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Enhancement Ear-based Biometric System Using a Modified AdaBoost Method

Abdulkareem Merhej Radhi [1*] *Subhi Aswad Mohammed* [2]

[1]Department of Computer Science, College of Sciences, Al-Nahrain University, Baghdad, Iraq.
[2]Department of Computer Engineering, Al-Farabi University, Baghdad, Iraq.
[*]Corresponding author: abdulkareemradhi@gmail.com
E-mail addresses: subhiaswad1958@gmail.com

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Abstract:

The primary objective of this paper is to improve a biometric authentication and classification model using the ear as a distinct part of the face since it is unchanged with time and unaffected by facial expressions. The proposed model is a new scenario for enhancing ear recognition accuracy via modifying the AdaBoost algorithm to optimize adaptive learning. To overcome the limitation of image illumination, occlusion, and problems of image registration, the Scale-invariant feature transform technique was used to extract features. Various consecutive phases were used to improve classification accuracy. These phases are image acquisition, preprocessing, filtering, smoothing, and feature extraction. To assess the proposed system's performance. method, the classification accuracy has been compared using different types of classifiers. These classifiers are Naïve Bayesian, KNN, J48, and SVM. The range of the identification accuracy for all the processed databases using the proposed scenario is between (%93.8- %97.8). The system was executed using MATHLAB R2017, 2.10 GHz processor, and 4 GB RAM.

Keywords: AdaBoost, Classifier, Ear, KNN, RMSE, SIFT, SVM.

Introduction:

Biometric systems have appeared as a response to the substance of automatic individual recognition [1]. Human characteristics such as ears are utilized to identify people. purposes that cannot be stolen or lost.

The ear structure is very distinct as shown in the 1 "it changes a little with age and is unaffected by facial expressions". "It is firmly fixed on the side of the head so, the immediate background is predictable, unlike that of the face". "Comparing the ear with the iris, the retina and the fingerprint declares that it is large and therefore more easily captured at a distance. Moreover, it has the same visual complexity as the face but it is unlike the face which lacks symmetry" [1].

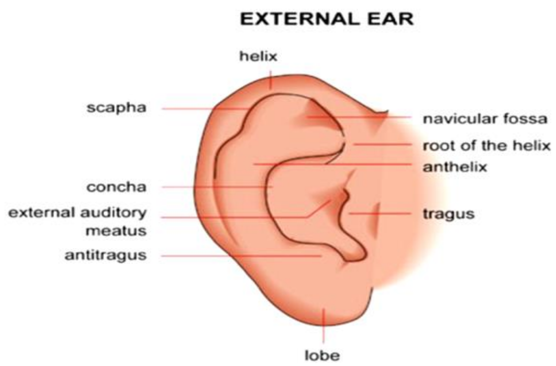

Figure 1. Ear Anatomy

Related Work

The ear structure is quite unique, and facial emotions have little impact on it. It's securely attached to the side of the head, thus the immediate background, unlike that of the face, is predictable. [2].

This section presents related work using ear recognition. Hourali, F., and Gharravi present a method that uses a transformed type of DCT to extract meaningful features from ear images [3].

Ahmed M. Alkababji., proposed a deep learning object detector for ear detection and feature extraction with principal component analysis for feature reduction [4]. Arulananth T S, and Baskar M, presented an overview of the field of automatic ear recognition (from 2D images) and focuses specifically on the most current, descriptor-based approaches proposed in this area [5]. Hokaew P. et. al. depicted an application of a statistical appearance model of the human face in assisting suspect identification based on witness's visual recollection [6]. Aishna Sharma et al. explored the field of ear biometrics where the database images are re-sized to 128 x 256 pixels and then converted to a grayscale image. Then numerous transforms were applied to extract ear features [7].

Ear Databases

In this paper, due to its new methodology, there are numerous databases accessible to the public and without charge for experiments. (UND) or University of Notre Dame Ear repository comprises 464 visible-light face side profile (ear) images from 114 human subjects [8]. The second database is the IIT Delhi ear image database contains ear images acquired from 125 different subjects and each subject has at least three ear images. The third database is Wild Ear Database: this database is collected in two groups. The first was employed in the development of statistical deformable models (Collection A), which consists of 605 ear images, while the second was used for ear verification (Collection B) and contains 2058 images. The final selected database for optimizing accuracy is the USTB-Helloear database: The total number of volunteers is 60.

