Iris Features based Gender Classification using Radial SVM Classifier

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***Abstract*: Identification of sex plays a vital role in forensic and medico legal investigations. Redial kernel SVM base classifier is used for gender identification in this work and crypt densities are considered as the features for classification. SVM classifiers discover amend individual when inert crypts in iris typically accessible technique is has less acknowledgment rate & less edge thickness. The paper conducted on 200 subjects (100 males and 100 females) in the age group of 18–60 years. Crypt densities on the right- and left-iris were determined using a newly designed layout and analyzed statistically, the proposed work results showed that females tend to have a higher iris-crypt density in both the areas examined, individually and combined. Differences in the crypt density can be used as an important tool for the determination of gender in cases where partial eye-iris are encountered as evidence.The work is done on MATLAB 2018b version & standard human face database is FERET for genuine comparison.**

***Keywords*: SVM, LoC, RoC, MATLAB, Crypts, Iris, FERET**

I.INTRODUCTION

Identification of sex plays a vital role in forensic and medico legal investigations. Identification means determination of the individuality of a person. It may be complete (absolute) or incomplete (partial). Complete identification means the absolute fixation of the identity of a person. Partial identification implies ascertainment of only some facts about the identity (like sex, age, stature, etc.) while others still remain unknown. The most successful approach for individualization utilizes a combination of more than one method.

The Facial Recognition Technology (FERET) database is a dataset used for facial recognition system evaluation as part of the Face Recognition Technology (FERET) program.

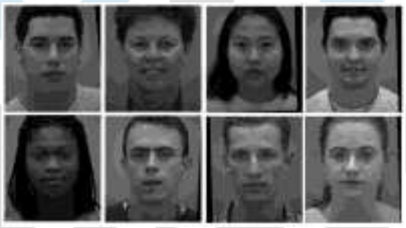


Figure 1: Face images in FERET database

No two people have exactly same iris. Even identical twins, with identical DNA, have various iris. This uniqueness allows iris to be used in all sorts of ways, including for background checks, biometric security, mass disaster identification, & of course, in criminal situations. Iris are unique patterns, made by friction furrows, which appear on pads of eyes. Friction furrows patterns are grouped into three distinct types—loops, whorls, & arches—each with unique variations, depending on shape & relationship of furrows. Figure 2 shows the Crypt types.

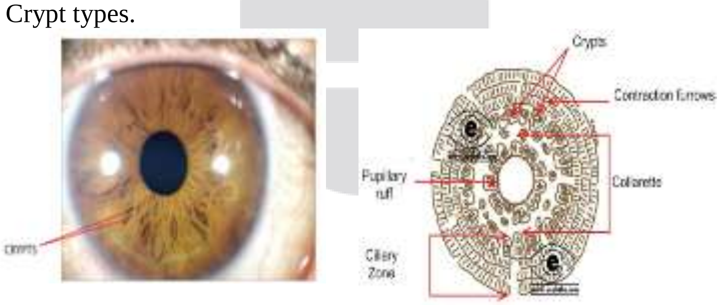


Figure 2 human iris features at various levels of detail. (a) Human iris in FERET database (b) Level-1 features

II. SUPPORT VECTOR MACHINE

A support vector machine (SVM) is a supervised machine learning model that uses classification algorithms for two-group classification problems. After giving an SVM model sets of labelled training data for each category, they're able to categorize new text. The basics of Support Vector Machines and how it works are best understood with a simple example. Let's imagine we have two tags: red and blue, and our data has two features: x and y. We want a classifier that, given a pair of (x,y) coordinates, outputs if it's either red or blue. We plot our already labelled training data on a plane:

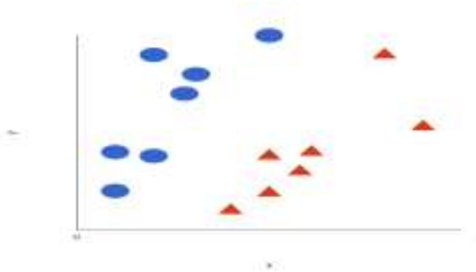


Figure 3: Labelled data in SVM

A support vector machine takes these data points and outputs the hyperplane (which in two dimensions it's simply a line) that best separates the tags. This line is the decision boundary: anything that falls to one side of it we will classify as blue, and anything that falls to the other as red. But, what exactly is the best hyperplane. For SVM, it's the one that maximizes the margins from both tags. In other words: the hyperplane (remember it's a line in this case) whose distance to the nearest element of each tag is the largest.

