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Classification of Ear Biometric Data using Support Vector Machine

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Authors' contributions

This work was carried out in collaboration between all authors. Author MAJ designed the study, performed the analysis, wrote the procedure, and wrote the first draft of the manuscript and managed literature searches. Authors GKP and ST managed the related computational experiments and literature searches. All authors read and approved the final manuscript.

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ABSTRACT

In this paper, a method to recognize persons using ear biometrics has been proposed. We propose a method to classify ears based on supervised learning using Support Vector Machine (SVM). For this, ear has been considered as a planar surface of irregular shape. The shape based features like distribution of area, moment of inertia (MI) with respect to minor and major axis and radius of gyration with respect to minor and major axis are considered.
A database of 605 ears were considered in the development of the model. SVM was able to classify the ears into three groups. A recognition accuracy of 93% has been recorded. The clusters so formed were analyzed for precision, recall, f-measure and kappa statistics. The results showed that the SVM is a robust method.

Keywords: Biometric; MI; SVM; SMO; RMSE; MAE.

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1. INTRODUCTION

Biometrics is physical or behavioral characteristics that can be used for human identification. Security plays an increasingly important role in our daily life, and biometric technologies are becoming the solution to highly secure recognition and verification of identity.

As there is an ever-growing need to automatically authenticate individuals, biometrics has been an active field of research over the course of the last decade. Traditional means of automatic recognition, such as passwords or ID cards, can be stolen, faked, or forgotten. Biometric characteristics, on the other hand, are universal, unique, permanent, and measurable. The characteristic appearance of the human outer ear (or pinna) is formed by the outer helix, the antihelix, the lobe, the tragus, the antitragus, and the concha. Ear images can be acquired in a similar manner to face images, and a number of researchers have suggested that the human ear is unique enough to each individual to allow practical use as a biometric.

1.1 Ear Biometrics

Alfred Iannarelli developed a new class of biometrics, based upon ear features were introduced for use in the development of passive identification systems [1]. Identification by ear biometrics is promising because it is passive like face recognition, but instead of the difficulties to extract face biometrics, it uses robust and simply extracted biometrics like those in fingerprinting. The ear is a unique feature of human beings. Even the ears of “identical twins” differ in some respects. Unlike face, ear has no expression changes, make-up effects, does not vary with age and more over the color is constant throughout the ear. It has the biometric traits like uniqueness, universality, permanence and collectability.

A biometric system is essentially a pattern recognition system which uses a specific behavioural or physiological characteristic of a person to determine the person’s identification. Therefore, a biometric system can be solved using the methodologies from the pattern recognition research. Researcher considers the use of both 2D and 3D images of the ear, using data [6].

The most famous work among ear identification is made by Alfred Iannarelli [1] when he gathered up over ten thousands ears and observed that all were different. In the set of five hundred ears only four characteristics were needed to state that ears are unique [2]. The performance is not significantly different between ear and face; for example 72.7% versus 69.3% respectively in one experiment [2]. Ear biometrics based on ear form are averagely permanent than other possible identification system e.g. fingerprint, hand geometry etc.

Ear biometrics is an unexplored biometric field, but has received a growing amount of attention over the past few years. There are three modes of ear biometrics: ear photographs, ear prints obtained by pressing the ear against a flat plane, and thermograph pictures of the ear. Ear as a biometric has been investigated with both 2D and 3D data. The iterative closest point (ICP) -based algorithm has demonstrated good scalability with size of dataset. The results are encouraging in that they suggest a strong potential for 3D ear shape as a biometric [6].

1.2 Related Works

Machine Learning is considered as a subfield of Artificial Intelligence and it is concerned with the development of techniques and methods which enable the computer to learn. In simple terms development of algorithms which enable the machine to learn and perform tasks and activities. Machine learning overlaps with statistics in many ways. Over the period of time many techniques and methodologies were developed for machine learning tasks [11].

Support Vector Machine (SVM) was first heard in 1992, introduced by Boser, Guyon, and Vapnik in COLT-92. SVMs are a set of related supervised learning methods used for classification and regression.