So, this work trained and evaluated the proposed ear recognition framework using seven distinct datasets. Images were obtained from the University of Notre Dame, the Indian Institute of Technology (IIT), "West Pomeranian University of Technology Ear Database (WPUTE), Annotated Web Ears database (AWE), In-the-Wild Ear Database (ITWE), and the Unconstrained Ear Recognition Challenge database (UERC)".
The following sections illustrate each of them.

IIT Ear Database

The IIT includes 493 photos with a combined size of 272 x 204 pixels from 125 different individuals. Each image depicts a region around the left ear and was taken in a controlled indoor setting, making this database a good baseline for a near-ideal ear identification situation. Fig. 2.a depicts several raw pictures from the IIT database that looks to have been captured in perfect conditions.

(a)

(b)

(c)

(d)

Figure 2. Models of images from (a) IIT, (b) WPUTE, (c) AWE and (d) ITWE databases [17]

WPUTE Database

The WPUTE was initially invented to assess the presence of texture classification in the wild. The pictures depict occlusions induced by hair, earrings, and headsets, which provide difficulty in-ear identification. Gender, ethnic background, posture, lighting, and acquisition sensor are all represented in the database.

This record includes 3348 pictures with a resolution of 380 x 500 pixels, representing a small area surrounding the ear, from 474 distinct people (each subject has at least four photographs). Nonetheless, 1388 of these are duplicated, perhaps inflating the claimed accuracy of certain works in the process.

AWE Database

The AWE [17] has 1000 pictures from hundred distinct subjects (i.e. 10 photographs per subject) that were gathered via Internet explorations for prominent personalities. The image size ranges from 15x 29 to 473 x1022 pixels, with an average of 83x 160 pixels.

ITWE Database

Group A and group B of the ITWE database are two separate collections. Group A comprises 605 pictures with no identifiers, but 55 manually labeled landmarks. This collection was divided into a training set of 500 photos and a test set of 105 images at random. It may be used to practice ear recognition and normalization techniques. Fig. 2.d depicts a few instances of ITWE pictures.

UERC Database

The UERC database was created as an augmentation of the AWE database for competitive reasons. The database is split into two sections: training (2304 pictures from 166 participants) and testing (9500 images from 3540 subjects). Participants in training have at least 10 pictures, whereas test subjects may have fewer.

AdaBoost

AdaBoost is an adaptive learning algorithm. The learning procedure in this algorithm and the outputs of a (‘weak learners’) are mutual into a weighted sum that signifies the final output. A boost is a classifier that can be depicted in Eq. 1.

$$F_T(x) = \sum_{f(t)}^{T}(x) \qquad 1$$

Where: f_t: is a weak learner, and (x): as input object and precedes a value specifying the object class. A weak learner yields for each sample in the training collection, an output hypothesis h (xi). , a weak learner is elected and assigned a coefficient α_t such that the sum of the training error (E_t) was minimized, as shown in Eq. 2.

$$E_t = \sum_i E[F_{t-1}(x_i)+\boldsymbol{\alpha}\mathrm{h}(\mathrm{x_i})] \qquad 2$$

Where $\sum_i E[F_{t-1}(x_i)]$ is the boosted classifier” that has been feeding to the earlier phase of training; E (F) is the error function and $f_t(x) = \alpha h(x_i)$ is the weak learner [8] .

Proposed Methodology

Fig. 3 depicts the block diagram of the proposed system. There are various phases: filtering, pre-processing, detection, feature extraction using AdaBoost, and classification phase. These phases will be introduced in the following sections:

