LBP and Iris Features based Human Gender Classification using radial Support Vector Machine

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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 Iris crypt densities,Histogram of Oriented Gradients (HOG) and Local Binary Patterns (LBP)and are considered as the features for classification.The thesis conducted on 200 subjects (100 males and 100 females) in the age group of 18–60 years. Along with the Crypt count this work uses Histogram of Oriented Gradients (HOG) features for detection of orientation of human face. On basis of only HOG features we can only recognize the orientation and we get 67.85% accuracy of gender classification. Local Binary Patterns (LBP) found different in male and female face; hence this work uses LBP as another feature for classification, we get 80.55% classification rate when only LBP features are used. Iris 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. On basis of Crypt densities, we get 90% accuracy of gender classification.This work merged all three features and found 98.5% gender classification rate with Redial kernel Support Vector Machine (SVM) classifier.The work is done on MATLAB 2018b version and standard human face database is FERET for identification.**

***Keywords*—LBP, HOG, FERET, SVM, MATLAB, Iris, Crypt densities**.

I. INTRODUCTION

Classification of sex plays a vital role in forensic and medicolegal investigations. Identification means determination of theindividuality of a person. It may be complete (absolute) orincomplete (partial). Complete identification means the absolutefixation of the identity of a person [7,13]. Partial identificationimplies ascertainment of only some facts about the identity (like sex, age, stature, etc.) [5,14] while others still remain unknown. Themost successful approach for individualization utilizes a combinationof more than one method [6].The objective of this workis to determine any significant difference in the iris crypt density, HOG [2,10] and LBP [15,8]of males and females in a FERET [1,2,3] database to enable thedetermination of gender.Objective of presented thesis is to develop an optimised classificationtechnique which works better than available methods of identification of gender in aspect of time taken for identification and rate of identification [4].Gender classification uses facial images to assign automatically one of the male or female labels [3]. Such that, it has been proved that the humans are able to accurately differentiate the faces of male and female with a decision accuracy up to 96% [2]. This accuracy associates with the age factor, such that it reduces significantly when considering child faces [1]. However, the classification of gender faces is easy task for human but is still a challenging task for machines in spite of the differences in physical features between males and females [1]. This work combines the features like LBP, HOG and also included human eyes crypt counts for classifications of genders.

A. Related Work

Table 1 below discussed some similar works done in gender recognition methods and their outcomes in past by researchers.

TABLE 1: LITERATURE WORK

Author	Brief work	Outcome
A. Venugopal et al [1]	Predict the gender of kids between 6 to 8 years by analysing there features with various methods like Histogram Oriented Gradients (HOG),Local Directional Pattern (LDP),Local Binary Pattern (LBP), and the SVM-Support Vector Machine is utilized in defining the gender	accuracy of 96.66 percentage
Herman Khalid et al [2]	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
E Torres et al [3]	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
O.K. Mohame et al [3]	Propose an approach for gender classification from faces images that is based on support vector machine (SVM).	accuracy of 92.87 percentage

II. 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. This work combines the features like LBP, HOG and also included human eyes crypt counts for classifications of genders. Proposed work is new procedure where three image features are used for classification of human gender, The features used for classification are as follow: -

- Local Binary Patterns
- Histogram of Oriented Gradients
- Human Eye Iris Crypt densities

SVM [5] is used for the gender classification.The proposed design work flow shown in figure 3 has Six major parts.

A. *Database face Acquisition*

FERET face standard database [2] is been used.We have taken FERET which is standard database in Iris recognition. FERET have total 225 human faces.

Figure 1 Face acquired from FERET database

An example face image is shown in figure 1. Proposed work use FERET database,FERET iris is a Standard Database images which are available in the public domain. The FERET database contains 9 face each of 25 distinct persons. Therefore, we have total 225 faces in the database.

B. *Pre-processing*

The acquired image pre-processed first by Morphological operation [11].Pre-processing is applied to images before we may extract features from noisy images.

C. *Eye Feature Extraction*

Eye feature extraction includes three operations

- *Eye identification*
- *Eye Pre-Processing*
- *Crypt densities as features*

Eye Detection:The characteristics of iris detection from face, the simple features used are reminiscent of Haar[9] basis functions. Iris detected from Face in voila Jones method using Two-rectangle feature where Difference between the sums of the pixels within two rectangular regions is used for eye feature. it is used to isolate that a rectangle type feature is available or not.

