Gender classification based on similarity features through SURF and SVM

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Abstract: The recognisable proof of people in view of their biometric body parts, for example, face, fingerprint, walk, iris, and voice, assumes an imperative part in electronic applications and has turned into a prominent territory of research in image pre-processing. It is likewise a standout amongst the best utilisations of computer-human interaction and understanding. Out of all the previously mentioned body parts, the face is one of most well known qualities in view of its extraordinary feature. In reality, people can process a face in an assortment of approaches to characterise it by its personality, alongside various different attributes. In this paper, we proposed a new algorithm to extract the facial features using SURF algorithm, features are invariant to extract affine transformations are extracted from each face using speeded up robust features (SURF) method (Morteza and Yousefi, 2011) and shows best accuracy on real-time face images compared with different licence datasets like ORL database and FGNet database and with different training ratios by using SVM algorithm (Rahman et al., 2013; Moghaddam and Yang; 2000; Swaminathan, 2000).

Keywords: biometrics; gender classification; facial features; speeded up robust features; SURF; support vector machine; SVM.

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1 Introduction

Nowadays, all over the world a large amount of data being collected, stored in database/dataset for recognition and analysis. Classification (Kishore and Babu Reddy, 2018; Kishore, 2017) is a form of the data analysis that can be used for extracting models and predict categorical class labels. Gender identification and discrimination is both beneficial for psychological and computational areas. It is an attractive subject for psychology literature but very few methods have been introduced for learning.

2 History

Gollomb et al (Moghaddam and Yang, 2000) trained a fully connected two layer neutral networks SEXNET to identify full 30 faces, their experiment was to test 90 images (45 male and 45 female) giving error rate of 8.1%. Cottrell and Metcalfe also applied neural networks for face emotion and gender (Cerit et al., 2016) classification using 160, 64×64 face image reduced from 4,096 of 40 with auto-encoder. These were sent as inputs to other training subjects resulted perfect. Brunelli (Moghaddam and Yang, 2000) and Poggio developed hyperBF networks which had two competing RBF network one for male another female using 16 geometric figures including pupil to eyebrow separation, eyebrow thickness and nose width. A dataset of 168 images (21 male and 21 female) have error rate of 21% using Golomb (Moghaddam and Yang, 2000) and Cottrell and Metcalfe, Tamura used multi-layer neural network to classify ender from face images at multiple resolutions (from 32×32 to 8×8 pixels) their experiments on 30 people was able to determine gender from 8×8 images with error rate 7%. Wiskott used labelled graphs of 2D views to describe faces. The nodes are represented by wavelet based local jets and edges were labelled with distance vector similar to geometric features (Fazl-Ersi et al., 2014). They used a small set of modelled graphs of males and females to encode ‘general face knowledge’. For each new face, new information was added in the dataset. The general majority of the nodes in the composite graph is used for classification. Seemanthini and Manjunath (2018) detecting the human objects in video and recognised using cluster segmentation approach for object detection and classification done by support vector machine (SVM) with 89.59% accuracy. Dhomne et al. (2018) automatic gender recognition by using VGGnet architecture and deep-CNN technique worked as neural system on unfiltered face images for gender recognition. Antipov et al. (2016) performed in embedded systems by using CNN model. Mansanet et al. (2016) use the local features for learning through deep networks. Parkhi et al. (2015) and Simonyan and Zisserman (2015) training phase implementation is different for recognition of objects through different layers by using VGG-face CNN model. It contains nearly five blocks. Bukar et al. (2016) automatic gender classification implemented by using supervised appearance model (SAM) with 92.50 percentage accuracy on HQ faces database, 75.70 percentage on Dartmouth database and 76.65 percentage on FGNET-AD database. In this paper also discuss about gender classification through different ages with different accuracies. Unnikrishnan et al. (2016) texture features are implemented grey level co-occurance matrix for calculate contrast, correlation, energy and homogeneity measurements for computing features. Here, SVM classifier and KNN used for gender classification. Afifia and Abdelhamed (2017) human recognise on foggy faces by using CNN with Ada-boost based. In this paper, gender recognition algorithm is applied on four different types of datasets those are labelled faces in the wild (LFW) images of groups dataset, face recognition technology (FERET), the specs on faces (SoF) dataset. Atallah et al. (2018) discuss about various classification algorithms with different accuracies. Ban and Yoon (2016) proposed GC using MCT-AdaBoost algorithm for gender classification on low resolution facial images with different datasets along with different accuracies. Here MCT-AdaBoost algorithm compared with algorithms those are SVM, PCA and LDA classifiers. Dileep and Dant (2018) proposed a new algorithm for fast with more accurately and effectively that algorithm is dependent on NN and three sigma control limits in a final level with 95% of success rate. Liew (2016) discussed on convolutional neural network, to reduce the number of levels and getting more accuracy on AT&T and SUMS databases. Khalifa et al. (2018) implement on FERET and UTD databases with different classification and feature extraction algorithms; those are histograms of oriented gradients (HOG), local binary patterns (LBP) for feature extraction, to combine these feature algorithms and k-nearest neighbour (k-NN) and SVM for gender classification. Here to analyse the results are trained by one type of dataset and utilise trained database to test the another dataset with different accuracies. Selvam and Muneeswaran (2017) estimate the face image location and the face region for recognition through local features of face. To implement RLBP algorithm for feature extraction and Adaboost for classification on LFW, FERET, Gallagher and children images. Kaur et al. (2017) also introduce the new algorithms for feature extraction and classification (Özbulak and Aytar, 2016) of human gender half face and full face images with 94 percentage of accuracy on FERET and FEI databases. Wang et al. (2017) discuss about gender classification (Ali et al., 2016; Wang et al., 2017) on GA face dataset with 90.33 percentage through SVM and pre-trained deep model algorithms. Deshpande and Ravishankar (2017) proposed an algorithm for face detection and recognition (Da'san et al., 2015) using principle component analysis and ANN techniques with 94 percentage of accuracy. Ramesh et al. (2017) proposed a snakes algorithm for face recognition on skin BGR dataset.