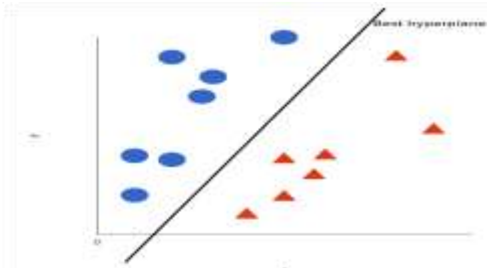


Figure 4: In 2D, the best hyper-plane is simply a line in SVM

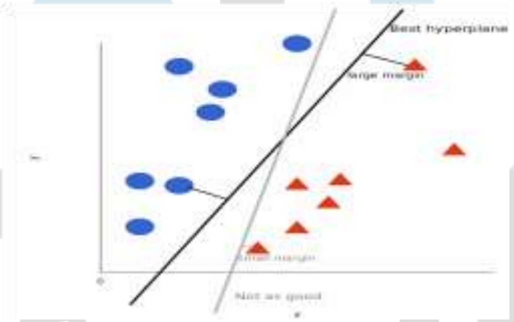


Figure 5: SVM hyper planes

III. LITERATURE WORK

TABLE 1 LITERATURE SUMMARY

Author/Journal/Year	Brief work	Outcome
Anand Venugopal/ IEEE/2020	predict the gender of kids between 6 to 8 years by analyzing there features with various methods like Local Binary Pattern (LBP), Histogram Oriented Gradients (HOG) Local Directional Pattern (LDP), and the SVM-Support Vector Machine is utilized in defining the gender	accuracy of 96.66 percentage
Herman Khalid Omer/IEEE/ 2019	new approach which consists in combining the local binary patterns (LBP) and the face geometric features to classify gender from the face images.	accuracy of 97.2 percentage
Edgar A. Torres/ IEEE/2019	Extract features and evaluate them according to the spatial relationships and angles between these characteristics and developed SVM algorithms and apply them to each feature to classify classes	accuracy of 87.2 percentage
oulad kaddour Mohamed/IEEE/2015	propose an approach for gender classification from faces images that is based on support vector machine (SVM)	accuracy of 92.87 percentage

IV. METHODOLOGY

Proposed design of human gender classification is an improvement of all previous designs of original objective of presented work is to develop a procedure which is significantly faster than old work and it has high classification rate. After doing a literature work and studies many research articles related to human gender classification, presented work is been developed. Proposed work is new procedure which include pre-processing of human eye iris image based on census transform which helps to convert human iris into a binary image and also perform image filtering with fine boundaries and clear features then previous Bayes's theorem based method on behalf of Likelihood ratio of crypt density probabilities human SVM redial kernel classifier isolate Male or Female classes. The work is done on MATLAB 2018b version & standard human iris database is FERET for genuine comparison.

The proposed design work flow shown in figure 3.1 has four major parts

- Database face Acquisition: : FERET face standard database is been used,
- Eye identification: Eye are detected from face acquisition can be done by viola Jones haar feature method.
- Pre-Processing : Census Transform is been used for pre-processing
- Feature Extraction LoC and RoC Crypt densities: The output of census transform contains features of iris LoC and RoC the crypt densities are the features.
- SVM redial kernal based gender Classification using LoC and RoC crypt densities as feature.

