Support Vector Machine Used for Gender Classification

Meena Tiwari and Ashish Mishra

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Meena Tiwari[1]and Ashish Mishra[2]

[1]SRK University Bhopal M.P. India

[2]Gyan Ganga Institute of Technology and Sciences Jabalpur MP, India

phmeenatiwari@gmail.com

ashishmishra@ggits.org

Abstract. Biometric technology has applications in the field of example confirmation, for example single brand confirmation, face confirmation, iris confirmation, palm print confirmation, etc. Grouping by sexual orientation is a test that enables PC agencies to organize gender data and assess age based on images of unique trademarks. Therefore it becomes a staple of PC vision and is confirmed by examples due to its basic application possibilities in character confirmation, video files, robot vision and human-machine interface. In the field of vision of the PC. Highlighting the position is an essential advance in disposition of sexual orientation, because the extraction calculations performed in gender order must remove highlighting from fingerprint. The display of the unique brand confirmation will be affected by the accuracy of the sexual orientation grouping.

Keywords: Support vector machine, Fuzzy C-implies, Gender characterization, unique mark pictures, affiliation rule mining.

1 Introduction

Over time, fingerprints are increasingly used in personally identifiable login and certification applications, as is actual access control and bank security. Although a variety of expanded unique trademark coordination strategies and a wide range of biometric applications are available in various ways, reliable, correct and unique trademark-based gender arrangement technology remains impossible. For single trademark confirmation analysts, characterization of sexual orientation is one of the most tested questions [2]. The extraction of highlights and the order of the samples are two important steps in grouping by gender. It seems that support vector machines are developed in it [9]. There are several applications for grouping by gender. For example, a sexual orientation substantial arrangement framework may provide a reason to use segmented data for inactive observations or to collect valuable measurements of shoppers at strip clubs. Grouping by sexual orientation can improve the presentation of the biometric framework, such as facial verification and confirmation, fingerprint confirmation of inappropriate scenes, etc.

1.1 Gender Classification Using SVM

When performing gender characterization through fingerprints, border widths and white lines will be determined. The disposition of sexual orientation depends on various combinations of these priorities. Highlights include edge inspection, valley count, white line count, and the ratio of edge thickness to valley thickness (RTVTR). Support vector machines are used to organize sexual orientation according to a given fingerprint. This depends on the idea of the choice plane that characterizes the choice boundary. A group of projects with unique class entry requirements are isolated by a selection plane. SVM is a non-linear classifier, often used to create incomparable permutations. The proposed SVM classifier plan for the characterization of sexual orientation is shown in Fig 1.

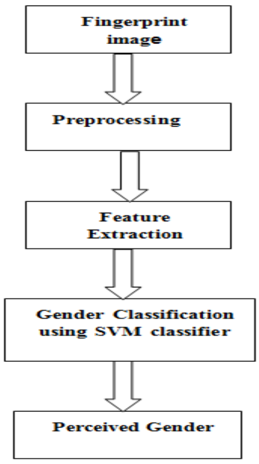


Fig.1. Scheme of the proposed gender classification

2 Related Work

Verma and Agarwal [1] use border thickness, RTVTR, and border width to identify gender. Using the SVM classifier, the completion rate for men reached 86% and that for women reached 90%.

Wang [2] Use markers for border, border thickness and finger size to organize the genre. The separate key content of 57 male and 58 female subjects (age range 18 to 35 years) in Taiwan has been broken down. The proposed approach is to test the progress of the gender separation test and the multilayer perceptron (MLP) as a classifier. The best order accuracy of 86% was obtained by edge checking and finger size highlighting.

Eshak [3] Use edge markup, square area, and edge thickness as unique markup highlights. In this survey, 380 Egyptian men and 372 women, aged between 20 and

30, were used. The recurring variants survey using multivariate calculations performed measurable inspections in gender groups and established an accuracy of 82%.

Sanders G [4] the number of ridges and the density of the ridges seriously affect the size of the fingertips. If males have higher number of ridges and lower density of ridges than females, then the size of the fingers is more important than the characteristics of the number of ridges and the density of ridges compared to males and females.

Ashish Mishra[5] uses a set of fingerprint data, one is female data and the second male data. This process converts the image data of each fingerprint into a sequence of digital text code and use the predefined minimum confidence and minimum condition support to minimize association rules in the filtered data set. For each text file, classification processing is done by classification and association rule extraction. After classification, the data can be classified as male or female data. This method is based on two fundamental principles of data mining.