They belong to a family of generalized linear classifiers. In another terms, SVM is a classification and regression prediction tool that uses machine learning theory to maximize predictive accuracy while automatically avoiding over-fit to the data.

Support Vector machines can be defined as systems which use hypothesis space of a linear functions in a high dimensional feature space, trained with a learning algorithm from optimization theory that implements a learning bias derived from statistical learning theory. Support vector machine was initially popular with the Neural Information Processing Systems (NIPS) community and now is an active part of the machine learning research around the world. SVM becomes famous when, using pixel maps as input; it gives accuracy comparable to sophisticated neural networks with elaborated features in a handwriting recognition task.

It is also being used for many applications, such as hand writing analysis, face analysis and so forth, especially for pattern classification and regression based applications. The foundations of Support Vector Machines (SVM) have been developed by Vapnik [11] and gained popularity due to many promising features such as better empirical performance. The formulation uses the Structural Risk Minimization (SRM) principle, which has been shown to be superior [12], to traditional Empirical Risk Minimization (ERM) principle, used by conventional neural networks. SRM minimizes an upper bound on the expected risk, where as ERM minimizes the error on the training data. It is this difference which equips SVM with a greater ability to generalize, which is the goal in statistical learning. SVMs were developed to solve the classification problem, but recently they have been extended to solve regression problems [13].

Umadevi [14] has compared two main classifiers SVM and Decision Tree (DT) for Sentiment Analysis. In this work two popular supervised machine learning algorithms namely DT and SVM were used for sentiment analysis. Support vector machines, a supervised machine learning approach took less time to build model and showed great accurate results on SMS spam text classification than Decision tree learning approach.

Justino et al. [15] have compared SVM and HMM classifiers under two specific conditions, the first being the number of samples used for training, and the second being the use of different types of forgeries. Under both conditions, the SVM showed better results. However, in terms of random forgery acceptance and small number of samples used to training, the SVM showed promising results, demonstrating SVM_s ability to identify simple and simulated forgeries without previous knowledge.

Abdullah et al. [16] have compared the performance of three known text classification techniques namely, SVM classifier, Naïve Bayes (NB) classifier, and C4.5 Classifier. These three techniques are compared using a set of Arabic text documents that are collected from different websites. The text documents pass through a set of pre-processing steps such as removing stop words, normalizing some characters, removing non Arabic text and symbols. These documents are then converted to the appropriate file format that can be used to run the three classification techniques on WEKA toolkit. After conducting the experiments the Naïve Bayes classifier achieves the highest accuracy followed by the SVM classifier, and C4.5 classifier respectively. The SVM requires the lowest amount of time to build the model needed to classify Arabic documents, followed by Naïve Bayes Classifier, and C4.5 classifier respectively.

Ramirez et al. [17] have developed Handshake biometric system based on feature extraction methodology which is novel. In this work, Identification experiments were carried out using the feature vectors as inputs to recognition system using SVM technique. An average recognition system of 98.5 is claimed. The verification included False Acceptance Rate and False Rejection Rate.

Tobias et al. [18] have developed a Biometric User Authentication System based on dynamic hand writing classification of persons. In this work Support Vector Machines are employed to classify dynamic hand writing sample. The goal of SVM in this work is to carry out binary classification and to handle multiple class problems using a combination of different Support Vector Machines.

Scheirer et al. [19] have reported Face Recognition algorithm which is based on similarity surfaces and Support Vector Machines. Their work has shown that prediction of biometric system failure can be done reliably using SVM approach.

1.3 Data for the Model

The five shape based features of ears considered for classification are listed in the Table 1.

Ear images for this classification work were acquired from the pupils of Siddaganga group of institutes. In order to safeguard ethical issues, written consent was obtained by all the participants. The subjects involved were mostly students and faculty numbering 605. In each acquisition session, the subject sat approximately one meter away with the side of the face in front of the camera in outside environment without flash.