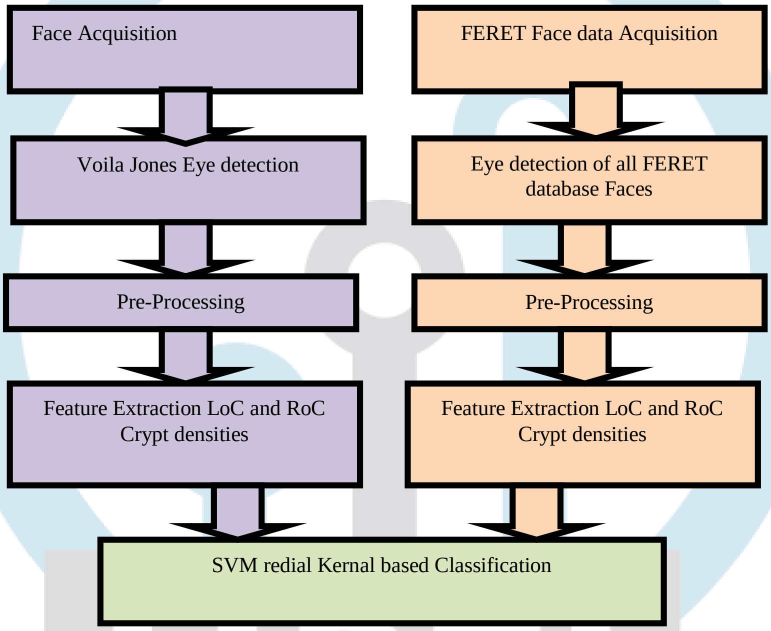


Figure 6: dataflow for system design

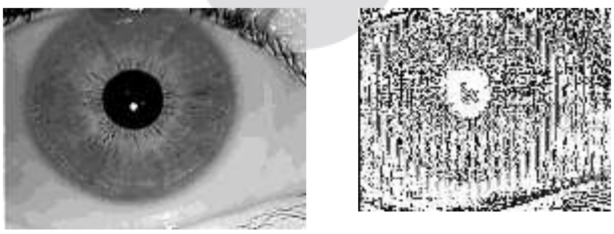
***4.1 Census transform**:* Census Transform is a non-parametric local transform which is used to map the intensity values of the pixels within a square window to a bit string to capture the image structure. This type of local transformation relies on the relative ordering of local intensity values rather than the intensity values them. The idea is to order the information among data, rather than the physical data values. census model as given in the equation

127	127	129
126	128	129
127	131	125

→

0	0	1
0	x	1
0	1	0

Figure 7: Census transform of 3x3 segment of image



Before census transform After census transform

Figure 8: census transform

4.2 Feature Extraction: After census transform the eye-iris crypt densities at the left of centre (LoC) and right of centre (RoC) are calculated for the MALE and FEMALE classes. The LoC crypt density, RoC crypt density, LoC+RoC crypt density are consider as the feature of human eye also the Likelihood Ratio (LR) and /1/LR considered as feature for gender classification.

A new and improved method for eye-iris crypt density calculation was devised. On a transpProposed work identifies the probability of correlated crypt and total count and then uses that probability in the SVM redial kernel algorithm to calculate Likelihood Ratio (LR). The favored odds were also calculated as:

$$LR = \frac{\text{Probability of a given Iris originating from a male contributor (C)}}{\text{Probability of a given Iris originating from a female contributor (C)}}$$

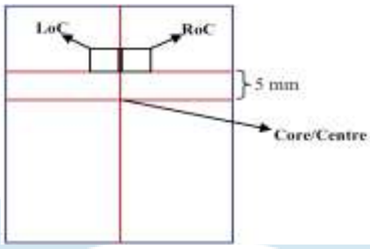


Figure 9: The format drawn on the transparency sheet used in the present thesis. (Not to scale.)

4.3 Redial kernel SVM: we found a way to classify nonlinear data by leverly mapping our space to a higher dimension. However, it turns out that calculating this transformation can get pretty computationally expensive: there can be a lot of new dimensions, each one of them possibly involving a complicated calculation. Doing this for every vector in the dataset can be a lot of work, so it'd be great if we could find a cheaper solution.

