Different Classifier Approaches Used For Fingerprint Classification

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Abstract—Fingerprints play an important role in public safety and criminal investigations such as: B. Legal Investigations, Law Enforcement, Cultural Access, and Social Security. It can also help to give people a comfortable and secure life. Various gender segregation strategies have been proposed. In this article, the fingerprint algorithm uses a variety of Naive Bayes classifiers, SVM, Logistics Regression and Random Forest which they use to obtain the best results of gender segregation, a new fingerprint method can be created by Naive Bayes classifier, SVM, Logistics Regression and The Random Forest used and compiled proposed from different divisions obtained the best possible division of results by Random Forest, with 98% accuracy compared to Naive Bayes, SVM and Logistics Regression, based on Random. The forest is the most sensitive to gender segregation.

Index Terms—Naïve Bayes, SVM, Logistic Regression, Random Forest, Gender classification, Fingerprint database, Association Rule Mining.

I. INTRODUCTION

Separation of fingerprints refers to the separation of each fingerprint in a section in a consistent and reliable way so that anonymous fingerprints can be searched and only need to be compared with the fingers in the details of the section. Comparison of fingerprints is usually based on small finger functions, such as apex and branches, while fingerprint classification is often based on larger functions, such as the shape of the rib cage.

To identify a person, you must compare your finger with all fingerprints in the message. A common strategy is to reduce the number of comparisons in finger recognition, thereby extending the recognition process to distinguish fingerprints through the various categories described previously [1]. The actual control of human thought is based on the development of models. Advanced computers support pattern recognition. Separation is an example of pattern recognition, which attempts to assign each input value to a different category. Your main goal is to find the best role model support under certain circumstances and to differentiate one category from another. Divorce performance is very important in making good decisions. However, the function of classification depends largely on the identity of the data to be categorized. Major Headings Major headings should be typeset in boldface with the first letter of important words capitalized.

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A. Gender Classification

There are a number of ways to determine the most important gender, such as reducing the speed of detection of criminals in cybercrime, thereby reducing the time spent on application. The abuse of biological agents has created many ways to identify sex, such as face, finger, voice samples, etc. This allows sexual determination based on fingerprints. Fingerprint recognition completed. Two operations, one is used to find the number of fingers in the male and female numbers, the size of the ribs, the size of the ribs, and the base size and width of the ribs. And fingers. Model. Used for gender segregation. Second, measurement compares only the incoming finger with other information, which is very important in accelerating finger recognition. Recovery technology and automatic hunting. [25] With the availability of cheap and high-quality scanners and their good compatibility with a variety of biometric technologies, many citizens and commercial applications are beginning to get bored or get involved with fingerprints.

II. CLASSIFIERS USED

In this paper four classifier are used for fingerprint classification which are as follows:

A. Naive Bayes Classifier

Naive Bayesian Separator is an algorithm that uses the Bayes theorem to separate objects. The ignorant Bayesian separator assumes strong or irrational independence between data point signals. Popular use of Bayesian naive classifiers for spam filtering, text analysis, and medical diagnostics. This separator is widely used in machine learning because it is easy to use.

Unjustified Bayesian segregation can be easy opportunities supported by Bayesian theory and with a stable sense of independence. For example, suppose domain variables are separate categories and each variable contains a limited number of values.

B. SVM Classifier

Support Vector Machine is a learning program that uses speculative space for specific tasks in large spaces. SVM is trained using a learning algorithm designed for processing that considers learning bias based on mathematical learning concepts. In the late 1970's, Vapnik and colleagues introduced this learning strategy and combined it with various mathematical, mechanical, and neural networks. Risk reduction (SRM) policy is contained in SVM. It turns out that this is an improvement in the traditional goal of minimizing the high-risk (ERM) used by conservative neural networks. Compared to ERM, SRM reduces the expected amount of risk by reducing errors in training data. Therefore, SVM is unique and comes with excellent summaries and capabilities to achieve mathematical learning objectives. In fact, SVM is a binary separator.

C. Random Forest

Random Forest is a widely used machine learning engine and is a trademark of Leo Braiman and Adele Cutler. Combine results from multiple decision trees to get one result. Easy use and flexibility lead to acceptance because you can overcome differences and frustrations.