Gnanaswamy [6] suggested using a method to classify details in time by subdividing the fingers to determine gender, thus identifying the genes used by the fingers. These components are obtained from the acceleration of the transformation of the medium, the discrete cosine transformation and the power spectral density. Add a single database of 400 data on different ages and sexual orientations. The estimated value of the digital statistical model and its comparison with the recommended conditions. They obtained results of 92.88% and 94.85% for men and women, respectively.

S. Sudha Ponnarasi [7] relies on the identifiable uniqueness test strategy of the toothpaste. The subject of the survey is more than 500 people, of which 250 are men and 250 women between 1 and 90. Number of white lines, number of chains and type conditions. The vector machine was used for the most important part and got serious results.

Meena Tiwari et al. [8] in this work used four divisions: the Bassey organization, the multi-stakeholder organization, the closest neighbors, and additional vector equipment. 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.

3 Proposed Methodology

The proposed technique uses an SVM classifier to classify the distinguishable sexual orientation of uniquely labeled images in one or the other male or female. The use of the SVM classifier to organize the sexual orientation of the uniquely marked images depends on the reflections obtained,it shows an obvious gender. To summarize the sexual orientation sequencing strategy for any uniquely marked image, a general SVM-based grouping calculation has been proposed using fingerprint highlighting.

3.1 Algorithm

STEP 1: Acquire the training set and test set of fingerprint images.
STEP 2: Preprocess the image.
STEP 3: Calculate Ridge Thickness, Valley Thickness, White lines Count.
STEP 4: Compute RT to VT Ratio (RTVTR).STEP 5: Input RTVTR, RC, WC to SVM Classifier.
STEP 6: Classify the gender according to RTVTR, RC, WC. STEP 7: Obtain the test set image.
STEP 8: Repeat step 2 - 6 for various test images until the end of the test image.

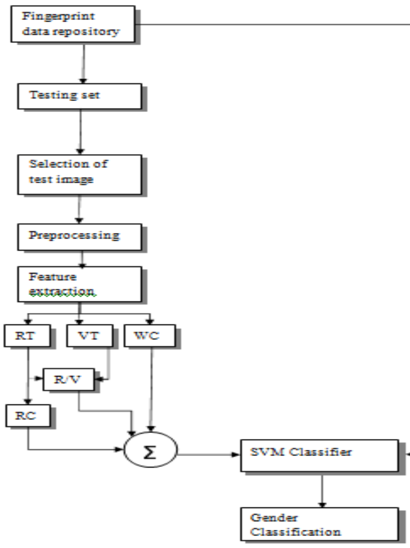


Fig.2. Flowchart for the proposed algorithm

4 RESULT AND DISCUSSION

In this part, the exhibition of the proposed strategy for characterization has been explored. At first twenty fingerprints are chosen. The info pictures of the fingerprints are given as information consistently as appeared in Fig 3. Fig 4. shows the separated picture of the unique mark picture. Parallel pictures contain just two qualities either 0 or 1. It is given in Fig 5. Fig 6. shows the diminished picture of the binarized picture. Along these lines the preprocessing strategies are completed to get the exact outcomes. In the subsequent stage, the element extraction is completed.

Fig.3. Input image for gender classification

Fig.4. Filtered image gender classification

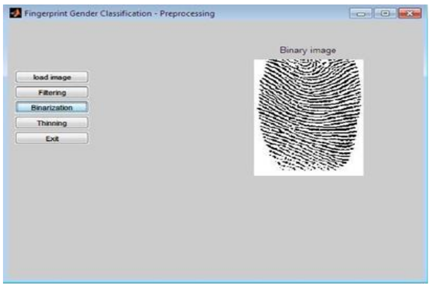


Fig.5. Binarized image for gender classification

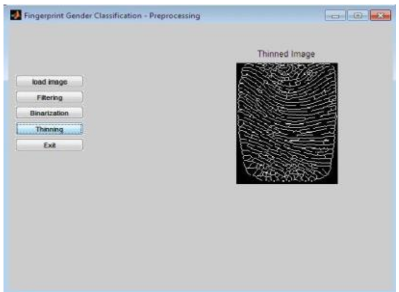


Fig.6. Thinned image gender classification

Table 1 shows the border verification of randomly selected male and female fingerprints, as shown below. The related histogram is shown in Fig 7. Table 2 shows the bottom count of randomly selected male and female fingerprints. he histogram comparison is shown in Fig 8.