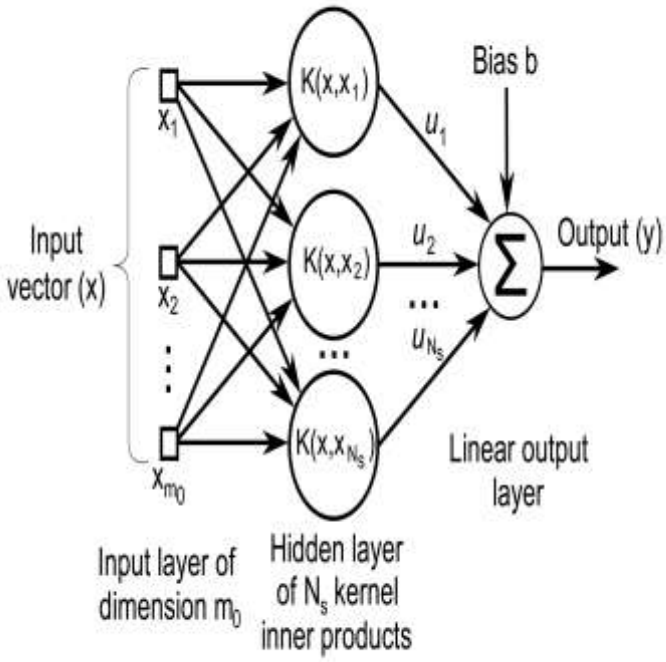


Figure 10: SVM based classification

SVM doesn't need the actual vectors to work its magic, it actually can get by only with the dot products between them. This means that we can sidestep the expensive calculations of the new dimensions! This is what we do instead:
Imagine the new space we want:

$$z = x^2 + y^2$$

Figure out what the dot product in that space looks like:

$a \cdot b = x_a \cdot x_b \ + \ y_a \cdot y_b \ + \ z_a \cdot z_b$

$a \cdot b = x_a \cdot x_b \ + \ y_a \cdot y_b + \ (x_a^2 + y_a^2) \cdot (x_b^2 + y_b^2)$

V. RESULTS

Figure 11 shown below shows FERET Database uploading and LoC and RoC of human eye iris crypt densities it also shows the census transform output. Figure 12 shows test FERET database male test image correctly classify as MALE Figure 13 shows test FERET database female test image correctly classify as FEMALE. figure 12 and 13 also show input features and output results parameters observe for the gender classification.