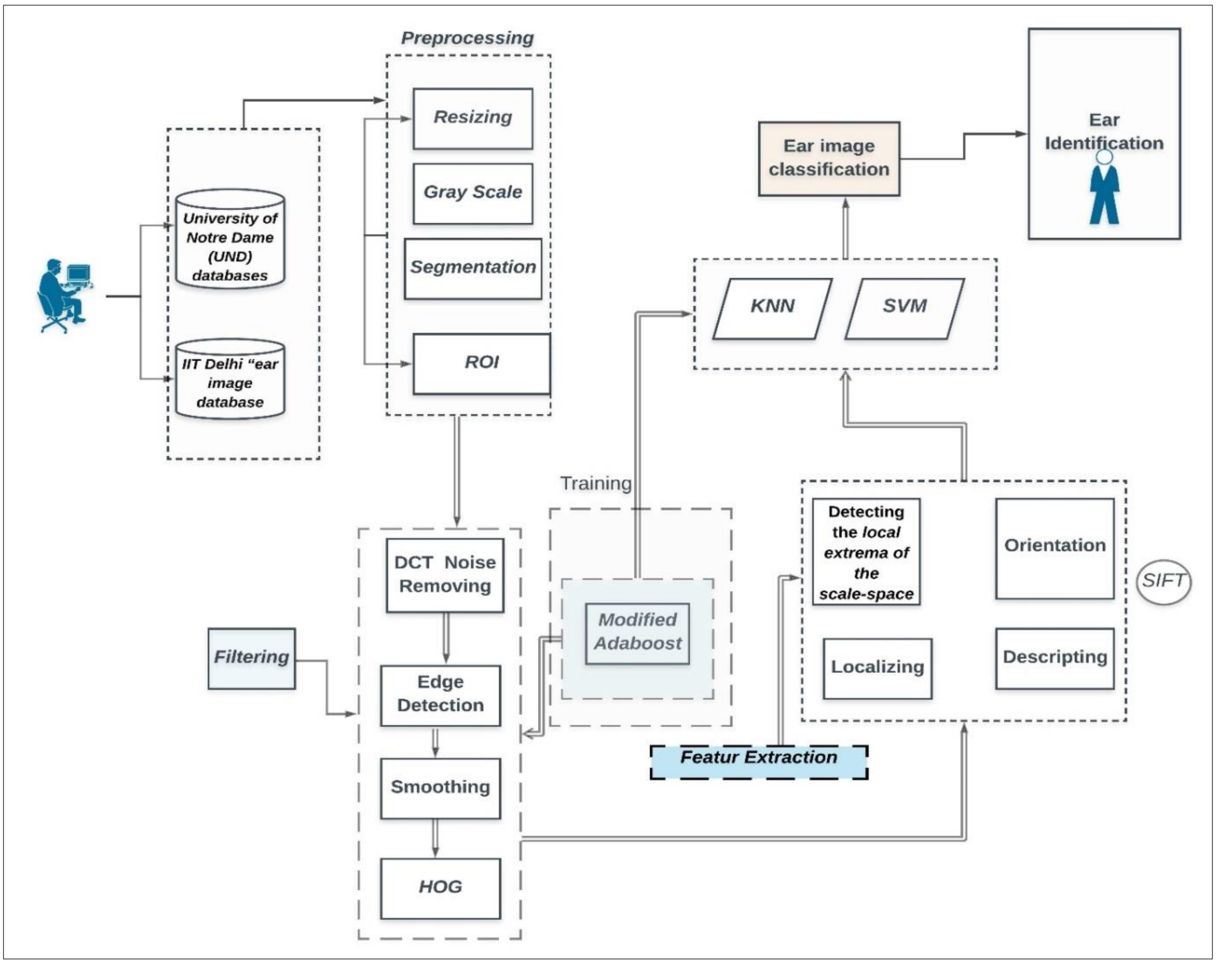

Figure 3. The framework of the proposed system

Preprocessing

With pre-processing, the proposed system ensured that the ear images are: I) tightly cropped, ii) all images are of equal dimensions, and iii) all eare are centered, and mutually aligned. Pre-processing and image enhancements procedures **c**an be summarized as follows.

I. Resizing: due to having the identical size of images in the aimed repository, the resizing in this work was [272 X 204] pixels.

II. The captured image was converted from Blue, Green, and Red (BGR) color space to Grayscale (17). Conversion from RGB to Grayscale: Images converted to grayscale using a weighted method or luminosity method to be suitable for the next processing and filtering steps, as shown in Eq. 3.

$$New\ grayscale\ image = \big((0.3 * R) + (0.59 * G)\big) + (0.11 * B)) \quad 3$$

III. Segmentation: in this paper, a worthy segmentation was adopted such that: pixels in the same class have comparable greyscale of "multivariate values and form a connected region."

IV. ROI: express a region of interest by producing a specific binary mask of the same size as the image such that, the pixels that define the "**ROI** is set to (1), and all other pixels are els set to (0). This phase intends to speed up the training phase [9].