Table 1. Ear features considered

Sl. no	Attributes
1	Area mm^2
2	Moment of Inertia Y (Imax) mm^4
3	Radius of gyration Y (RGy) mm
4	Moment of Inertia X (Imin) mm^4
5	Radius of gyration X (RGx) mm

The surface area of the ear is the projected area of the curved surface on a vertical plane. This area is assumed to be formed out of segments. The area of an ear to the right side of the major axis is considered to be made out of six segments. Each of the segments thus subtends 30º with respect to the point of the intersection of the major axis and minor axis. The extreme edge of a sector is assumed to be a circular arc. Thus converting each segment into a sector of a circle of varying area. A measurement involved over such segment is presented in Fig. 1.

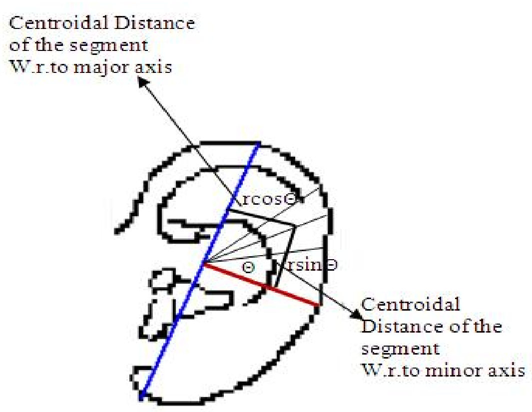

Fig. 1. Centroid location of the circular sector area and MI parameters

To isolate important and relevant information from the image, canny edge detection is used with threshold of 0.3. Major and minor axes were identified. Major axis is the one which has the longest distance between two points on the edges of the ear. The minor axis is drawn in such a way that it passes through tragus and is orthogonal to the major axis.

2. METHODOLOGY

2.1 Support Vector Machines

Support Vector Machines (SVM) are supervised learning models with associated learning algorithm that analyses data and recognize patterns, used for classification and regression analysis. It takes a set of input data and predicts, for each given input which of two possible classes forms output, making it a non-probabilistic binary linear classifier [20].

As a final step of the proposed methodology, we conduct the experiment. The classification algorithm under test is a support vector machine (SVM) algorithm. The resulting dataset will be classified into three classes; it will be used to assess the performance and efficiency of the Sequential Minimal Optimization (SMO) which is The WEKA version of the support vector machine algorithm.

SMO implements the sequential minimal optimization algorithm for training a support vector classifier, using polynomial or Gaussian kernels. Missing values are replaced globally, nominal attributes are transformed into binary ones, and attributes are normalized by default. One advantage of using this implementation is that the amount of memory required by SMO is linear to the size of the data.

We employ SVM as a classification algorithm because it has been shown to perform well on classification problems. We incorporate SVM for its classification power and robustness. SVM is able to handle hundreds and thousands of input values with great ease due to its ability to deal well with noisy data.

2.2 Sequential Minimal Optimization

Sequential Minimal Optimization (SMO) is a simple algorithm that can quickly solve the SVM QP problem without any extra matrix storage and without using numerical QP optimization steps at all. SMO decomposes the overall QP problem into QP sub-problems, using Osuna's theorem to ensure convergence.

Unlike the previous methods, SMO chooses to solve the smallest possible optimization problem at every step. For the standard SVM QP problem, the smallest possible optimization problem involves two Lagrange multipliers, because the Lagrange multipliers must obey a linear equality constraint. At every step, SMO chooses two Lagrange multipliers to jointly optimize, finds the optimal values for these multipliers, and updates the SVM to reflect the new optimal values.There are four steps to implement in SMO which is shown in Fig. 2.

The advantage of SMO lies in the fact that solving for two Lagrange multipliers can be done analytically. Thus, numerical QP optimization is avoided entirely. The inner loop of the algorithm can be expressed in a short amount of C code, rather than invoking an entire QP library routine. Even though more optimization sub-problems are solved in the course of the algorithm, each sub-problem is so fast that the overall QP problem is solved quickly.

In addition, SMO requires no extra matrix storage at all. Thus, very large SVM training problems can fit inside of the memory of an ordinary personal computer or workstation. Because no matrix algorithms are used in SMO, it is less susceptible to numerical precision problems.