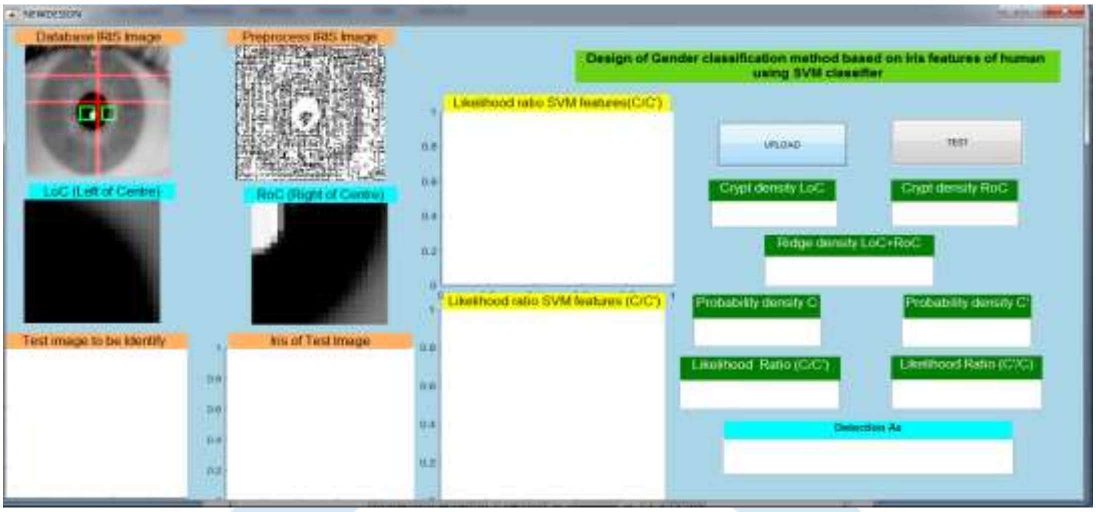


Figure 11 Data base FERET uploading

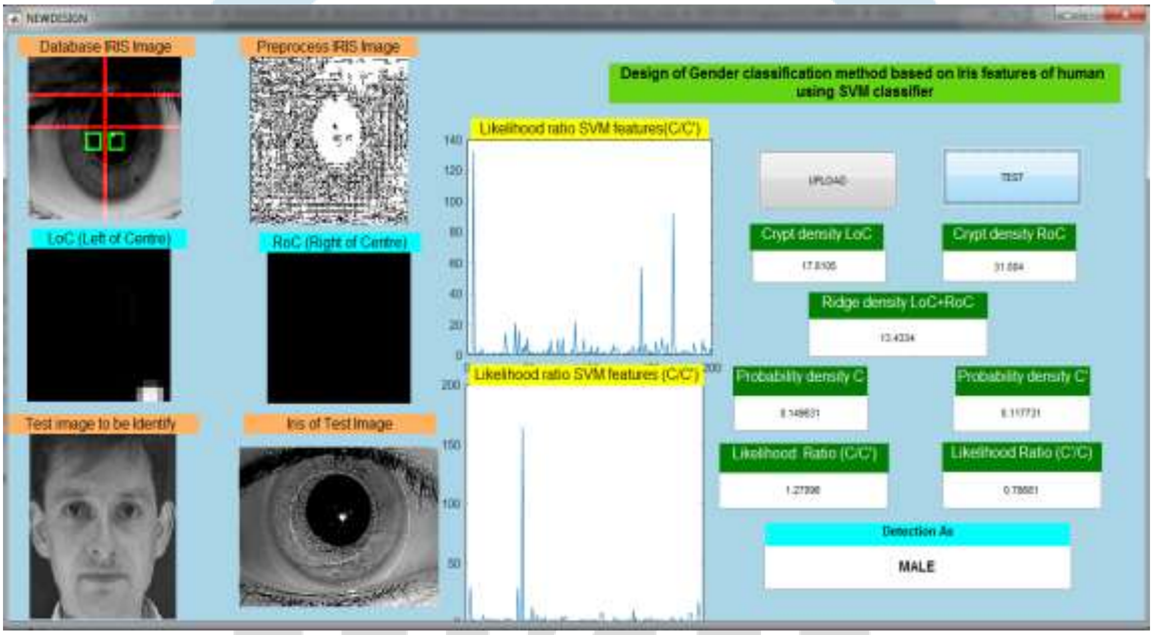


Figure 12 FERET database gender classify of male test image as MALE

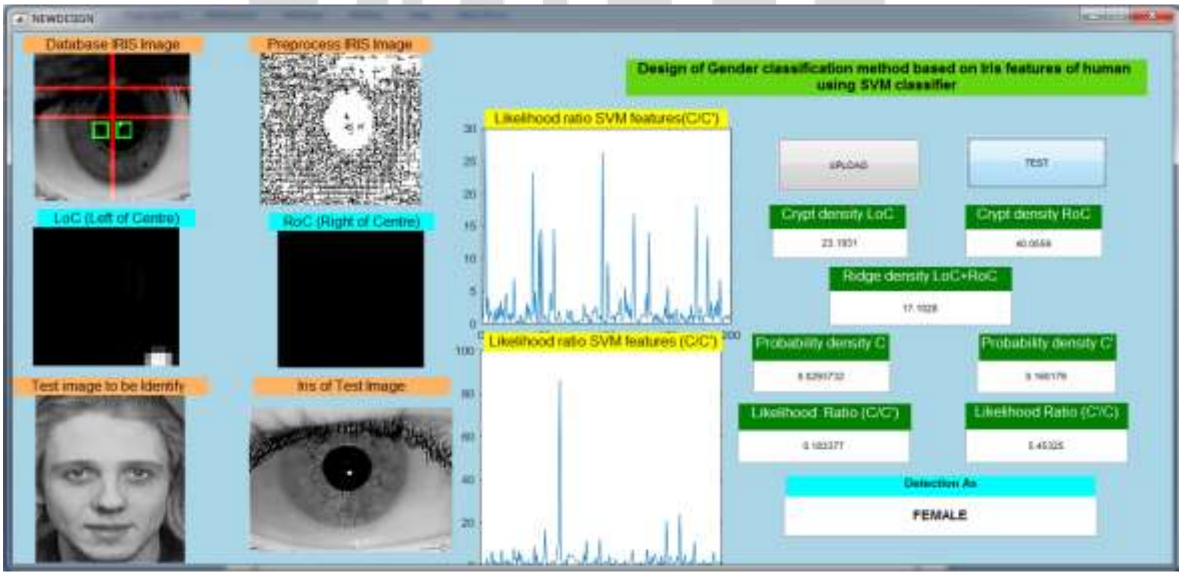


Figure 13 FERET database gender classify of female test image as FEMALE

Descriptive statistics of SVM classifier based crypt densities (LoC, RoC and combination of LoC and RoC) in males and females is shown in Table 2.

TABLE 2 DESCRIPTIVE STATISTICS OF THE CRYPT DENSITY IN BOTH MALES AND FEMALES

Parameter	Male			Female		
	SVM feature Left of Centre (LoC)	SVM feature Right of Centre (RoC)	SVM feature Combined LoC+RoC	SVM feature Left of Centre (LoC)	SVM feature Right of Centre (RoC)	SVM feature Combined LoC+RoC