Ear Enrolment and Normalization

The ear enrollment procedure comprises ear detection and ear normalization. The detected ear is exposed to an enhancement via normalization that changes the range of pixel intensity values and removes influencing issues: hair or skin around the ear before extracting features. So, this normalization transforms an n-dimensional grayscale image into a new image with the desired intensity values in the range (newMin, newMax). So, to have the optimum intensity (0-255), the range of the selected intensity value of the newMin and newMax is subtracted from the actual value, as shown in Eq. 4.

$$DI = (AI - Min)\frac{255}{Max - Min} \quad 4$$

Where DI = Desired intensity for the grayscale value of the image after normalization, AI= Actual intensity for the grayscale value of the original image, Min= minimum grayscale for the original

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image, and Max = maximum grayscale for the original image. In this paper, Gaussian smoothing filters, have been used to minimize the noise level. So, in this paper the following Gaussian filter Eq. 5 was, used to smooth the ear image:

$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{-(x^2+y^2)/2\sigma^2} \qquad 5$$

Where x and y are the image pixels' coordinates, σ is the standard deviation.

Methodology of the Proposed AdaBoost Algorithm and Edge Detections

Ear detection methodology under complex background has two phases: offline cascaded classifier training and online ear detection. The cascaded classifier is composed of multiple strong classifiers [10].

The images have been scanned using a rectangular arrangement of features. The key element of the weak classifier: (h (x; f; p; Θ)), where (p) is the polarity representing the route of the inequality and Θ is a threshold:

$$h(x,f,p,\emptyset) = \begin{cases} 1 & if\ pf(x)<p\theta \\ 0 & otherwise \end{cases} \qquad 6$$

The AdaBoost algorithm for feature mining tries to construct strong classifiers as a linear combination of these weighted weak classifiers [11], as shown in Eq. 7:

$$F(x)=a_1f_1(x)+a_2f_2(x)+a_3f_3(x)+\ldots+a_nf_n(x) \qquad 7$$

Such that F(x) denotes the strong classifier, while $f_1(x)$, $f_{,2}(x)$ and so on represent weak classifiers, while a_1, $a_{2,}$ and, so on are weighted quantities, and x is an image [12]. The modified AdaBoost algorithm is an effective mechanism for refining the expecting capability of the learning system and the most typical method in synchronizing learning[13]. The modified AdaBoost algorithm is simpler to implement, implicit feature selection, and overfitting resistance, than other algorithms, but it is sensitive to noisy data. Fig. 4, presents the learning scenario of this algorithm. This algorithm constructs a strong classifier from weak classifiers as a cascading ensemble model. In the training phase, the boosting iterations also decrease the classification error of the combined classifier. The proposed modification of this algorithm was to reduce the error rate via introducing learning transfer for each model and updating the weight value in all iterations.

Modified AdaBoost Algorithm

Input Training Data: D= {(x_1, y_1), (x_n , y_n), Introduce Number of rounds R
Initialize Weights and prediction rate α
Set error threshold rate $\varepsilon = \frac{N}{\sum w}$ $\quad \varepsilon \leq \alpha$
Training:
Distribute weights ∀ examples N using $w_i = \frac{\sum w_i}{N}$ *,∀ i=1, 2… N*
For j=1 to R do
Form a model K_j ∈ the training set using the distribution w_i
Update w_i according to α (Tuning weights)
Increment weights of examples that are out of model by K_j or
Decrement weights of examples which are out of model by K_j
end for
Prediction: For a new example x', harvest the weighted w_i and assessment of the (prediction rate):
Specify models {m_1, m_2,M_N)

Figure 4. A Modified AdaBoost Algorithm

Discrete Cosine Transformation (DCT) for Noise Removal

This phase presents applying a Gaussian filter as shown in equation[8] to remove noise. Then images have been converted to binary images via implementing Discrete Cosine Transformation to reduce file information. The detected ear has been exposed to an enhancement monotonous that recovers the fidelity of the image.

Low frequencies account for a large portion of the signal energy in most images; these can be seen in the DCT's upper left corner. As a result, the DCT input is an 8 by 8 array of integers. Eight-bit pixels have grayscale levels from zero to 255. The DCT has been applied from left to right and top to bottom using Eq. 8.

$$F^{\wedge}(u,v) = 4 \times \sum_{i=0}^{N-1}\sum_{j=0}^{M-1} f(i,j) \times \cos\left[\frac{\Pi.\mu}{2N}(2i+1)\right] sin\left[\frac{\Pi.v}{2M}(2j+1)\right] \qquad 8$$

Where the image is N by M; f (i, j) is the intensity of the pixel; F (u, v) is the Discrete Cosine Transformations Coefficient.