Eye Image Enhancement/ pre-processing:Census Transform is used as preprocessing for eye images before crypt counts [9]. 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.

Eye Feature Extraction: After census transform the eye-iris crypt densities at the left of center (LoC) and right of center (RoC) are calculated for the MALE and FEMALE classes. The LoC crypt density, RoC crypt density, are considered as the feature of human eye.

D. *HOG Feature of Face*

Histogram of Oriented Gradientsfeature [1] obtained from the pre-processed output FERET face image.The technique counts occurrences of gradient orientation in localized portions of a facial image of human. This method is similar to that of edge orientation histograms, scale-invariant feature transform descriptors, and shape contexts, but differs in that it is computed on a dense grid of uniformly spaced cells and uses overlapping local contrast normalization for improved accuracy.

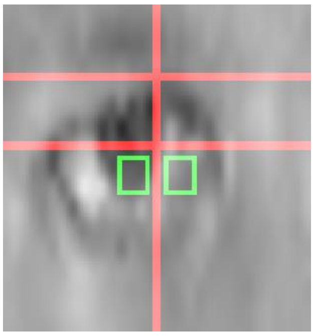

Figure 2 The format drawn on the transparency sheet used in the present thesis. (Not to scale.)

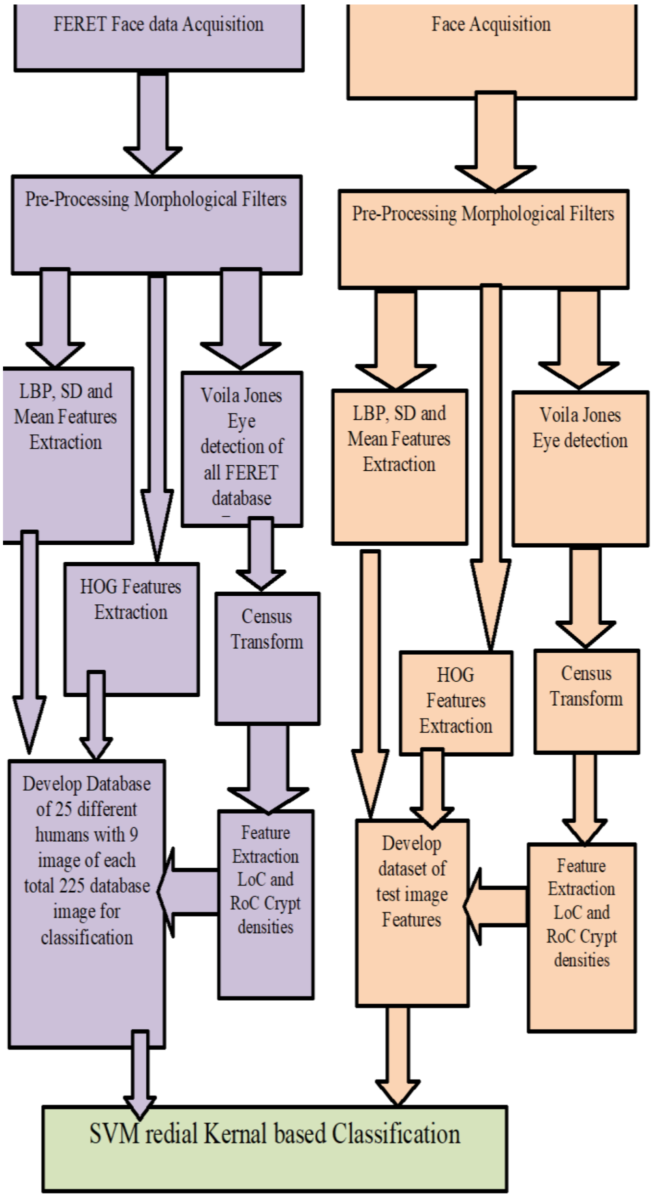

Figure3 dataflow for system design

E. *LBPFeature of Face*

Local Binary Patternsfeatures obtained from the pre-processed output FERET [3] face image. By the definition above, the basic LBP operator is invariant to monotonic gray-scale transformations preserving pixel intensity order in the local neighbourhoods. The histogram of LBP labels calculated over a region can be exploited as a texture descriptor.