The Random Forest (or the Forest Forest) are trademarks of various species. It contains a lot of stems, the first step to removing the stem from the tree. A random forest is a group of slightly different trees.

D. Logistice Regression

Asset recovery is an independent control system algorithm used to predict the probability of target variation. The type of target or variation you rely on is dichotomous, that is, there are only two possible categories.

Simply put, the dependent variable is binary and the data is encoded as 1 (indicating success / yes) or 0 (indicating failure / no).

Statistically, the systematic model predicts P(Y = 1) as the X function. It is one of the simplest ML methods used for diagnostic problems such as spam detection, diabetes prognosis, cancer detection, etc.

III. RELATED WORK

Nithin MD et al. [3] 200 A study of the age group 18 to 30 years (100 men and 100 women) was used. Use the newly designed structure to determine left-to-left compression and perform a statistical evaluation. Tests show that women in both study areas, either individually or in combination, tend to have more than one fingerprint.

Pattanawit Soanboon et al. [4] used the size of the fingertips and also explained that males have stronger fingers than females, meaning that males have smaller glands than females in a given region and therefore less soaps. The high prevalence of female fingerprints is due to the fact that the epidermal columns of women tend to be smoother than those of men. Men tend to have stronger mountains than women, with a difference of around 10%.

Ashish Mishra et al. [5] in this article, The difference in overcrowding between men and women in some areas may be due to the fact that the proportion of men is greater than that of women, so the amount of overcrowding is the same. Placed in a larger area of males, so males are smaller in size. Suchita Tarare et al. [6] also explain the whole process of the scheme above. The DWT modification provides multiple fingerprint structures from a data set (image reading) to create a database of functions used as a viewing table to distinguish unknown fingerprints from other fingerprints (fingerprints) used for testing. The divider Knn designates one of the two sets for testing fingerprints.

Alessandra Lumini et al. [7] describes the many systems and structures associated with the integration of biometric systems, both informal and multidisciplinary, and classifies them according to certain tax statistics. In addition, we address the issue of testing biometric systems and discuss performance indicators and processes.

Swapnil R. Shinde et al. [8] described a complete comparison of conventional domain strategies, with a particular focus on DWT and its combinations. It also uses a canvas on the edge of the Canny and a DWT-based hair filter.

Neeti Kapoor et al. [9] to find a significant difference in the strength of tread between boys and girls in most Indians, a study was conducted on 200 subjects (100 boys and 100 girls) aged 18 years to find a sexual relationship - Year 30.

Meena Tiwari et al. [10] in this work, the study used four divisions: the Bases organization, the multi-stakeholder organization, the closest neighbors, and additional vector equipment. In addition, classification was tested in four prominent studies. These are cases that are questioned with 70% correction, 30% test, 60% preparation, 20% test, finally 60% preparation, 40% test, 10 cases. From the results it can be concluded very well that all the emergence of a common division completes representation of more than 90%. However, SVM is still the best divider proposed to be counted. Fingerprints are strong evidence of legitimacy in court. With regard to the amazing power as a finger recognition system, this post tries to explore relationships between women. Reading and standing are the result of our statistics and part of the basic meaning, to see the right values for sex. This design requires a proven test structure for unique products to reduce numerical time and improve performance.

IV. RESULTS AND DISCUSSION

The purpose of this proposed project is to utilize new technologies based on mindless Bayesian classifiers, vector support machines, random forests and retrospect in order to properly train and test fingerprint scanners. The proposed system is based on the results of comparing the four categories selected by the categories: Support Vector Machines and Naive Bayes, Random Forest and Logistic Regression which are divided into left and right category categories. Specifically, it has two independent modules: a training data selection module and a fingerprint separation module. Fig. 1 shows a block diagram for the implementation of the finger splitting system.

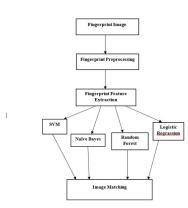


Fig.1. Block diagram of the system implemented to classify fingerprints.