The DCT segments the image into fragments concerning the image's visual quality. To get a matrix for a specific image using DCT via Eq. 9:

$$T_{i,j=}\begin{bmatrix} \frac{1}{\sqrt{N}} & if\ i=0 \\ \sqrt{\frac{2}{N}}\ cos\left[\frac{(2j+1)i\pi}{2N}\right] & if\ i>0 \end{bmatrix} \qquad 9$$

Histogram of Oriented Gradients

In feature extraction approaches, a histogram of oriented gradients (HOG) is widely utilized. The images are separated into 50 percent overlapped blocks, with each block segmented into cells. The gradients in the x and y directions (Gx and Gy) are computed for each pixel in each cell. [14]. For all cells a histogram of orientations is generated**;** where the unsigned gradients go from dark to bright or from bright to dark. The angles below 0^0 are increased by 180^0, while angles above 180^0 are decreased by 180^0. The histograms are then normalized concerning the cells in the same block.

Feature Extraction

Compared with the face, the ear has its specific features. SIFT has been used to extract these features to transform the image into a group of local feature vectors.

The feature extracted in this paper proposes a scale-invariant feature transform (SIFT). The image is converted into a set of relevant feature vectors by the SIFT technique. These feature vectors are intended to be separate and unaffected by image scale, rotation, or translation. The extracted features are very robust matching over a basic domain of affine distortion, three-dimensional viewpoint change, adding noise, and changing in lightness.

A regular of local properties of an image is mining from each image. Each of those properties includes an archive of Pixel location, a Scale described by the standard deviation σ, Orientation, and Detailing of the image's local structure. The feature locations are determined as the local extrema of Difference of Gaussians (DOG), which is given by Eq.10. To implement the DOG pyramid the input image is convolved iteratively with a Gaussian kernel as shown in Eq. 11. This procedure is recurrently repeated. Each collection of images of the same (octave), forms together with the so-called Gaussian pyramids by Eq.12, which is signified by a 3D function [15].

$$L(x,y,\sigma) = G(x,y,\sigma) * I(x,y) \qquad 10$$

$$G(x,y,\sigma) = \frac{1}{2\pi\sigma^2} e^{-(x^2+y^2)/2} \qquad 11$$

$$D(x,y,\sigma) = (G(x,y,\sigma) - G(x,y,\sigma) * I(x,y) = L(x,y,k\sigma) - l(x,y,\sigma)) \qquad 12$$

There are four steps of computations for generating the group of properties:

A. **Detecting the *local extrema of the scale-space*-** the property positions are set as the local extrema of the DOG pyramid as shown in Fig.5. For building the pyramid of DOG the input image iteratively undergoes convolution with a Gaussian kernel of σ = 1.6. The last convolved image undergoes down-sampling in every one of the image directions by a factor equal to 2, and the convolving procedure was implemented again.

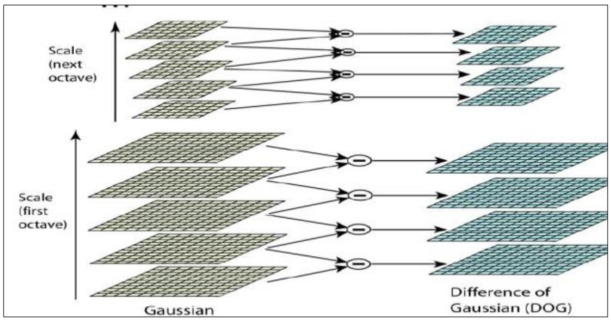

Figure 5. Construction of difference-of-Gaussian images

"The DOG pyramid *D (*x, y, σ) is calculated from the difference of every two neighboring images in Gaussian pyramid", as shown in Fig. 6.