F. *SVM redial kernel-based gender Classification*

Using HoG features, LBP features, Standard Deviation, Mean, LoC crypt densities and RoC crypt densities. The SVM algorithm is implemented in practice using a kernel. The learning of the hyperplane in linear SVM is done by transforming the problem using some linear algebra, which is out of the scope of this introduction to SVM. A powerful insight is that the linear SVM can be rephrased using the inner product of any two given observations, rather than the observations themselves. The inner product between two vectors is the sum of the multiplication of each pair of input values.

III. RESULTS

Figure 4 shown below is the GUI developed on MATLAB for Gender classification, Figure5 shown below shows FERET Database uploading and LoC and RoC of human eye iris crypt densities it also shows the census transform output. Figure 6 shows test FERET database male test image correctly classify as MALE Figure 7 shows test FERET database female test image correctly classifies as FEMALE. figure 6 and 7 also show input features andoutput results parameters observe for gender classification.

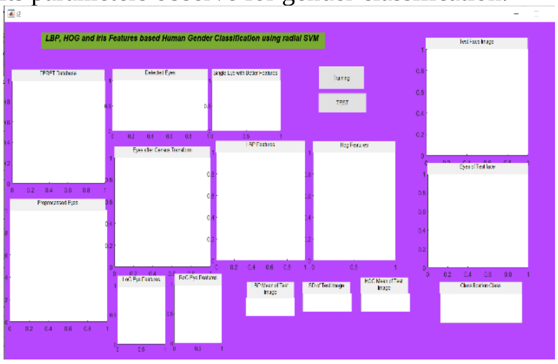

Figure 4 GUI developed on MATLAB for Gender classification

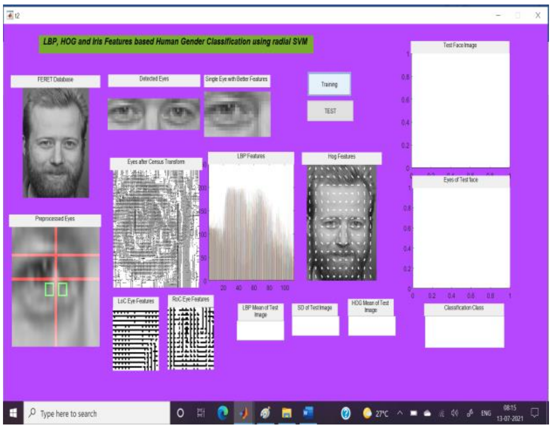

Figure 5 Data base FERET uploading

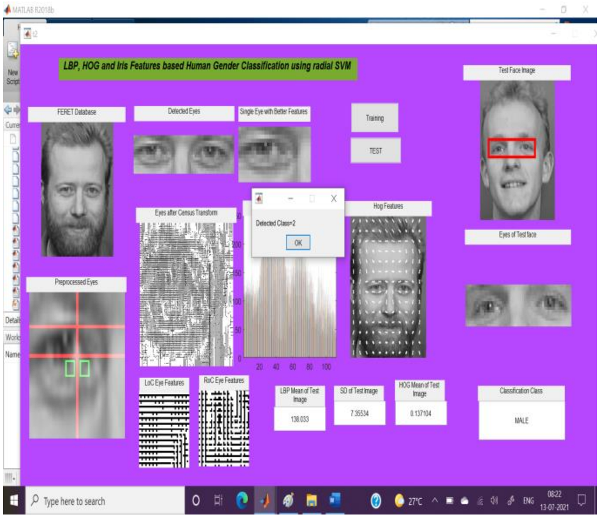

Figure 6FERET database gender classify of male test image as MALE

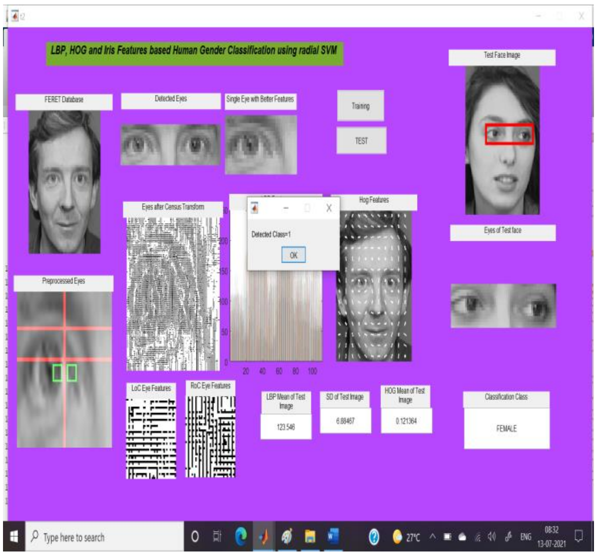

Figure 7 FERET database gender classify of female test image as FEMALE

Table 2Descriptive statistics of the Mean LBP obtained for the database in both males and females during dataset training.