Step 1: Find α^1 as the initial feasible solution. Set $k = 1$

Step 2: If α^k is a stationary point of (2), stop. Otherwise, find a two-element working set $B = \{i, j\} \subset \{1, \ldots, l\}$.

Define $N \equiv \{1, \ldots, l\} \setminus B$ and α_B^k and α_B^k as sub vector of α^k corresponding to B and N respectively.

Step 3: If $a_{i,j} = K_{ii} + K_{jj} - 2K_{ij} > 0$

Solve the following sub-problem with the variable

$$\alpha_B : \min \frac{1}{2} \begin{bmatrix} \alpha_i & \alpha_j \end{bmatrix} \begin{bmatrix} Q_{ii} & Q_{ij} \\ Q_{ij} & Q_{jj} \end{bmatrix} \begin{bmatrix} \alpha_i \\ \alpha_j \end{bmatrix} + (p_B + Q_{BN} \alpha_N^k)^T \begin{bmatrix} \alpha_i \\ \alpha_j \end{bmatrix} \quad (4)$$

Subject to, $0 \le \alpha_i, \alpha_j \le C,$

$y_i \alpha_i + y_j \alpha_j = \Delta - y_N^T \alpha_N^k,$

else
solve

$$\min \frac{1}{2} \begin{bmatrix} \alpha_i & \alpha_j \end{bmatrix} \begin{bmatrix} Q_{ii} & Q_{ij} \\ Q_{ij} & Q_{jj} \end{bmatrix} + (p_B + Q_{BN} \alpha_N^k)^T \begin{bmatrix} \alpha_i \\ \alpha_j \end{bmatrix} \quad (5)$$

$$\frac{\tau - \alpha_{ij}}{4} ((\alpha_i - \alpha_i^k)^2 + (\alpha_j - \alpha_j^k)^2)$$

subject to constraints of (4)

Step 4: Set α_B^{k+1} to be the optimal solution of (4) and

$\alpha_N^{k+1} = \alpha_N^k$ set $k \leftarrow k + 1$ and go to **step 2.**

Fig. 2. The SMO algorithm

Support Vector Machine classifier separates a set of objects into their respective groups with a line. Hyper plane classifiers separate objects of different classes by drawing separating lines among the objects. Support Vector Machine (SVM) performs classification tasks by constructing hyper planes in a multidimensional space. SVM supports both regression and classification tasks and can handle multiple continuous and categorical variables. Training in SVM always finds a unique global minimum. A flow diagram that conceptually depicts the stages of model development is shown in Fig. 3.

3. RESULTS AND DISCUSSION

3.1 Experimental Results

10-fold cross-validation technique is used to evaluate the performance of SVM classifier method. Data set was randomly sub divided into ten equal sized partitions. Evaluation of performance is compared using Mean absolute error, root mean squared error and kappa statistics. Large test sets gives a good assessment of the classifier's performance and small training sets which result in a poor classifier. The Table 2 gives the correctly classified instance and incorrectly classified instances out of 605 instances.

3.2 Performance Evaluation

The algorithm performance is partitioned into several sub item for easier analysis and evaluation. In first part, the sensitivity, specificity and accuracy are used. All measures can be calculated based on four values, namely True Positive (TP, a number of correctly classified that an instances positive), False Positive (FP, a number of incorrectly classified that an instance is positive), False Negative (FN, a number of incorrectly classified that an instance is negative), and True Negative (TN, a number of correctly classified that an instance is negative). These values are defined in Table 3.