Mean crypt density	11.58	11.82	23.40	14.6	14.56	29.16
Minimum crypts	9	9	19	12	12	24
Maximum crypts	15	15	27	19	18	36
Standard deviation	1.46	1.37	1.995	1.68	1.54	2.57
Standard error	0.1	0.09	0.14	0.11	0.10	0.18
Range	9-15	9-15	19-27	12-19	12-18	24-36

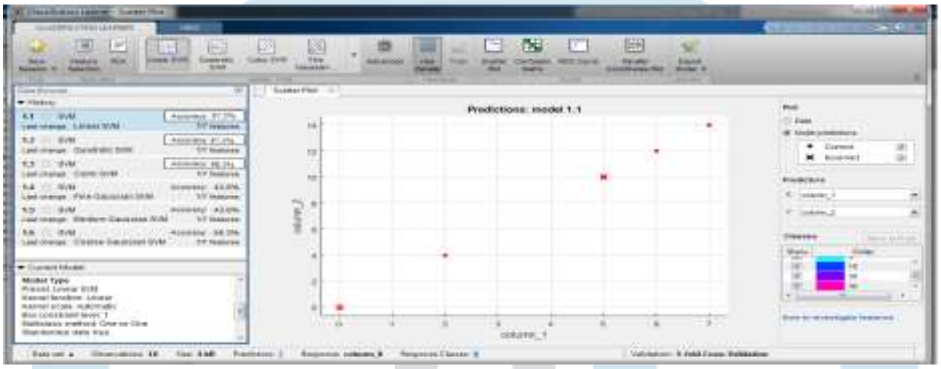


Figure 14 Scatter plot of binary class Male and Based on Crypt densities

Figure 15 shows the Scatter plot of binary class Male and Based on Crypt densities developed using redial SVM classifier.

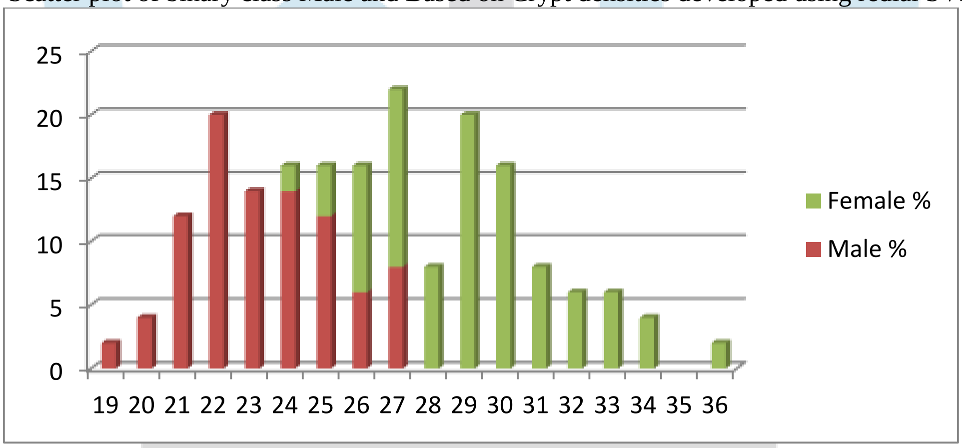


Figure 15 Percentage distributions of samples based on the combined crypt density analyzed using Redial kernel SVM classification.