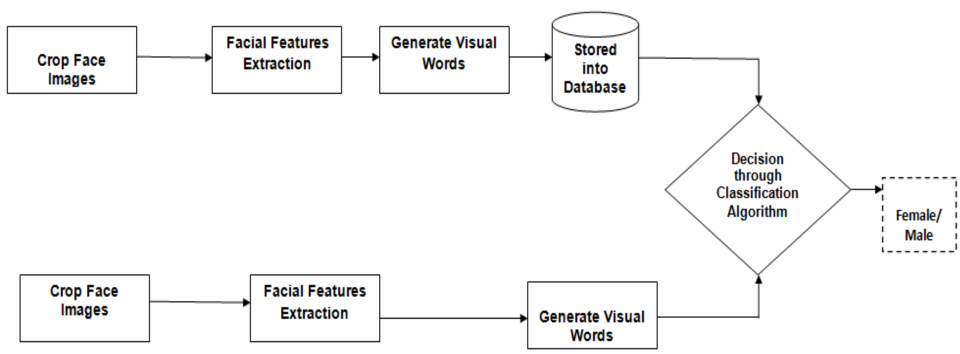
- *SURF feature extraction algorithm:* feature extraction (Al Mashagba, 2016) includes diminishing the measure of resources required to depict a large size of data. When performing analysis of complex information one of the significant issues comes from the quantity of variables included. Analysis with countless by and large requires a lot of memory and calculation control, likewise it might make a classification algorithm over fit to preparing samples and sum up inadequately to new samples. Feature extraction (Al Mashagba, 2016) is a general term for strategies for developing mixes of the variables to get around these issues while as yet representing the data with adequate accuracy. Bay and his colleagues are proposed the SURF algorithm (Jain et al., 2017). SIFT algorithm is similar functionality to SURF but, SERF reduces the complexity of computational. In SURF feature extraction algorithm to extract the features are corner points, edge points, key points and spot points (Jain et al., 2017) of the image.

