0.0034       | 0             |
| Ear3| 0.0040  | 0.0048  | 0.0034  | 0.0050       | 0             |
| Ear4| 0.0096  | 0.0029  | 0.0060  | 0.0063       | 0.0006       |
| Ear5| 0.0073  | 0.0049  | 0.0058  | 0.0076       | 0.0007       |
| Ear6| 0.0027  | 0.0047  | 0.0059  | 0.0055       | 0.0009       |
| Ear7| 0.0012  | 0.0012  | 0.0068  | 0.0057       | 0.0090       |
| Ear8| 0.0028  | 0.0058  | 0.0035  | 0.0068       | 0.0006       |
| Ear9| 0.0048  | 0.0042  | 0.0051  | 0.0065       | 0.0004       |
| Ear10| 0.0025 | 0.0037 | 0.0063 | 0.0069       | 0.0065       |
| Ear11| 0.0030 | 0.0031 | 0.0030 | 0.0052       | 0.0050       |
| Ear12| 0.0058 | 0.0045 | 0.0069 | 0.0065       | 0.0005       |
| Ear13| 0.0069 | 0.0034 | 0.0050 | 0.0052       | 0.0003       |
| Ear14| 0.0037 | 0.0041 | 0.0037 | 0.0043       | 0.0052       |
| Ear15| 0.0028 | 0.0013 | 0.0033 | 0.0059       | 0.0025       |
| Ear16| 0.0035 | 0.0039 | 0.0067 | 0.0041       | 0.0050       |
| Ear17| 0.0039 | 0.0046 | 0.0058 | 0.0064       | 0.0076       |
| Ear18| 0.0028 | 0.0019 | 0.0021 | 0.0065       | 0.0063       |
| Ear19| 0.0010 | 0.0037 | 0.0040 | 0.0054       | 0.0034       |
| Ear20| 0.0041 | 0.0043 | 0.0022 | 0.0041       | 0.0092       |
| Ear21| 0.0017 | 0.0028 | 0.0067 | 0.0062       | 0.0082       |
| Ear22| 0.0046 | 0.0032 | 0.0039 | 0.0022       | 0.0045       |
| Ear23| 0.0027 | 0.0045 | 0.0040 | 0.0040       | 0.0054       |
| Ear24| 0.0037 | 0.0014 | 0.0020 | 0.0026       | 0.0087       |

Table: 4 Comparison results for Specificity of using Ear images
Table: Comparison results for Precision of using Ear images