TABLE 2 FERET DATABASE IMAGES MEAN LBP VALUES

Parameter	Male	Female
Mean of 225 FERET LBP-Means	151.63	189.462
Minimum out of 225 FERET LBP-Means	142.303	157.808
Maximum out of 225 FERET LBP-Means	170.505	209.212

$$Classfication\ in\ \%\ using\ LBP\ means$$
$$= \left(100 - \frac{Common\ Range}{Total\ Range} X100\right)$$
$$= \left(100 - \frac{(MaxM - MinF)}{MaxF - MinM} X100\right)$$
$$= \left(100 - \frac{(170 - 157)}{209 - 142} X100\right) = 80.59\%$$

With using LBP features only, we can get 80.59% of gender classification rate.

Table 3Descriptive statistics of the Mean HOG obtained for the database in both males and females during dataset training.

TABLE 3 FERET DATABASE IMAGES MEAN HOG VALUES

Parameter	Male	Female
Mean of 225 FERET HOG-Means	0.545081301	0.68643
Minimum out of 225 FERET HOG-Means	0.475865854	0.60247
Maximum out of 225 FERET HOG-Means	0.693109756	0.75046

$$Classfication\ in\ \%\ using\ HOG\ Means$$
$$= \left(100 - \frac{Common\ Range}{Total\ Range} X100\right)$$
$$= \left(100 - \frac{(MaxM - MinF)}{MaxF - MinM} X100\right)$$
$$= \left(100 - \frac{(0.69 - 0.60)}{0.75 - 0.47} X100\right) = 67.85\%$$

With using HOG features only, we can get 67.85% of gender classification rate.

Table 4 Descriptive statistics of the Standard Deviation obtained for the database in both males and females during dataset training.

TABLE 4 FERET DATABASE IMAGES MEAN HOG VALUES

Parameter	Male	Female
Mean of 225 FERET Standard deviations	6.963428	7.840487
Minimum of 225 FERET Standard deviations	5.956544	6.87924
Maximum of 225 FERET Standard deviations	8.060907	8.74975

$$Classfication\ in\ \%\ using\ Standard\ Deviation$$
$$= \left(100 - \frac{Common\ Range}{Total\ Range} X100\right)$$
$$= \left(100 - \frac{(MaxM - MinF)}{MaxF - MinM} X100\right)$$
$$= \left(100 - \frac{(8.06 - 6.87)}{8.74 - 5.25} X100\right) = 57.34\%$$

With using Standard Deviation features only, we can get 57.34% of gender classification rate.