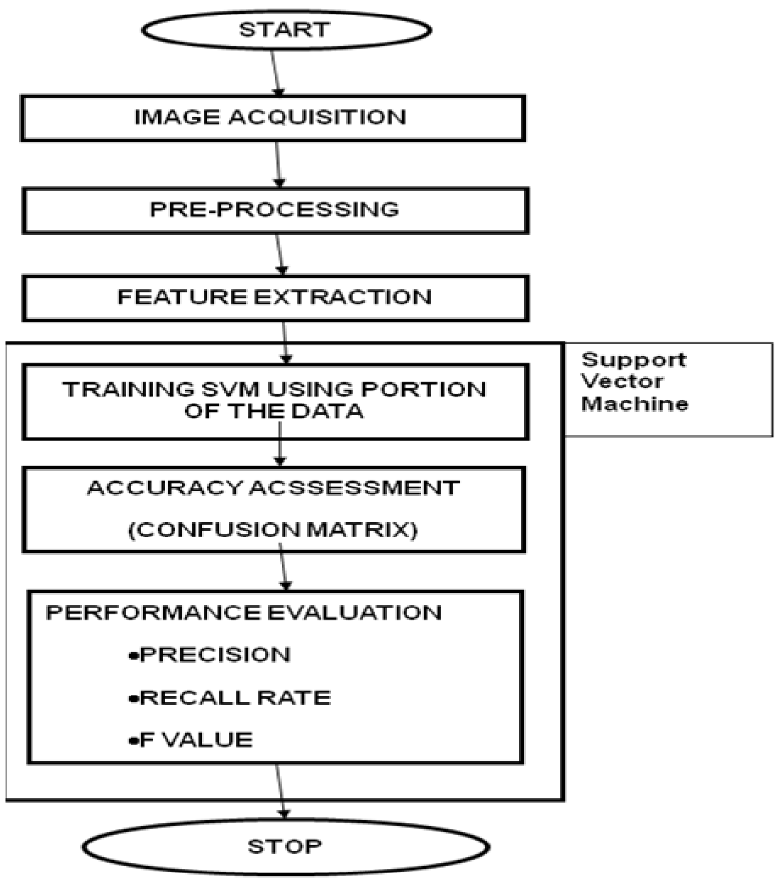

Fig. 3. Flowchart of the model development

Table 2. Classified Instances for ear biometric data (testing stage)

Performance rate	No. of test instances	Correctly classified instances	Incorrectly classified instances
SMO Classifier	200	186 (93%)	7%

Table 3. Predicted class

True class	Yes	No	Total
Yes	TP	FN	TP+FN
No	FP	TN	FP+TN
Total	TP+FP	FN+TN	TP+FN+FP+TN

From these quantities, the sensitivity and specificity computed by using following equations.

$$Sensitivity = \frac{TP}{TP + FN} \quad (6)$$

$$Specificity = \frac{TP}{TP + FP} \quad (7)$$

Thus “Sensitivity” is defined as percentage of correctly classified instances, and “Specificity” is defined as percentage of incorrectly classified instances. Also, “Accuracy” is the overall success rate of the classifier and computed by using equation (8).

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \quad (8)$$

In the second part, we also explained about the relative MAE, RMSE, and Kappa Statistics for reference and evaluation.

3.2.1 Kappa statistics

Kappa is a normalized value of agreement.

$$K = \frac{P(A) - P(E)}{1 - P(E)} \quad (9)$$

Where P(A) = percentage agreement
P(E) = chance agreement.

If K =1 agreement is perfect between the classifier and ground truth.
If K=0 indicates there is a chance of agreement.
Kappa Statistics for Ear Biometric Data is 0.8928.

3.2.2 Mean Absolute Error(MAE)

The mean absolute error is a quantity used to measure predictions of the eventual outcomes. The mean absolute error is given by

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n} |f_i - y_i| = \frac{1}{n}\sum_{i=1}^{n} |e_i|. \quad (10)$$

3.2.3 Root Mean Squared Error(RMSE)

Root mean squared error is the square root of the mean of the squares of the values. It squares the errors before they are averaged [18] and RMSE gives a relatively high weight to large errors.