TABLE 3 PROBABILITY DENSITIES AND LIKELIHOOD RATIOS DERIVED FROM THE OBSERVED COMBINED CRYPT COUNT.

Crypt density at LoC+RoC	Probability density		Likelihood Ratio	
	Male(C)	Female(C')	C/C'	C'/C
9	0.01	0	999	0.001
10	0.00	0	999	0.001
11	0.02	0	999	0.001
12	0.02	0	999	0.001
13	0.02	0	999	0.001
14	0.03	0	999	0.001
15	0.03	0	999	0.001
16	0.07	0	999	0.001
17	0.01	0	999	0.001
18	0.02	0	999	0.001
19	0.06	0	999	0.001

20	0.03	0	999	0.001
21	0.03	0	999	0.001
22	0.03	0	999	0.001
23	0.04	0.01	4	0.25
24	0.04	0.00	999	0.001
25	0.03	0.02	1.5	0.67
26	0	0.02	0.001	999
27	0	0.03	0.001	999
28	0	0.05	0.001	999
29	0	0.01	0.001	999
30	0	0.05	0.001	999
31	0	0.06	0.001	999
32	0	0.10	0.001	999
33	0	0.06	0.001	999
34	0	0.04	0.001	999
35	0	0.02	0.001	999
36	0	0.01	0.001	999
37	0	0.01	0.001	999
38	0	0.01	0.001	999

For the Combined crypt density (LoC +RoC), the statistical analysis of the likelihood ratio and the odds ratio shows that a crypt density of 625 crypts per mm2 is more likely to be of male origin (p= 0.96), whereas a crypt density of crypts per mm2 is more likely to be of female origin (p = 0.64) (Table 8). Posterior probability using Modified SVM theorem shows that a iris with a crypt density of crypts per mm2 will have a higher probability of belonging to a male (p = 0.99). Similarly, a crypt density of crypts per mm2 will be more indicative of females (p =0.99).