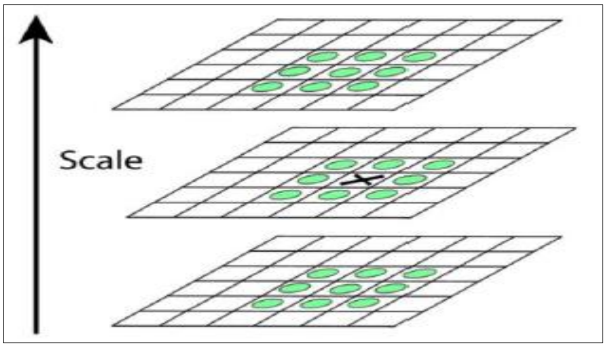

Figure 6. "Pixel assessments to find the difference-of-Gaussian image's maximum and minimum values"

B. **Localizing -** the detected local extrema are efficient nominees for key points. The quadratic function is calculated with the use of a second-order Taylor expansion that has its origin at the sample point with low contrast and high sensitivity to noise.

C. **Orientation**– For every one of the pixels of the area surrounding the property position the gradient magnitude and orientation are calculated according to Eq.13 and Eq.14:

M (X, Y) = √ (L (X+1, Y, ∂)) x^2+(L (X, Y+1, ∂) –L (X, Y−1,∂)) x^2 13

Θ (X, Y) = arctan ((l (x. y+1, ∂)-l (x, y-1, ∂))/ (l (x=1, y, ∂) −l (x−1, y, ∂))) 14

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D. **Descripting -** the area that is surrounding a key point is split into 4X4 boxes, as shown in Fig. 7. An appropriate Gaussian window calculates and weights the gradient magnitudes and directions in each box, and the coordinates of each pixel and its gradient direction rotate according to the key-points direction.

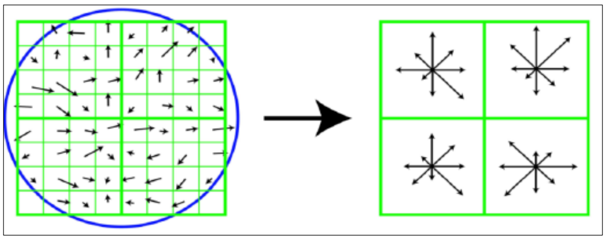

Figure 7. Computation of the key point descriptor

Experiments and Results Discussion:

The University of Notre Dame presents a large variety of image databases, which can be used for biometric performance evaluation[16]. Moreover, there are various free downloaded databases available for academic studies which are presented previously in this research such as IIT, WPUTE, AWE, and ITWE databases[17], for evaluation comparison.

This paper depicts testing various experimentations to estimate the performance of the presented technique. The tests were approved on the two described repositories. Eq.15 utilized for evaluating the performance:

$$Recognition\ rate = \frac{No.of\ Classified\ persons}{Total\ No.of\ Persons} \quad 15$$

When assessing diagnostic tests, an optimal test is to compute the sensitivity and specificity of the test to estimate its efficacy. Diagnostic test sensitivity is defined as the likelihood (in percentage) that a sample will test positive if the individual has the condition.

A test sensitivity can be described by the following equation:

$$Senseitivity = \frac{TP}{TP+FN} \quad 16$$

Test specificity is defined as the likelihood (in percentage) that a test will produce a negative result if the individual does not have the condition. A test specificity can be depicted as follows:

$$Specificity = \frac{TN}{TP+FN} \quad 17$$

While F1- Score can be presented as follows:

$$F1\ Score = \frac{2TP}{(2TP+FP+FN)} \quad 18$$

Tables 1 and 2, illustrate the comparative assessments of classification accuracy for the proposed method and other described classifiers using SIFT as a feature extraction approach. The presented technique harvests the optimum recognition rate irrespective of sensitive data. The results obtained from identification using the modified AdaBoost method are between (93.8%- and 97.8%) for all the processed databases.

Table 1. Comparison of a classification accuracy performance using Naïve Bayes and KNN

Database	Classifier											
	NB				KNN				Proposed Modified AdaBoost			
	SN%	SP %	FI%	AC%	SN%	SP%	F1%	AC%	SN%	SP%	F1%	AC%
UND	79	76	0.81	74.7	73	71	0.81	88.2	86	83	0.97	93.8
IIT Delhi	77	73	0.85	78.1	71	70	0.75	84.4	88	86	0.94	97.5
Wild Ear	76	71	0.79	81.1	70	66	0.75	86.0	84	83	0.95	97.6
USTB	78	75	0.88	87.8	73	72	0.77	84.4	81	79	0.88	97.8
WPUTE	80	79	0.89	81	70	69	0.75	84.6	85	84	0.88	96
AWE	77	76.4	0.81	80.1	72	70	0.78	80.2	79	76	0.91	92
UERC	79	76	0.91	76	79	76	0.91	82.5	79	76	0.91	94.9