TABLE 5 FERET-MALE IRIS CRYPT DENSITY CALCULATIONS

Crypt density (In a square of 25 mm^2)	Male	
	Left of Centre	Right of Centre
FERET-M1	7.90963	11.6621
FERET-M2	12.4801	13.1403
FERET-M3	9.46502	14.3488
FERET-M4	10.6764	12.1789
FERET-M5	6.19328	9.9808
FERET-M6	8.69041	11.0204
FERET-M7	9.81188	12.9905
FERET-M8	12.6993	12.7127
FERET-M9	9.05994	10.3661
FERET-M10	7.31866	8.3173
FERET-M11	4.67092	4.64689
FERET-M12	11.8174	12.6157
FERET-M13	13.3669	12.7058
FERET-M14	6.45643	11.1538
FERET-M15	6.6787	9.70133
FERET-M16	4.91644	4.51901
FERET-M17	7.10366	7.96388
FERET-M18	6.4735	10.3745
FERET-M19	10.0599	9.628
FERET-M20	3.29358	5.32206
FERET-M21	7.91663	9.30992
FERET-M22	6.44383	8.13528
FERET-M23	9.50813	13.7433
FERET-M24	11.5761	14.5558
FERET-M25	10.4527	13.4297
FERET-M26	9.33093	11.3734
FERET-M27	12.1144	12.7478
FERET-M28	10.3572	8.50912
FERET-M29	5.92033	8.21801
FERET-M30	8.13107	7.07013
FERET-M31	8.38106	7.86521
FERET-M32	11.4938	10.5203
FERET-M33	9.51569	9.95914
FERET-M34	4.37502	7.1543
FERET-M35	6.41947	10.36
FERET-M36	8.03253	8.95651
FERET-M37	7.44436	9.66824
FERET-M38	10.6517	11.8045
FERET-M39	13.6292	11.249
FERET-M40	10.0854	8.33568
FERET-M41	11.8057	10.7992
FERET-M42	11.372	10.5693
FERET-M43	12.7214	12.3276
FERET-M44	12.5103	7.17861
FERET-M45	3.67683	5.51368
FERET-M46	6.10481	9.06498
FERET-M47	7.02164	8.55325
FERET-M48	6.56204	8.05759
FERET-M49	5.23054	6.77596
FERET-M50	8.59774	8.32261

TABLE 6 FERET-FEMALE IRIS CRYPT DENSITY CALCULATIONS

Crypt density (In a square of 25 mm^2)	Female	
	Left of Centre	Right of Centre
FERET-F1	16.97	15.71
FERET-F2	19.72	18.81
FERET-F3	17.1	16.91
FERET-F4	16.86	16.00
FERET-F5	16.64	14.21
FERET-F6	14.48	17.27
FERET-F7	12.76	13.15
FERET-F8	15.111	12.14
FERET-F9	14.53	16.25
FERET-F10	13.24	15.38
FERET-F11	15.78	16.93
FERET-F12	18.6064	15.0508
FERET-F13	17.2168	15.4207
FERET-F14	17.719	15.9255
FERET-F15	14.4285	16.3774
FERET-F16	13.2664	12.6251
FERET-F17	13.9184	14.3327
FERET-F18	17.0477	15.3609
FERET-F19	17.4225	15.289
FERET-F20	14.2936	15.232
FERET-F21	14.7966	14.3676
FERET-F22	13.3207	15.0493
FERET-F23	17.9264	16.4152
FERET-F24	17.7098	17.4415

FERET-F25	17.1616	16.9878
FERET-F26	11.4546	15.9106
FERET-F27	16.1849	16.684
FERET-F28	15.7826	16.2095
FERET-F29	14.8137	16.5439
FERET-F30	16.1286	16.9919
FERET-F31	14.2082	13.2735
FERET-F32	15.0469	13.2073
FERET-F33	17.883	17.9032
FERET-F34	17.4315	19.6989
FERET-F35	15.4287	13.421
FERET-F36	15.3498	16.284
FERET-F37	15.1278	15.6244
FERET-F38	15.3084	15.7347
FERET-F39	15.7885	15.7304
FERET-F40	10.8818	12.3656
FERET-F41	17.719	15.9255
FERET-F42	14.4285	16.3774
FERET-F43	13.2664	14.6251
FERET-F44	13.9184	14.3327
FERET-F45	17.0477	15.3609
FERET-F46	17.7098	17.4415
FERET-F47	17.1616	16.9878
FERET-F48	11.4546	15.9106
FERET-F49	16.1849	16.684
FERET-F50	15.7826	16.2095

Form table 5 above it may be observed that, Male minimum LoC crypt density observe in male is 4, Male maximum LoC crypt density observe in male is 13, Male minimum RoC crypt density observe in male is 4, Male maximum RoC crypt density observe in male is 14. Average minimum Crypt densities in Male obtain is 4, Average maximum Crypt densities in Male obtain is 13.5.

Form table 6 above it may be observe thatFemale minimum LoC crypt density observe is 11, Female maximum LoC crypt density observe is 19, Female minimum RoC crypt density observe is 13, Female maximum RoC crypt density observe is 19. Average minimum Crypt densities in Female obtain is 12, Average maximum Crypt densities in Female obtain is 19.

$$Classfication\ in\ \%\ using\ Crypt\ densities$$
$$= \left(100 - \frac{Common\ Range}{Total\ Range} X100\right)$$
$$= \left(100 - \frac{(MaxM - MinF)}{MaxF - MinM} X100\right)$$
$$= \left(100 - \frac{(13.5 - 12)}{19 - 4} X100\right) = 90\%$$

With using iris Crypt features only, we can get 90% of gender classification rate.