W			Х			1		
termin ation x	termin ation y	Angle	bifurca tion x	bifurca tion y	Angle 1	Angle 2	Angle 3	Class
115	15	109	133	32	137	39	120	1
17	121	20	54	80	58	130	60	1
204	21	114	84	76	106	76	94	1
22	108	24	80	81	82	139	87	1
111	33	130	146	90	228	92	167	1
40	104	41	93	143	97	162	98	1
110	42	166	168	103	190	109	115	1
47	107	51	110	88	112	52	114	1
100	53	145	173	120	196	120	108	1
57	189	57	123	56	125	200	125	1
70	61	235	80	130	123	132	162	1
63	181	64	132	156	134	128	137	1
76	65	187	202	138	53	140	219	1
65	59	66	141	237	144	232	148	1
193	67	71	174	157	166	163	115	1
70	179	74	166	84	168	76	180	1
186	77	211	52	181	82	183	151	1
		81	-	-			196	1
81	218		184	47	187	110		-
178 88	83	78 88	57 199	198	48	199	68	1
187	126 89	177	159	60 221	204 85	57 233	217 74	1
93	183	96	238	0	0	0	0	1
78	100	176	0	0	0	0	0	1
103	182	105	0	0	0	0	0	1
103	107	128	0	0	0	0	0	1
107	122	114	0	0	0	0	0	1
176	127	177	0	0	0	0	0	1
134	205	149	0	0	0	0	0	1
89	161	104	0	0	0	0	0	1
163	147	170	0	0	0	0	0	1
154	171	57	0	0	0	0	0	1
172 174	88 174	173 183	0	0	0	0	0	1
174	134	178	0	0	0	0	0	1
141	179	156	0	0	0	0	0	1
179	98	180	0	0	0	0	0	1
109	185	169	0	0	0	0	0	1
190	52	192	0	0	0	0	0	1
124	192	65	0	0	0	0	0	1
193	38	197	0	0	0	0	0	1
179	198	161	0	0	0	0	0	1
200	148	201	0	0	0	0	0	1
78	206	164	0	0	0	0	0	1

The editorial board is edited by Naive Bayes and delivered to a unique library. half of the information index is used for preparation, and the remaining half is used for testing. The specifications found are shown in Table 1. Repeat the same rehash system (W, X, Y), separated by fingers left (1) and right (2). These three types are a combination of X coupling, Y coupling, point, X branch, Y branch, point 1, point 2, and point 3.

Table.2.The results obtained from the naive Bayes classification applied to the class $\left(W,\,X,\,Y\right)$ on CASIA DB fingerprints

	W			Х			Y		
		natio		bifur catio n x	catio	Angl		Angl e 3	Class
Accuracy (%)					71				

Table.3.The results obtained from the SVM classification are applied to 3 classes $(W,\,X,\,Y)$ in CASIA DB . Fingerprint database

		W			Х			Y		
		termi natio n x	termi natio n y	Ang	bifur catio n x	bifur catio n y	Δησ	Angl e 2	Angl e 3	Class
Accu (%	•					68				

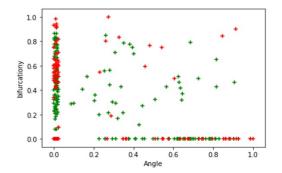


Fig.2. Plot the classification boundaries and visualize the svm classifier

TABLE 4. RESULTS OBTAINED FROM RANDOM FOREST, APPLIED IN 3 CLASSES

	W			Х			Y		
	termi natio n x	termi natio n y	Ang		bifur catio n y	Δng	Angl e 2	Angl e 3	Class
Accuracy (%)					98				

Table.5. The results obtained from logistic regression, applied in 3 classes (W, X, Y) in CASIA DB . Fingerprint database

	W	W			Х			Y	
	termi natio n x	natio	Angl		catio	Angl e 1	Angl e 2	Angl e 3	Class
Accuracy (%)					88				

A. Comparison Accuracy Naive Bayes, SVM method, Random Forest and Logistic Regression

This comparison tests the ability to distinguish by simple separators commonly used in image classification. Four classifiers were selected for the test: Naive Bayes, SVM, Random Forest, Logistic Regression and related categories to compare classification results. Compared to the Bayesian classifier class, SVM classifier and logistic regression, the random forest division has yielded excellent results. Random forest planning sets well 98% model attributes and reduced model sets. Depending on these results, it can be improved by further processing the data and synchronizing the separation. Accurate comparisons of the mindless Bayes approach, random forest and logistic SVM regression are shown in Table 2 and Table 3.