Table 2. Comparison of a classification accuracy performance using SVM and J48

Database	SVM				J48				Proposed Modified AdaBoost			
	SN%	SP %	FI%	AC%	SN%	SP%	F1%	AC%	SN%	SP%	F1%	AC%
UND	83	97	0.80	87.4	74	72	0.79	88	87	85.5	0.95	93.8
IIT Delhi	79	76.2	0.87	95	77	74	0.78	93.1	89	85	0.96	97.5
Wild Ear	77	76	0.79	92.2	77	71	0.72	91	86	84	0.94	97.6
USTB	78	73	0.88	87.8	77	74	0.78	90	84	81.6	0.86	97.8
WPUTE	86	83.5	0.90	89.2	84	83	0.79	88.3	87	85.7	0.89	96
AWE	80	79.4	0.81	84.2	83	79.2	0.79	83.3	83	81	0.92	92
UERC	77	71	0.89	87.1	74.9	71.8	0.81	86.3	82.7	80.9	0.90	94.9

Table 3. presents the time complexity of the proposed method with seven different databases, while Table 4., illustrates the comparison of the proposed work with the related methods in terms of accuracy.

Table 3. Time Complexity of the Proposed Method with Seven Different Databases

Database	Classifier				Proposed Modified AdaBoost	No. Samples	Time (sec.)
	Naïve Bayesian	KNN	SVM	J48			
UND	%74.7	%88.2	%87.4	%88	%93.8	464	318
IIT Delhi	%78.1	%84.4	%95	%93.1	%97.5	125	160
Wild Ear	%81.1	%86.0	%92.2	%91	%97.6	205	210
USTB	%87.8	%84.4	%87.8	%90	%97.8	334	225
WPUTE	%81	%84.6	%89.2	%88.3	%96	500	412
AWE	%80.1	%0.78	%84.2	%83.3	%92	605	410
UERC	%76	%82.5	%87.1	%86.3	%94.9	230	188

Table 4. Comparison of the proposed Technique with Related Methods

Author (year)	Method	Accuracy (%)
Hourali - 2017	KNN-LSVM	93.5
Alkababji A-2021	CNN	97.8
Proposed Method	Modified AdaBoost	97.8

Fig. 8, presents a comparison of error distribution and recognition rate for the proposed model.

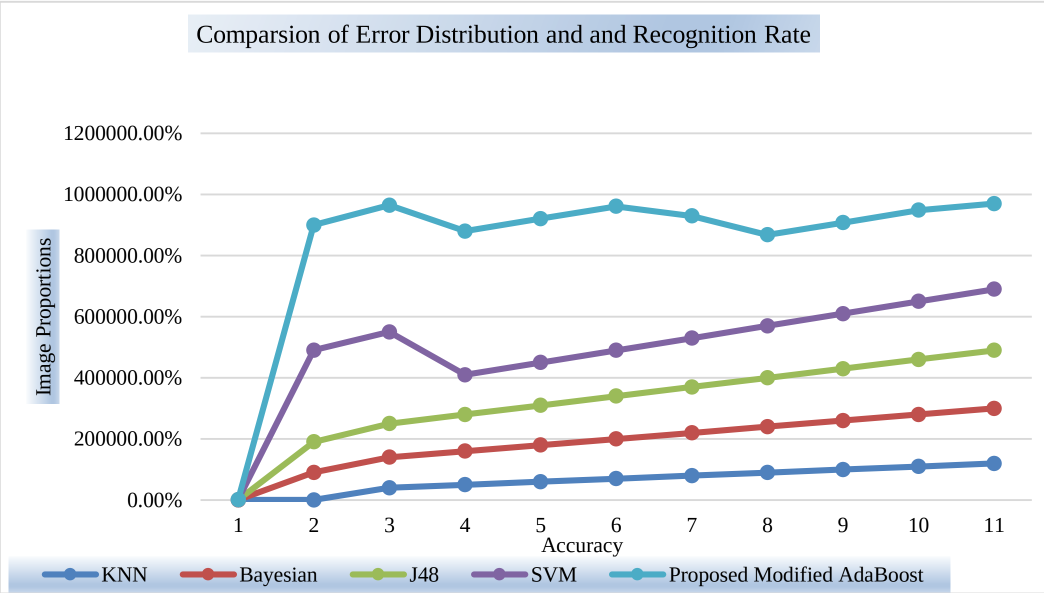

Figure. 8 A comparison of error distribution and recognition rate

In this paper, Root Mean Square Error (RMSE), has been used to find the prediction errors of the classifications. It is the standard deviation of the residuals. Eq.19 depicts the root of the mean square error using the modified AdaBoost algorithm.