As the standard deviation features give less classification rate hence this work develop method uses LBP features, HOG features and crypt Densities features only for classification on SVM classifier.Figure 8Statistically significant sex differences are observed in theeye-iris crypt density, HOG feature and LBP feature areas analyzedusing SVM classifier in this thesis. It is found that the females have a higher eye-iris crypt density than males. Figure 9 shows the confusion matrix plot obtained after SVM classification.

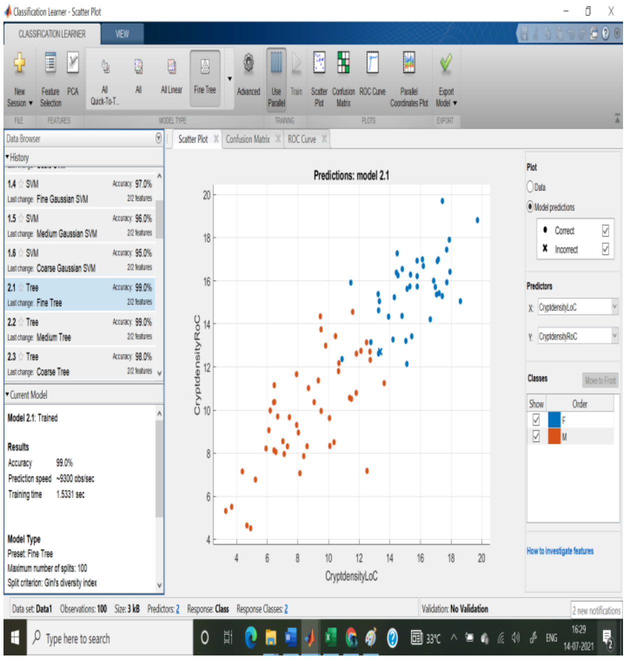

Figure 8 Scatter plot of binary class Male and Based on Crypt densities, mean HOG & Mean LBP

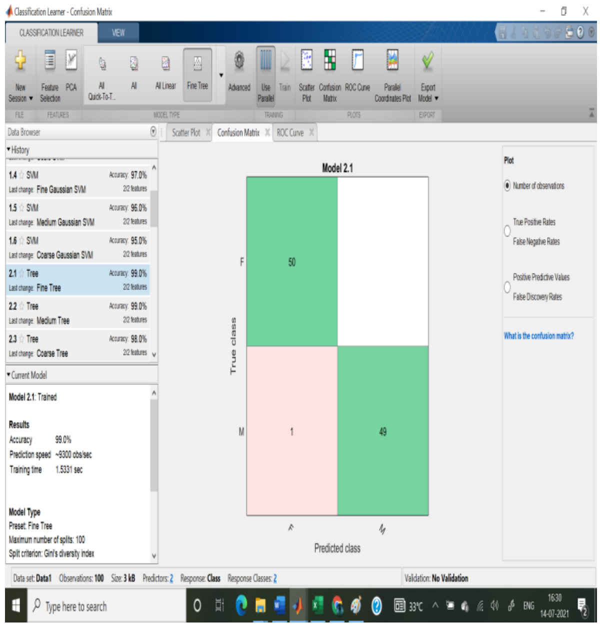

Figure 9confusion matrix plot obtained after SVM classification

*Throughput:*Simulation time obtained for presented design is 139.123 sec needed for 10x200 images ofFERETdatabase [10] hence

$$\text{Image processed in 1 second} = \frac{10x200}{139.123} = 14.375768$$

Each image has 100x100 pixels of 8 bit each, hence total 100x100x8 bits in a single Imageandin 1 second total 14.375768 images are been processed in presented work hence

$$\text{number of bit processsed in one seconds (throughput)} = \frac{100x100x8x14.375768}{1000000} Mbps = 1.15006144\ \ \text{Mbps}$$

Classification Rate: Out of 250 time of checking of humanface test image, 247times we obtained humangender identifies as Male or Female correctly on SVM classifier.