| Sl:No: | CNN [14] | PCA [16] | SVM [16] | Proposed CART | Proposed ANFIS |
|-------|----------|----------|----------|---------------|---------------|
| Ear1  | 0.0116   | 0.0256   | 0.0256   | 0.0194        | 0.0664        |
| Ear2  | 0.0340   | 0.0457   | 0.0468   | 0.0251        | 0.0263        |
| Ear3  | 0.0486   | 0.0659   | 0.0498   | 0.0711        | 0.0158        |
| Ear4  | 0.0698   | 0.0239   | 0.0648   | 0.0570        | 0.0641        |
| Ear5  | 0.0364   | 0.0375   | 0.0688   | 0.0769        | 0.0190        |
| Ear6  | 0.0362   | 0.0313   | 0.0411   | 0.0459        | 0.0477        |
| Ear7  | 0.0382   | 0.0308   | 0.0424   | 0.0446        | 0.0617        |
| Ear8  | 0.0424   | 0.0206   | 0.0300   | 0.0438        | 0.0528        |
| Ear9  | 0.0202   | 0.0292   | 0.0381   | 0.0628        | 0.0470        |
| Ear10 | 0.0272   | 0.0206   | 0.0389   | 0.0248        | 0.0606        |
| Ear11 | 0.0335   | 0.0378   | 0.0407   | 0.0297        | 0.0597        |
| Ear12 | 0.0366   | 0.0276   | 0.0419   | 0.0268        | 0.0547        |
| Ear13 | 0.0395   | 0.0362   | 0.0414   | 0.0487        | 0.0681        |
| Ear14 | 0.0183   | 0.0260   | 0.0553   | 0.0657        | 0.0550        |
| Ear15 | 0.0301   | 0.0346   | 0.0593   | 0.0268        | 0.0694        |
| Ear16 | 0.0257   | 0.0274   | 0.0600   | 0.0609        | 0.0630        |
| Ear17 | 0.0346   | 0.0390   | 0.0499   | 0.0409        | 0.0635        |
| Ear18 | 0.0355   | 0.0374   | 0.0560   | 0.0688        | 0.0543        |
| Ear19 | 0.0123   | 0.0303   | 0.0577   | 0.0609        | 0.0525        |
| Ear20 | 0.0206   | 0.0264   | 0.0593   | 0.0688        | 0.0667        |
| Ear21 | 0.0361   | 0.0299   | 0.0609   | 0.0898        | 0.0668        |
| Ear22 | 0.0184   | 0.0353   | 0.0639   | 0.0498        | 0.0694        |
| Ear23 | 0.0122   | 0.0208   | 0.0587   | 0.0468        | 0.0694        |
| Ear24 | 0.0148   | 0.0340   | 0.0627   | 0.0688        | 0.0531        |
| Ear25 | 0.0163   | 0.0307   | 0.0427   | 0.0648        | 0.0685        |
| Ear26 | 0.0126   | 0.0241   | 0.0468   | 0.0256        | 0.0598        |
| Ear27 | 0.0162   | 0.0386   | 0.0586   | 0.0839        | 0.0698        |
| Ear28 | 0.0146   | 0.0306   | 0.0442   | 0.0659        | 0.0639        |
Table 6: Comparison results for F-score of using Ear images

| Sl:No: | CNN [14] | PCA [16] | SVM [16] | Proposed CART | Proposed ANFIS |
|-------|----------|----------|----------|---------------|---------------|
| Ear1  | 0.0289   | 0.0908   | 0.0177   | 0.0586        | 0.1245        |
| Ear2  | 0.0179   | 0.0901   | 0.0629   | 0.0198        | 0.0512        |
| Ear3  | 0.0541   | 0.0620   | 0.0389   | 0.0498        | 0.0311        |
| Ear4  | 0.0059   | 0.0464   | 0.0278   | 0.0639        | 0.1205        |
| Ear5  | 0.0339   | 0.0655   | 0.0343   | 0.0539        | 0.0373        |
| Ear6  | 0.0219   | 0.0488   | 0.0339   | 0.0489        | 0.0911        |
| Ear7  | 0.0248   | 0.0508   | 0.0579   | 0.0416        | 0.0231        |
| Ear8  | 0.0847   | 0.0519   | 0.0877   | 0.0486        | 0.0446        |
| Ear9  | 0.0256   | 0.0489   | 0.0409   | 0.0699        | 0.0526        |
| Ear10 | 0.0355   | 0.0423   | 0.0499   | 0.0689        | 0.0209        |
| Ear11 | 0.0598   | 0.0676   | 0.0419   | 0.0699        | 0.0387        |
| Ear12 | 0.0519   | 0.0400   | 0.0319   | 0.0679        | 0.0670        |
| Ear13 | 0.0537   | 0.0277   | 0.0624   | 0.0428        | 0.0919        |
| Ear14 | 0.0537   | 0.0339   | 0.0647   | 0.0619        | 0.0676        |
| Ear15 | 0.0339   | 0.0519   | 0.0584   | 0.0599        | 0.0758        |
| Ear16 | 0.0423   | 0.0268   | 0.0454   | 0.0379        | 0.0257        |
| Ear17 | 0.0117   | 0.0357   | 0.0336   | 0.0378        | 0.0459        |
| Ear18 | 0.0403   | 0.0389   | 0.0566   | 0.0569        | 0.0663        |
| Ear19 | 0.0324   | 0.0221   | 0.0789   | 0.0389        | 0.0997        |
| Ear20 | 0.0508   | 0.0325   | 0.0709   | 0.0691        | 0.0520        |
| Ear21 | 0.0468   | 0.0369   | 0.0716   | 0.0399        | 0.1252        |
| Ear22 | 0.0176   | 0.0252   | 0.0385   | 0.0458        | 0.1298        |
| Ear23 | 0.0049   | 0.0395   | 0.0355   | 0.0688        | 0.1298        |
| Ear24 | 0.0328   | 0.0363   | 0.0776   | 0.0369        | 0.0827        |
| Ear25 | 0.0189   | 0.0398   | 0.0487   | 0.0329        | 0.1279        |
| Ear26 | 0.0272   | 0.0396   | 0.0428   | 0.0469        | 0.1269        |
| Ear27 | 0.0426   | 0.0214   | 0.0508   | 0.0328        | 0.1369        |
| Ear28 | 0.0221   | 0.0417   | 0.0415   | 0.0696        | 0.0648        |
| Ear29 | 0.0374   | 0.0208   | 0.0315   | 0.0320        | 0.0929        |
| Ear30 | 0.0230   | 0.0212   | 0.0353   | 0.0429        | 0.1198        |
| Average| 0.034567 | 0.04323  | 0.04913  | 0.050234      | 0.078807      |
Table 7: Comparison results for Ear Recognition Rate and Running Time