$$RMSE_{fo} = \left[\sum_{i=1}^{N}(Z_{f_i} - Z_{o_i})^2/N\right]^{1/2} \qquad 19$$

Where: N = sample size. The prediction errors using the modified AdaBoost algorithm are RMSE=1.59 and training time = 40.928 sec.

Conclusions:

This paper presents a proposed model to enhance a biometric authentication classification using the ear as a distinct biometric part for the recognition of persons. The proposed algorithm comprises numerous procedures starting with image acquisition, preprocessing, feature extraction, and identification. To verify the system performance, four databases experimented. Then assess the classification accuracy of the presented technique via means of ear identification and recognition rate. To overcome the limitations of illumination, occlusion, and the problems of image registration, (SIFT) or scale-invariant feature transformation technique was used in this work to extract features. The last phase in this work presents classification results using different classifiers for the processed database. The results obtained of identification using the modified AdntaBoost method are between (93.8%- 97.8%) and RMSE for predicting error =1.59 in training time = 40.928 sec. A comparison between the proposed work and the related methods in terms of accuracy is illustrated in this work.

Authors' declaration:

- Conflicts of Interest: None.
- We thus certify that all of the manuscript's Figures and Tables are my own. Furthermore, authorization has been granted for the re-publication of the manuscript's figures and graphics, which are not mine or ours.
- Ethics Approval: The study received approval from Al-Nahrain University's local ethical council.

Authors' contributions statement:

A.M.R.: The role of this researcher is to contribute to selecting a data set, as well as adopting the scenario of this research, and then design and implement the main idea of improving image recognition, after reprocessing. As well as finding a suitable way to overcome the problems that can be an obstacle to image recognition.

S.A.M.: is the second author of this research. He compared and analyzed the results obtained via the implementation of the proposed idea with the work related to this research, and then corporate with the first author to extract conclusions and suggestions for future work.

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تحسين نظام التعرف البايومتري بأستخدام الأذن بالأعتماد على تحوير تقنية تعزيز المصنف

عبد الكريم مرهج راضي[1] **صبحي أسود محمد[2]**

[1] قسم علوم الحاسبات، كلية العلوم، جامعة النهرين، بغداد، العراق.
[2] قسم هندسة الحاسوب، كلية الفارابي، بغداد، العراق.

الخلاصة:

أن الهدف الرئيسي من هذا البحث هو تعزيز نموذج المصادقة البيومترية والتصنيف باستخدام الأذن كجزء مميز من الوجه لأنها لا تتغير بمرور الوقت ولا تتأثر بتعابير الوجه. النموذج المقترح هو سيناريو جديد لتعزيز دقة التعرف على الأذن من خلال تعديل خوارزمية تعزيز المصنف (AdaBoost) لتحسين التعلم التكيفي. للتغلب على قيود إضاءة الصورة والانسداد وسوء تسجيل الصورة نستخدم تقنية تحويل ميزة المقياس الثابت لاستخراج الميزات. تم استخدام مراحل متتالية مختلفة لتحسين دقة التصنيف. هذه المراحل هي الحصول على الصور والمعالجة المسبقة والتصفية والتنعيم واستخراج الميزات. لتقييم أداء الطريقة المقترحة، تمت مقارنة دقة التصنيف باستخدام أنواع مختلفة من المصنفات. هذه المصنفات هي Naïve Bayesian و KNNو48J و.SVM، خلصنا إلى أن مدى دقة التعريف لجميع قواعد البيانات التي تمت معالجتها باستخدام السيناريو المقترح يتراوح بين (٪ 93.8-٪ 97.8). تم تنفيذ النظام باستخدام MATHLAB R2017 بمعالج 2.10 جيجا هرتز و4 جيجا بايت رام.

الكلمات المفتاحية: المصنف المعزز، المصنف، الأذن، مصنف KNN، معدل الجذر التربيعي للخطأ، المقياس الثابت، مصنف SVM،