B. Confusion Matrix

Confusion matrices are used to measure the performance of a two-step task on a given data set. False negative) incorrect sample classification.

Actual Class	Predicted Class				
	Positive	Negative			
Positive	True Positive (TP)	False Negative			
Negative	False Positive (FP)	True Negative (TN)			

TABLE.6. CONFISION MATRIX

Total number of copies = items ordered correctly + items ordered correctly

Classification example = TP + TN

Example of misclassification = FP + FN

Table 5 uses non-statistical records. 185 cases. The fingerprint category is randomly selected from the fingerprint record. When using the algorithm for the design of the Bayesian naive in a set of data, a confusion matrix is generated in a two-digit finger class, i.e. Left thumb and right thumb.

TABLE .7. NAIVE BAYES CLASSIFIER CONFUSION MATRIX

Actual Class	Predicted Class				
185	Positive	Negative			
Positive	71	7			
Negative	9	41			

The table above is suitable for calculating the matrix of confusion of these actual and hypothetical scales, where 185 is perfectly correct in grade 71 and is not entirely accurate. True lies in seventh grade. Not at all. The absolute best result of the category was 9 and nothing. The positive result of lying in class was 41.

TABLE.8. SVM CONFUSION MATRIX

Actual Class	P	redicted Class
185	Positive	Negative
Positive	68	37
Negative	32	48

Table - 8 sets of data used do not match. 185 cases. The fingerprint category is randomly selected from the fingerprint record. When the SVM partition algorithm is applied to a data set, the fingerprint confusion matrix is made up of two values; Left and Right Thumbs The table above is used to calculate the confusion matrix of this real and predicted phase, i.e. the true positive result of this phase is 68 and is negligible. From false good to section 37. Impossible. The best result for the class was 32 points, which was not the case. The positive class result of the class was 48.

TABLE.9.RANDOM FOREST CONFUSION MATRIX

Actual Class	Predicted Class			
185	Positive	Negative		
Positive	98	7		
Negative	9	51		

The table uses countless records. 185 cases. The fingerprint category is randomly selected from the fingerprint record. When using a random forest algorithm in a data set, the confusion matrix is created for a two-digit fingerprint category, i.e.. Left and Right Thumbs The table above is used to calculate the confusion matrix of this real and predicted phase, i.e. the actual positive result of this phase is 98, at all. True lies in seventh grade. Not at all. The absolute best result of the category was 9 and nothing. The positive result of lying in class was 51.

TABLE. 10. LOGISTIC REGRESSION CONFUSION MATRIX

Actual Class	Actual Class	Actual Class		
185	Positive	Negative		
Positive	88	7		
Negative	8	65		

Table - 10 of the used data sets do not match. 185 cases. The fingerprint category is randomly selected from the fingerprint record. When using a logistic regression algorithm on a data set, a two-digit confusion matrix is developed for the fingerprint category, i. Left and Right Thumbs The table above is used to calculate the confusion matrix of this real and predicted phase, i.e. the true positive result of this phase is 88, but not at all. True lies in seventh grade. Not at all. The overall good result for the class was 8 points, which was certainly not true. The positive result of lying in class was 65.

C. Accuracy

Described as the ratio between well-separated samples and the total number of samples. Figure 2 shows the comparative accuracy of the Naive Bayes, SVM, Random Forest and Logistic Regression.

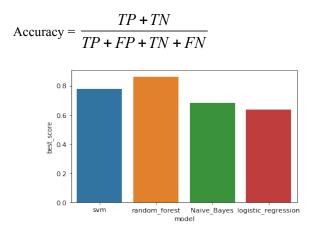


Fig.2. Comparative accuracy with naive Bayes, SVM method, random forest and logistic regression

VI. CONCLUSIONS

Gender segregation can be done through the Naive Bayes Classifier, SVM, Random Forest and job adjustment. By limiting the following search categories to the sixth left and right information, the search time is effectively reduced. Once the left and right face thumbs are separated, the biological features of each can be used for further separation. In this category, four categories have been selected: Naive Bayes, SVM, Random Forest and Logistic Regression. Compared to the mindless Bayesian, SVM and logistic regression classifier, the best results were obtained with random forest planning.

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