- *SVM:* it is a one type of machine learning algorithm that is supervised machine learning. It can be utilised for both classification and regression purposes. Nonetheless, it is for the most part utilised as a part of classification issues. In this algorithm, we plot every data as a point in n-dimensional space (where n is number of features you have) with the estimation of each feature being the estimation of a specific coordinate. It has been utilised in many number of classification applications of image.

2.1 Methodology

Figure 1 shows about gender classification (Jia et al., 2017) on crop face images. In this methodology, facial recognition is done for training purpose and testing purpose. Features (Fazl-Ersi et al., 2014) are invariant to affine renovations are extracted from each face using 'speeded up robust features (SURF) method'. Those features are converted to visual-words; visual-word means the central point of the clustering features. Those training image visual words are stored in database. After training crop face images also extract the features and converted to visual-words and compared with existing database visual words and finally give the decision as male or female.

Figure 1 Workflow of proposed gender classification system



2.2 Experimental result

The proposed algorithm implemented in MATLAB and applying on different datasets (Kishore and Babu Reddy, 2017) those are already existing datasets, i.e., ORL database and FGNet database and also applying on private database (Shan, 2012). In this paper, we utilise three different types of databases about the first database is ORL database contains totally 322 facial images in those images male images are 151 and female images are 171 from the 151 male images are divide only 58 images are trained images that means nearly 38% of images, female images are 62 trained images out-off 171 that means 37%, other images are used for testing. Second database is FGNet database contains totally 90 images out-off 90 images 46 images are female and 44 images are male images, clearly discuss about FGNet database divide three categories 0–15 years, 16–30 years and

31–50 years. In 0–15 years database contains totally 30 images out-off 20 female images and 10 male images.16–30 years database contains totally 30 images out-off 13 female images and 17 male images. 31–50 years database had totally 30 images out-off 13 female images and 17 male images. And finally private database contains totally 117 images out-off 73 images are female images and 54 images are male images. In private database, 40% of images used as trained images and another 60% used for testing images for testing.

Figure 2 ORL dataset sample images (male and female) (see online version for colours)

Table 1 Classification of image as male with different training ratios using UCI database

S. no.	*Training ratio (%)*	*Testing ratio (%)*	*No. of extracted features*	*K-means clustering no. of iterations*	*Avg. time for iterations (Sec)*
1	10	90	184,320	49	1.76
2	20	80	368,640	26	4.01
3	30	70	552,960	27	5.20
4	40	60	737,280	31	7.39
5	50	50	952,320	33	10.83
6	60	40	1,136,640	15	11.28
7	70	30	1,320,960	19	12.90
8	80	20	1,505,280	29	14.70
9	90	10	1,689,600	33	16.08

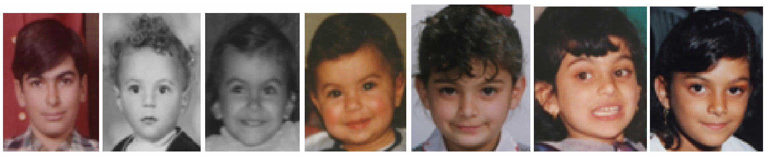
S. no.	*Predicted training accuracy*	*Predicted test accuracy (%)*	*Average accuracy (%)*	*CCI/ICI*
1	100	73	86.5	CCI
2	92	76	84	CCI
3	94	72	83	CCI
4	85	82	83.5	CCI
5	85	80	82.5	CCI
6	84	81	82.5	CCI
7	88	72	80	CCI
8	89	79	84	CCI
9	85	67	76	CCI

Table 2 Classification of image as female with different training ratios using UCI database

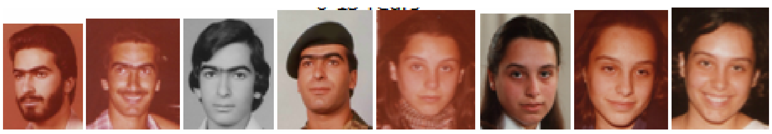
S. no.	*Training ratio (%)*	*Testing ratio (%)*	*No. of extracted features*	*K-means clustering no. of iterations*	*Avg. time for iterations (Sec)*
1	10	90	184,320	27	1.72
2	20	80	399,360	28	3.77
3	30	70	583,680	19	5.48
4	40	60	768,000	17	7.64
5	50	50	983,040	27	9.76
6	60	40	1,167,360	20	11.71
7	70	30	1,351,680	24	15.47
8	80	20	1,536,000	19	14.28
9	90	10	1,751,040	33	16.65