Table 1. Comparison of ridge count of male and female

Sl.No	Male	Female	Sl.No	Male	Female
1.	13	15	11.	14	15
2.	12	16	12.	13	16
3.	13	16	13.	11	17
4.	11	15	14.	12	17
5.	13	17	15.	13	16
6.	14	15	16.	13	15
7.	12	15	17.	12	16
8.	11	17	18.	11	17
9.	14	17	19.	13	16
10.	12	15	20.	14	15

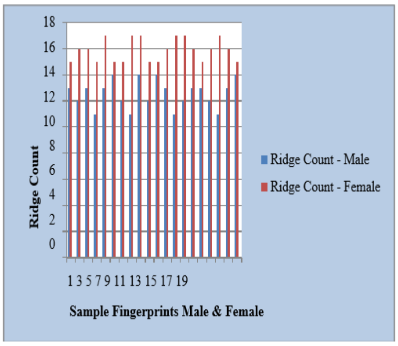


Fig.7. Histogram of the ridge count

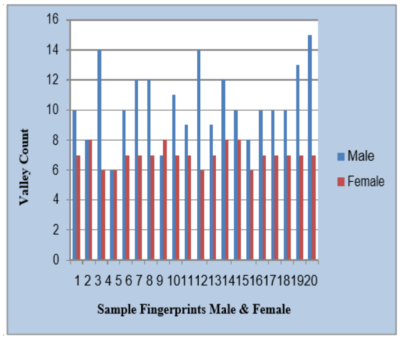


Fig.8. Histogram of the valley count

Table 2. Comparison of valley count of male and female

Sl.No	Male	Female	Sl.No	Male	Female
1.	10	7	11.	14	6
2.	8	8	12.	9	7
3.	14	6	13.	12	8
4.	6	6	14.	10	8
5.	10	7	15.	8	6
6.	12	7	16.	10	7
7.	12	7	17.	10	7
8.	7	8	18.	10	7
9.	11	7	19.	13	7
10.	9	7	20.	15	7

Table 3 shows the relationship between edge thickness and background thickness (RTVTR) of 20 uniquely marked randomly selected male and 20 female images. Additionally, the male and female RTVTR histograms are drawn independently and are typically spoken to simplify correlation. They appear in Fig 9, Fig 10, and Fig 11.

Table 3. Comparison of RTVTR of male and female

Sl.No	Male	Female	Sl.No	Male	Female
1.	1.3	2.1	11.	1.0	2.4
2.	1.5	2.0	12.	1.4	2.3
3.	0.9	2.5	13.	0.9	2.2
4.	1.6	2.6	14.	1.2	2.0
5.	1.2	2.4	15.	1.5	2.6
6.	1.1	2.3	16.	1.3	2.0
7.	1.0	2.2	17.	1.2	2.4
8.	1.4	2.0	18.	1.1	2.3
9.	1.2	2.5	19.	1.0	2.2
10.	1.3	2.1	20.	0.9	2.0

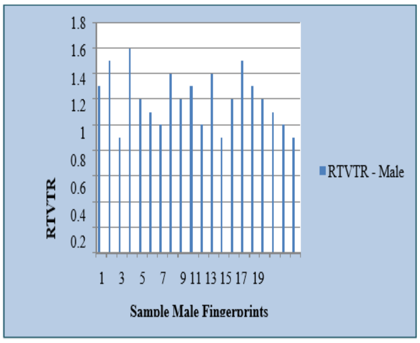


Fig.9. Histogram of the RTVTR (male)

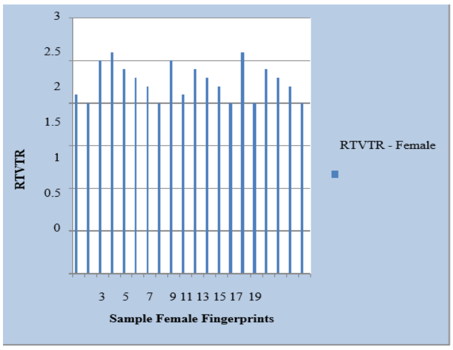


Fig.10. Histogram of the RTVTR (female)