The RMSE Ei of an individual program *i* is evaluated by the equation:

$$Ei = \sqrt{\frac{1}{n}\sum_{j=1}^{n}\left(\frac{P_{(ij)} - T_j}{T_j}\right)^2} \quad (11)$$

Where

$P_{(ij)}$ = the value predicted by the individual program
i = fitness case
Tj =the target value for fitness c

3.2.4 Precision and Recall

In pattern recognition and information retrieval with binary classification, precision (also called positive predictive value) is the fraction of retrieved instances that are relevant, while recall (also known as sensitivity) is the fraction of relevant instances that are retrieved. Both precision and recall are therefore based on an understanding and measure of relevance.

$$\mathrm{Pr}\,ecision = \frac{TP}{TP + FP} \quad (12)$$

$$\mathrm{Re}\,call = \frac{TP}{TP + FN} \quad (13)$$

3.2.5 F measure

In statistical analysis of binary classification, the F_1 score (also F-score or F-measure) is a measure of a test's accuracy. It considers both the precision *p* and the recall *r* of the test to compute the score: *p* is the number of correct positive results divided by the number of all positive results, and *r* is the number of correct positive results divided by the number of positive results that should have been returned. The F_1 score can be interpreted as a weighted average of the precision and recall, where an F_1 score reaches its best value at 1 and worst score at 0.

The traditional F-measure or balanced F-score (**F_1 score**) is the harmonic mean of precision and recall:

$$F1 = 2 \bullet \frac{precision \bullet recall}{precision + recall} \qquad (14)$$

3.2.6 Confusion matrix classification accuracy

Classification accuracy is the degree of correctness in classification. The degree of correctness is evaluated using SVM classifier for individual instances in the ear biometric data set. The Larger the training set and higher the classifier accuracy is.

In the field of machine learning, a confusion matrix, also known as a contingency table or an error matrix , is a specific table layout that allows visualization of the performance of an algorithm, typically a supervised learning one (in unsupervised learning it is usually called a matching matrix).

Each column of the matrix represents the instances in a predicted class, while each row represents the instances in an actual class. The confusion matrix as obtained in this work is presented in Table 4.

Table 4. Confusion matrix for ear biometric data

	C0	C1	C2
C0	75	29	0
C1	0	331	0
C2	0	8	162

3.3 Discussion on SMO

Kappa is a chance-corrected measure of agreement between the classifications and the true classes. It's calculated by taking the agreement expected by chance away from the observed agreement and dividing by the maximum possible agreement. A value greater than 0 means that our classifier is doing better than chance.

Kappa Statistics for SVM classifier is 0.8928 a value which is greater than 0 which means that SVM classifier is doing better than chance.

The error rates are used for numeric prediction rather than classification. In numeric prediction, predictions aren't just right or wrong, the error has a magnitude, and these measures reflect that. The values of kappa statistics and different error rates are presented in the Table 5.

Table 5. Performance evaluation measures

Kappa statistics	0.8928
Mean absolute error	0.2358
Root mean squared error	0.2961
Relative absolute error	59.691
Root relative squared error	66.641

The detailed presentation of evaluation measures for the classifier analysis after the successful execution of SVM algorithm is presented in Table 6.

Table 6. Evaluation measures for the classifier

	TP rate	FP rate	Precision	Recall	F-measure	ROC area	Class
	0.721	0	1	0.721	0.838	0.951	C0
	1	0.135	0.899	1	0.947	0.932	C1
	0.953	0	1	0.953	0.976	0.992	C2
Weighted avg.	0.939	0.074	.945	0.939	0.936	0.952	

4. CONCLUSION

This paper presented an application of SVM for the classification of ear biometric database and to use the classes for the identification of persons. Based on the research work rendered, following conclusions are drawn:

- The shape based ear biometric features related to moment of inertia and radii of gyration permitted SVM to classify the database of 605 ear images in to three groups.
- SVM, a well known supervised machine learning approach took less time to build the model (0.11 seconds).
- SVM established to be an adequate model with a small number of misclassification instances (37) out of 605 instances, thus showing a classification accuracy of 94%.
- The classification analysis showed high value of recall, precision and F-Measure and low value of Kappa statistics which are the testimony for its classification efficiency.
- The only lacuna in this work is that the system developed is not orientation invariant as all the ear images were obtained in direct view of the Camera.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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