S. no.	*Predicted training accuracy*	*Predicted test accuracy (%)*	*Average accuracy (%)*	*CCI/ICI*
1	100	68	84	CCI
2	88	78	83	CCI
3	87	73	80	CCI
4	86	83	84.5	CCI
5	86	74	80	CCI
6	89	76	82.5	CCI
7	85	76	80.5	CCI
8	84	69	76.5	CCI
9	88	92	90	CCI

Figure 3 FGNet dataset sample images based on age (male and female), (a) 0–15 years (b) 16–30 years (c) 31–50 years (see online version for colours)



(a)



(b)

(c)

About Tables 1 and 2 explained about gender classification accuracy based on training ratios of UCI Database images. Here, training ratio increased by 10% from 10% to 90% training database ratio. If training ratio increased automatically to increase the training images features and also increase the average time for iteration in secs, but predicted testing accuracy did not increase, because features are extracted from training database randomly. But general assumption increase the training database ratio then to increase the predicted test ratio and average accuracy ration also increases. But we observe in this experiment features are extractions are not dependence on human selected image's features. Table 2 another column is CCI/ICI, CCI means correctly classified instance per image, ICI means incorrectly classified instance per image. Finally, the average accuracy of male gender is 82.4% and female gender is 82.3% accuracy of all iterations from UCI Database through SVM classification algorithm (Cerit et al., 2016; Rahman et al., 2013; Moghaddam and Yang, 2000; Swaminathan, 2000).

Table 3 Classification of image as female or male with different training ratios using FGNet database (age between 0–15 years) (see online version for colours)

S. no.	*Training ratio (%)*	*Testing ratio (%)*	*Gender*	*No. of extracted features*	*K-means clustering no. of iterations*
1	10	90	Female	26,054	24
2	20	80	Female	19,968	34
3	30	70	Female	40,724	22
4	40	60	Female	59,264	29
5	50	50	Female	75,654	30
6	10	90	Male	5,914	14
7	20	80	Male	15,898	36
8	30	70	Male	39,698	29
9	40	60	Male	57,940	35
10	50	50	Male	63,852	20

S. no.	*Avg. time for iterations (Sec)*	*Predicted training accuracy*	*Predicted test accuracy (%)*	*Average accuracy (%)*
1	0.12	100	50	75
2	0.21	100	75	87.5
3	0.42	100	65	82.5
4	0.57	100	63	81.5
5	0.81	100	83	91.5
6	0.12	100	67	83.5
7	0.16	100	50	75
8	0.39	100	70	85
9	0.56	100	75	87.5
10	0.64	100	83	91.5

About Table 3 explained about gender classification accuracy based on training ratios of FGNet database images related to ages children (0–15 years), adult (16–31 years), old (31–50 years). Here explained about children (0–15 years) database, male and female training ratio increased by 10% from 10% to 50% training database ratio. If training ratio increased automatically to increase the training image features and also increase the average time for iteration in secs, but predicted testing accuracy did not increase, because features are extracted from training database randomly. But general assumption increase the training database ratio then to increase the predicted test ratio and average accuracy ration also increases. But we observe in this experiment features are extractions are not dependence on human selected image's features. Table 3 another column is CCI/ICI, CCI means correctly classified instance per image, ICI means incorrectly classified instance per image. Finally, the average accuracy of male gender is 84.5% and female gender is 83.6% accuracy of all iterations from FGNet database.