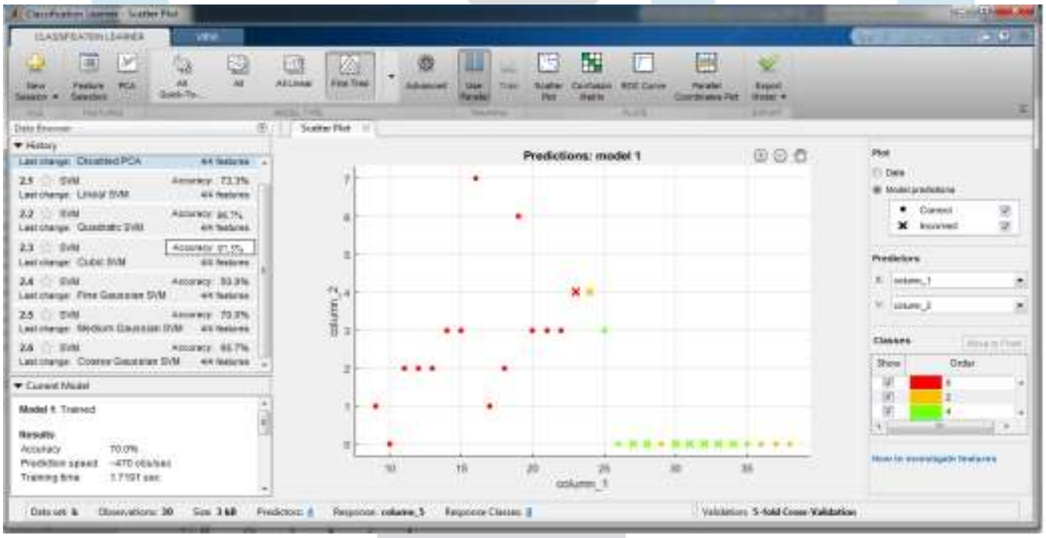


Figure 16 Scatter plot of binary class Male and Based on Likelihood Ratio

From Figure 16 Statistically significant sex differences are observed in the eye-iris crypt density in the LoC and RoC areas analyzed in this thesis. The females have a higher eye-iris crypt density than males in both these areas. Our findings are in agreement with the recent studies conducted on iris crypt density. Thus, even when the areas analyzed for eye-iris crypt density in our thesis differ from that of the earlier studies, the basic quantitative differences remain the same, i.e., females have a higher crypt density than males which is in accordance with earlier studies on different ethnic groups. crypt thickness and furrows are the two important factors which determine the density of crypts. [1] worked on the crypt thickness in irises and showed that males have coarser finger crypts than females which suggest that males will have less crypts in a given area than females and thus a lower crypt density. The higher iris crypt density in females is attributed to the fact that females tend to have finer epidermal crypts than males. Males generally have coarser crypts than females and the difference is approximately 10%. In addition to frequently cited reason(s), we support the reasons proposed by[2] that the difference between the finger crypt density in males and females in a given area may be attributed to the fact that on an average body proportions of males are larger than females and thus the same numbers of crypts are accommodated amongst the males in a larger surface area and thus, a lower density is observed amongst males. Findings of the present thesis did not show any marked differences between the crypt density for the left and right thumbs which is in contrast to the studies conducted by [1] in which the crypts of the right hand were found to be coarser than the left hand. Thus, for the same area, the right hand would have a fewer crypts than the left hand.

TABLE 4 FAR OBSERVATION

No of irises	Wrong identification	Correct identification	FAR
100	22	78	22/100=0.22
125	36	89	36/125=0.288
150	38	112	38/150=0.2533
175	46	129	46/175=0.2628
200	52	148	52/200=0.26

TABLE 5 FRR OBSERVATIONS

No of irises	Recognition correct	Could not recognised correct iris	FRR
100	79	21	21/100=0.21
125	95	30	34/125=0.24
150	112	38	38/150=0.25333
175	135	40	40/175=0.2285
200	151	49	49/200=0.245

TABLE 6 COMPARATIVE RESULTS

Work	Brief work	Outcome
Anand Venugopal [1]	Predict the gender by analyzing Local Binary Pattern (LBP), Histogram Oriented Gradients (HOG) Local Directional Pattern (LDP), and the SVM-Support Vector Machine is utilized in defining the gender	accuracy of 96.66 percentage
Herman Khalid [2]	Combining the local binary patterns (LBP) and the face geometric features to classify gender from the face images.	accuracy of 97.2 percentage
Edgar A. Torres [3]	spatial relationships and angles between features characteristics and developed SVM algorithms for gender classification	accuracy of 87.2 percentage
oulad kaddour [4]	propose an approach for gender classification from faces images that is based on support vector machine (SVM)	accuracy of 92.87 percentage
Proposed work	Use Human eye iris crypt densities count as feature and use redial kernel SVM classification for gender classification	accuracy of 97.52 percentage for FERET database

VI. CONCLUSION

This paper shows that women of the FERET database have a significantly higher eye crypt density than men. The differences between male and female eye-iris crypt density (in the studied areas) are statistically significant. The results of this thesis are encouraging and would promptly act as a supportive tool for forensic experts and in law enforcement,14,23 as they can be used as presumptive indicators of the gender of an unknown print left at a crime scene.21 This can be achieved simply by qualitatively examining if prints appear to be coarse or fine and then rapidly quantifying crypt density in a manner analogous to methods described in this thesis . The findings can also be useful in identification of mutilated remains when a dismembered hand is brought for medico-legal examination. This thesis overcomes the serious limitation14 where all ten iriss were required for the determination of the sex. Out of all the fingers, the eye is considered as the most motile digit of the palm and is more likely to leave its impression than its other counterparts.

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