| Techniques       | Datasets           | Recognition Rate (%) | Running Time (MS) |
|------------------|--------------------|-----------------------|-------------------|
| CNN [14]         |                    | 0.4618 %              | 5.71              |
| PCA [16]         | IIT Delhi Ear images 30 | 0.7148 %              | 4.92              |
| SVM [16]         |                    | 0.8034 %              | 4.68              |
| Proposed CART    |                    | 0.8578 %              | 3.64              |
| Proposed ANFIS   |                    | 0.9624 %              | 3.07              |

Table 8: Comparison results for Face Recognition Rate and Running Time

| Techniques       | Datasets           | Recognition Rate (%) | Running Time (MS) |
|------------------|--------------------|-----------------------|-------------------|
| CNN [14]         |                    | 0.4446 %              | 5.71              |
| PCA [16]         | ORL Face Database images 30 | 0.6917 %              | 4.92              |
| SVM [16]         |                    | 0.7965 %              | 4.68              |
| Proposed CART    |                    | 0.8371 %              | 3.64              |
| Proposed ANFIS   |                    | 0.8821 %              | 3.07              |

![Chart showing comparison results for various algorithms]
**Figure 2:** Shows the graphical representation of comparison results for ear recognition system of existing and proposed method a) Accuracy b) Sensitivity c) Specificity d) Precision e) F-score f) Recognition rate g) Running time.

![Multimodal Diagram](image)

**Figure 3:** Shows the window as person recognized when multimodal output as Ear recognition score level 1 and Face recognition score level 1.

![Multimodal Diagram](image)

**Figure 4:** Shows the window as person recognized when multimodal output as Ear recognition score level 0 and Face recognition score level 1.

![Multimodal Diagram](image)
Figure 4: Shows the window as person is not recognized when multimodal output as Ear recognition score level 0 and Face recognition score level 0.

5. CONCLUSION:

The purpose of the proposed system in this paper is to establish a multimodal biometric personal identification system. Two databases are used to perform this work and demonstrate that with short process time, Runge-Kutta threshold segmentation with Ring projection including ANFIS classifier improves the overall ear and face recognition efficiency. The AARK threshold segmentation with the ANFIS classifier acquires high precision in the identification of different ear and face images. Two distinct databases, namely the IIT Delhi ear database and the ORL face database, have been introduced in the proposed system. Experimental results have shown that high accuracy and protection are provided by a combined ear and face recognition.

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Conflict of Interest Statement

The authors declare no conflict of interest
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Code availability

Not Applicable

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