Table 4 Classification of image as female or male with different training ratios using FGNet dataset (age in between 15–30 years) (see online version for colours)

S. no.	*Training ratio (%)*	*Testing ratio (%)*	*Gender*	*No. of extracted features*	*K-means clustering no. of iterations*
1	10	90	Female	18,740	19
2	20	80	Female	20,564	19
3	30	70	Female	41,126	42
4	40	60	Female	41,452	22
5	50	50	Female	61,286	21
6	10	90	Male	18,740	34
7	20	80	Male	20,564	19
8	30	70	Male	40,602	27
9	40	60	Male	40,724	27
10	50	50	Male	62,016	36

S. no.	*Avg. time for iterations (Sec)*	*Predicted training accuracy*	*Predicted test accuracy (%)*	*Average accuracy (%)*
1	0.20	100	100	100
2	0.21	100	75	87.5
3	0.42	100	100	100
4	0.41	100	83	91.5
5	0.61	100	75	87.5
6	0.21	100	50	75
7	0.21	100	88	94
8	0.44	100	67	83.5
9	0.40	100	83	91.5
10	0.67	100	100	100

About Tables 4 and 5 explained about gender classification accuracy based on training ratios of FGNet database images related to ages children (0–15 years), adult (16–31 years), old (31–50 years). Here explained about adult database (16–31 years), old (31–50 years), male and female training ratio increased by 10% from 10% to 50% training database ratio. If training ratio increased automatically to increase the training image features and also increase the average time for iteration in secs, but predicted testing accuracy did not increase, because features are extracted from training database randomly. But general assumption increase the training database ratio then to increase the predicted test ratio and average accuracy ration also increases. But we observe in this experiment features are extractions are not dependence on human selected image's features. Table 5 another column is CCI/ICI, CCI means correctly classified instance per image, ICI means incorrectly classified instance per image. Finally, the average accuracy of male gender (Yu et al., 2009; Mäkinen and Raisamo, 2008) is 88.8% and female gender is 93.3% accuracy of all iterations from FGNet adult database and the average accuracy of male gender is 81.7% and female gender is 80.1% accuracy of all iterations from FGNet old database.

Table 5 Classification of image as female or male with different training ratios using FGNet Dataset (age in between 31–50 years) (see online version for colours)

S. no.	*Training ratio (%)*	*Testing ratio (%)*	*Gender*	*No. of extracted features*	*K-means clustering no. of iterations*
1	10	90	Female	20,160	17
2	20	80	Female	15,840	34
3	30	70	Female	39,860	21
4	40	60	Female	38,860	27
5	50	50	Female	59,980	20
6	10	90	Male	15,840	25
7	20	80	Male	20,160	30
8	30	70	Male	37,306	38
9	40	60	Male	37,140	34
10	50	50	Male	62,188	27

S. no.	*Avg. time for iterations (Sec)*	*Predicted training accuracy*	*Predicted test accuracy (%)*	*Average accuracy (%)*
1	0.21	100	38	69
2	0.17	100	66	83
3	0.40	100	67	83.5
4	0.38	100	55	77.5
5	0.59	100	75	87.5
6	0.17	100	75	87.5
7	0.21	100	50	75
8	0.36	100	67	83.5
9	0.38	100	50	75
10	0.69	100	75	87.5

Figure 4 Private dataset sample images (male and female) (see online version for colours)

Table 6 Classification as male image with different training ratios using private database

S. no.	*Training ratio (%)*	*Testing ratio (%)*	*Gender*	*No. of extracted features*	*K-means clustering no. of iterations*
1	10	90	Male	2,554	12
2	20	80	Male	3,788	19
3	30	70	Male	4,554	16
4	40	60	Male	5,978	32
5	50	50	Male	8,934	15
6	60	40	Male	9,972	34
7	70	30	Male	13,050	38
8	80	20	Male	12,556	34
9	90	10	Male	14,854	42

S. no.	*Avg. time for iterations (Sec)*	*Predicted training accuracy*	*Predicted test accuracy (%)*	*Average accuracy (%)*
1	0.06	100	79	89.5
2	0.08	100	92	96
3	0.08	100	92	96
4	0.13	100	70	85
5	0.17	100	50	75
6	0.18	100	100	100
7	0.14	100	75	87.5
8	0.18	100	75	87.5
9	0.15	100	100	100