$$\text{Classification Rate} = \frac{247X100}{250} = 98.8\%$$

*FAR:*false acceptance rate, or FAR, ismeasure ofproposed system will incorrectly accept an access attempt by an unauthorized user. A system's FAR typically is stated asratio ofnumber of false acceptances divided bynumber of identification attempts.

$$FAR = \frac{Wrong\ Identification}{Total\ trial\ for\ identification}$$

TABLE 7 FAR OBSERVATION

No of test face	Wrong classification	FAR
100	0	0
125	1	0.008
150	1	0.00677
175	2	0.0114
200	2	0.01
250	3	0.012

*FRR:*false identification rate, or FRR, ismeasure proposed system will incorrectly reject an access attempt by an authorized user. A system's FRR typically is stated asratio ofnumber of false recognitions divided bynumber of-identification-attempts.

$$FRR = \frac{Identified\ wrong\ As\ Correct}{Total\ Trial\ Of\ Identificaton}$$

TABLE 8 FRR OBSERVATIONS

No of test faces	Classifywrong as corrects	FRR
100	1	0.01
125	1	0.008
150	1	0.0067
175	2	0.01143
200	3	0.015
250	3	0.012

TABLE 9 COMPARATIVE RESULTS

Work	Brief work	Outcome
Anand Venugopal [1]	Predict the gender by analysing 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
ouladkaddour[4]	propose an approach for gender classification from faces images that is based on support vectormachine (SVM)	accuracy of 92.87 percentage
Proposed work	Use Human eye iris crypt densities count, HOG and LBP as feature and use redial kernel SVM classification for gender classification	accuracy of 98.8 percentage for FERET database

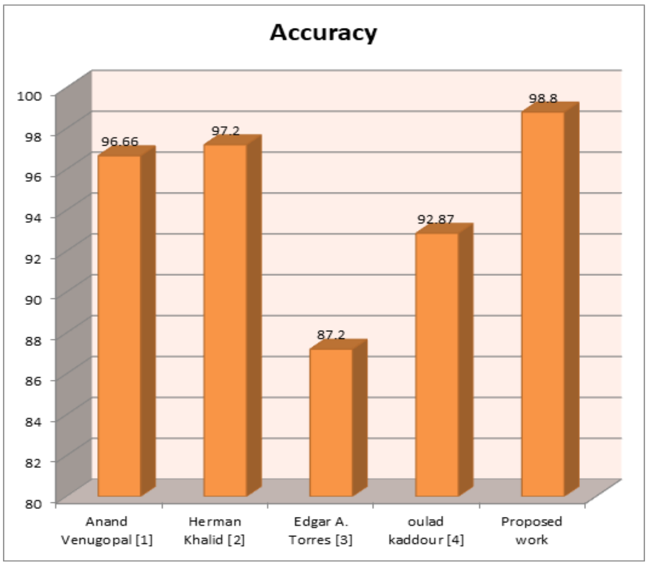

Figure 10 Accuracy Comparison

Figure 10 shows that proposed work has better classification accuracy then previous works.

IV. CONCLUSION

Proposed work uses three features HOG features of face, LBP features of Face and crypt densities of human eye in order to classify the gender of human. This thesis shows that women of the FERET database have a significantly higher eye crypt densitythan men. The differences between male and female eye-iris crypt density (in the studied areas) are statistically significant. The findings can also be usefulin identification of mutilated remains when a dismemberedhand is brought for medico-legal examination.Also found that only HOG cannot determine the human gender significantly however only LBP with SVM give 81% classification rate. But with only crypt densities features classification rate achieved around 90%. Many researchers have used LBP and HOG previously for gender classification but gender classification based on crypt densities is idea of this work only. It can be concluded that differences in the eye crypt density can be used as an importanttool for the determination of human gender.Proposed wok is a design of identification of sex based on iris crypt densities, HOG and LBP and to achieve that design goals proposed wok used SVM classifierand the database is taken for the FERET. Additional studies on individual fingerprints in different population groups are anticipated in the near future. proposed design is good in terms for identification rateandtime taken for identification, we have successfully identified gender. In near future methods can be developed for identification of gender with 100% by adding more optimized classifiers and advance GLCM features.The work is been doneandtested on Intel i5 processor in future it may be developed on various great processing capacity processor for less time delay, is been simulated forMATLAB in future it can be developed on advance tools like SCILAB.

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