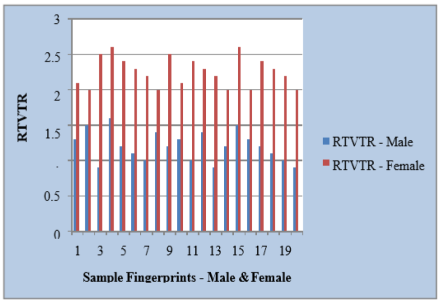


Fig.11. Histogram of the RTVTR

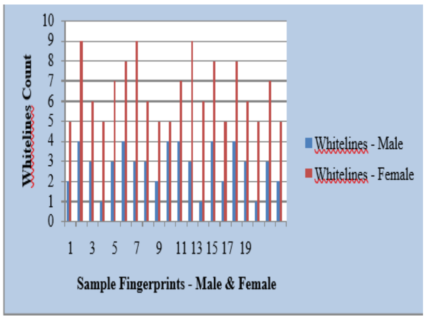


Fig.12. Histogram of the white lines count

The histogram for white lines include is outlined in Fig 12.

Table 4. Comparison of white lines count of male and female

Sl.No	Male	Female	Sl.No	Male	Female
1.	2	5	11.	4	7
2.	4	9	12.	3	9
3.	3	6	13.	1	6
4.	1	5	14.	4	8
5.	3	7	15.	2	5
6.	4	8	16.	4	8
7.	3	9	17.	3	6
8.	3	6	18.	1	5
9.	2	5	19.	3	7
10.	4	5	20.	2	5

Contingent on the element estimations of the prepared SVM classifier, the test pictures are being arranged regarding the sexual orientation them groups. The last yield is given in the GUI window as shown in Fig. 13.

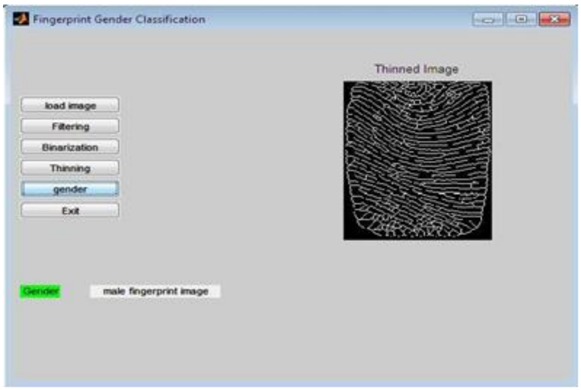
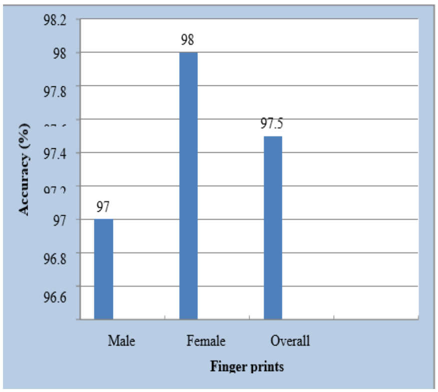


Fig.13. Gender classification

Table 5 shows the exposure of gender classification based on SVM. Table 6 shows the performance metrics for this job. The figure shows a graphical survey of this correlation.
See also Figure 14. The accuracy of Fig 15 depends on the number of images that are accurately grouped into the total number of images in the library of tested information. Execution time is determined using the Tic and Tac instructions in the MATLAB program. It can be seen that the precision of 200 images is 97.5%; execution time is 71.35 seconds.

Table 5. Accuracy of SVM based gender classification

No. of Images	Tested	Correctly Classified	Accuracy (%)
Male	100	97	97
Female	100	98	98
Total	200	195	97.5



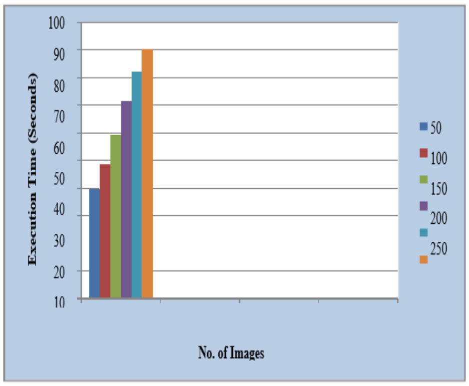


Fig.14 Accuracy of SVM based gender classification **Fig.15.** Graph execution time in sec

Table 6. Execution time for SVM based gender classification

No. of images	50	100	150	200	250	300
Execution Time (Seconds)	39.42	48.54	59.15	71.35	82.26	90.57

Conclusion

Tests on different images found that the best method and strategy for gender distribution from fingerprints is based on SVM. Comparing presentation metrics (such as execution time and precision of the proposed strategy) and presentation metrics (such as execution time and precision), these methods are used as different methods of sexual orientation classifiers. Therefore, the SVM-based classifier is a better decision.

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