Figure 5 Show the relation between training image set ration vs. classification accuracy of male database (see online version for colours)

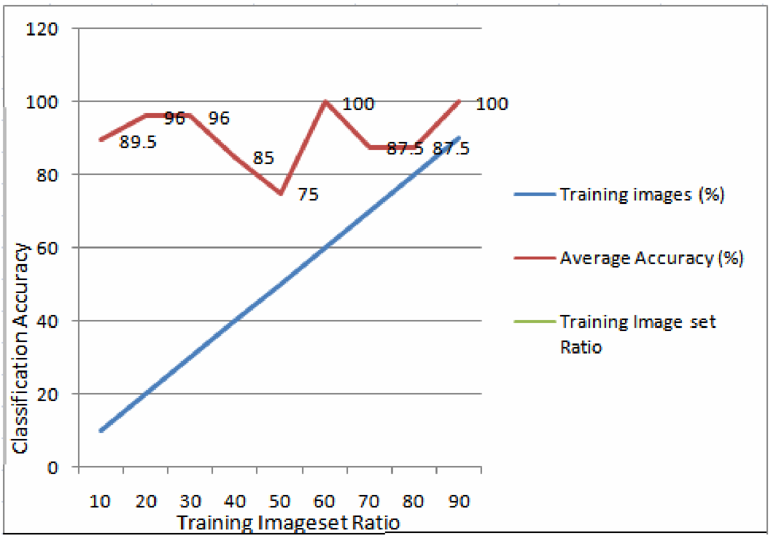
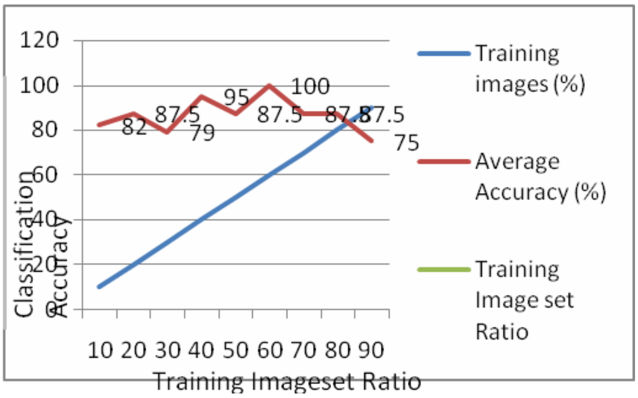


Table 7 Classification as female image with different training ratios using private database

S. no.	*Training ratio (%)*	*Testing ratio (%)*	*Gender*	*No. of extracted features*	*K-means clustering no. of iterations*
1	10	90	Female	2,068	10
2	20	80	Female	4,012	11
3	30	70	Female	4,012	21
4	40	60	Female	6,080	21
5	50	50	Female	9,140	28
6	60	40	Female	9,626	32
7	70	30	Female	12,428	20
8	80	20	Female	12,506	32
9	90	10	Female	15,552	16

S. no.	*Avg. time for iterations (Sec)*	*Predicted training accuracy*	*Predicted test accuracy (%)*	*Average accuracy (%)*
1	0.05	100	64	82
2	0.09	100	75	87.5
3	0.08	100	58	79
4	0.13	100	90	95
5	0.17	100	75	87.5
6	0.18	100	100	100
7	0.16	100	75	87.5
8	0.13	100	75	87.5
9	0.16	100	50	75

Figure 6 Show the relation between training image set ration vs. classification accuracy of female database (see online version for colours)



About Tables 6 and 7 explained about gender classification accuracy based on training ratios of private database images of SRKIT Here explained about male and female training ratio increased by 10% from 10% to 90% training database ratio. If training ratio increased automatically to increase the training image features and also increase the average time for iteration in secs, but predicted testing accuracy did not increase, because features are extracted from training database randomly by using SURF algorithm. But general assumption increase the training database ratio then to increase the predicted test ratio and average accuracy ration also increases. But we observe in this experimental features are extractions are not dependence on human selected image's features. Finally, the average accuracy of male gender is 90.72% and female gender is 83.3% accuracy of all iterations from private database. Also shows graphs constructed based on training image set ratio and classification accuracy.

Table 8 Confusion matrix for gender recognition on private database

	Gender	
	M	*F*
M	20	2
F	1	21

Table 8 explained regarding confusion matrix between male and female. We apply testing on totally 44 images, male images are 22 and females are 22. Applying our algorithm on private database when 20 images are correctly classified as male and two images are not recognised correctly, at the same as female images are also classified 21 images correctly out-off 22 but one image is recognised as incorrectly. Below, we show sensitivity, specificity and accuracy of private image database.

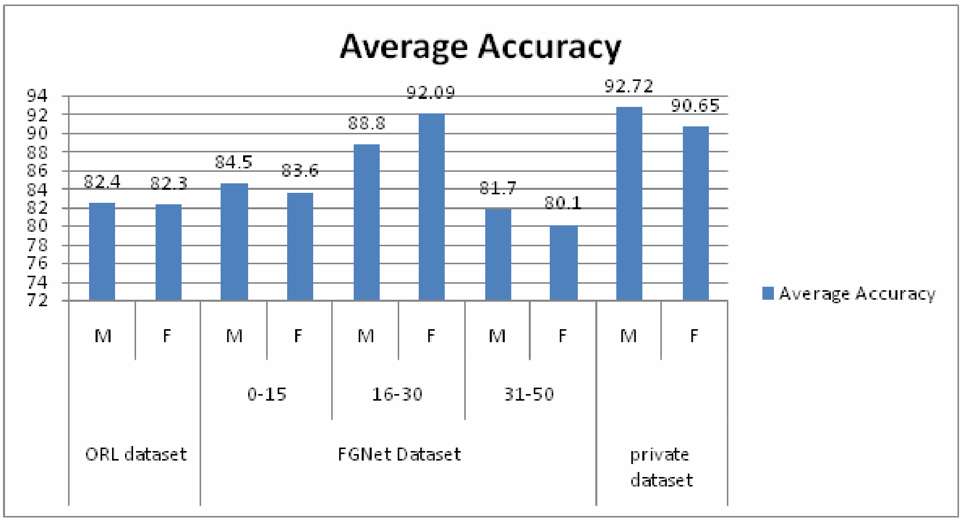
$$\text{Sensitivity} = \frac{20}{(20+2)} = 90.90 \quad \text{Specificity} = \frac{21}{(21+1)} = 95.45 \quad \text{Accuracy} = \frac{20+21}{(20+2+1+21)} = 93.18$$

Table 9 Comparison between different datasets with private dataset through average accuracy

Dataset name	*Age*	*Gender*	*Average accuracy*
ORL dataset		M	82.4
		F	82.3
FGNet dataset	0–15	M	84.5
		F	83.6
	16–30	M	88.8
		F	93.3
	31–50	M	81.7
		F	80.1
Own/private dataset		M	90.72
		F	86.79

Table 9 and Figure 7 explained about relation between different databases (ORL database, FGNet database and private database) through accuracy. We observe that our private database got highest average accuracy compared with licensed databases.

Figure 7 Show the relation between different databases and average accuracy (see online version for colours)



2.3 Applications of gender classification

Gender classification is used in wide range various applications those are demographic prediction, interaction between man and machine, detect diseases on face, smart doors implementation in rest rooms and railway bogies, business intelligence, image filtering, social media sites, close scrutiny systems, education and telecommunication applications, etc.

3 Conclusions

Final conclusion about this paper is to classify the human genders (Cerit et al., 2016; Ramesha et al., 2010) (male and female) based on similarity features. In this paper, we observe accuracy of different databases (ORL, FGNet and private database). We use three algorithms SURF for feature extraction through different features like colour, shape, edge, location, etc. and K-means for clustering the various facial features for fastly classification and SVM for better classification to get better accuracy. Observation of this paper our private database got very good accuracy compare to other databases. In private database, male accuracy is 92.72% and female accuracy is 90.65%. In the feature work will add any other objects for classification, to get more accuracy within the less time and also compare with different type of algorithms and with different metrics.

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