

# Extracting and Analysing of Heterogeneous Features for Robust FRS

S. Princy Suganthi Bai<sup>1</sup>, Dr. D. Ponmary Pushpa Latha<sup>2</sup>

<sup>1</sup> Research Scholar, Department of Computer Science, Bharathiar University, Coimbatore, India

<sup>1</sup> Associate Professor and Head, Department of Computer application, Francis Xavier Engineering College, Tirunelveli, India

<sup>2</sup> Associate Professor, Department of CA, Karunya Institute of Technology and Sciences (Deemed to be University), Coimbatore, India

**Abstract**— *Collecting, cleaning, combining and analysing of data are in demand in all the fields for acquiring accuracy in their task. In biometrics, this process is done for smart and secured life by means of extracting and analysing data for recognition task. Huge volume and variety of data are effectively extracted and analysed with Matlab2015 to identify the uniqueness of attributes for better accuracy in recognition process. Heterogeneous set of features that are extracted from ORL face dataset are analysed with Nearest Neighbour Rule in order to identify the unique facial features for robust FRS (Face Recognition System).*

**Keywords**— *Biometrics, FRS, Haralick features, ORL database.*

## I. INTRODUCTION

Biometrics is an art as well as science of identification and verification of person by his or her behavioural and physical features, not by the belongings of the person such as aadhar card, pan card etc....Finger print, palm print, eye-iris, face and DNA are some of the physiological features used for recognition process in the biometric system. The features which are having strong persistence for long period are marked as best features for recognition. Even though the features of finger-print, palm print and iris have high score of retention period, it is hard to cross check the performance manually in critical cases. CCTV Cameras are playing a vital role in the area of security in the public places, organizations, industries, household activities etc...[19].

Monitoring and controlling is the tough challenge for any management that be done by video surveillance. Image or video of a human face can be easily handled and analysed for the task of identification and verification. Face recognition is a simple and obvious biometric which is inevitable for smart and secured life. Smart life means does not need to carry documents for proof instead face is the identity proof that can be used for identification which did not get lost or stolen.

Researchers are scared of using face for recognition process because of the challenges like pose, illumination, age, occlusion, plastic surgery face, transgender and twins. The interest of using face for recognition is because of the application that it can be used without the co-operation of the user. Face recognition system generally uses the spatial features [2], frequency component [5] and geometric features [10]. Spatial features are more effectively used by haralick in the year 1973 on the satellite images and got accuracy of 83%.

In the field of biometrics, Haralick features are added and shown remarkable improvement in the performance metrics. In this paper, we have effectively utilized the some of the selective Haralick features added with frequency component which produce 92.5% of accuracy. Overview of existing FRS techniques is exposed in the section2. The section 3 has the detail about haralick features. The experiments and results are discussed in section 4. Finally, section 5 has the conclusion and future enhancement of the paper.

## II. EXISTING TECHNIQUES

Identification and verification can be achieved through unique features. Important phases of FRS are Feature extraction and classification. Facial features are classified as statistical features, geometric features, spatial features and frequency features. Geometric features [10] are extracted by fixing nodal points in face image. The spatial features are occurred through the parameters[2] like mean, median, entropy, energy, PCA [2][3][4][10] (Principal Component Analysis) etc...Frequency vectors are obtained by Fast Fourier Transform (FFT)[5], Discrete Cosine Transform (DCT)[2], Discrete Wavelet Transform[6] etc...

Nearest neighbour rule [7], Support Vector Machine [8] (SVM) and Neural Networks [9] are efficient classifiers for FRS. Similar sample images are grouped together for flawless classification. Facial features of different subject are classified as different classes. Performance of FRS [11] [12] can be measured with Falsely Accept Rate

(FAR) and False Reject Rate (FRR). EER (Equal Error Rate) which are calculated using FAR and FRR. ORL [13], CMU PIE [14], FRGC [15], AR [7], FERET [16], YALE [17], FG-NET [18] and MYCT [8] are the globally available databases which are used for analyzing the performance of FRS.

### III. HETEROGENEOUS FEATURES

Feature selection is the prominent task of any recognition process. In FRS, features can be acquired from spatial or frequency domain. In the proposed work, spatial and frequency domain are fused by using both Haralick features and FFT which are explained in this section.

#### 3.1 HARALICK FEATURES:-

The information of an image can be represented as  $f(x,y)$ . The features of the image are classified as spectral, textural and contextual [1] features. Tonal variation in different bands of an image is appeared as spectral features and variation in the same band is textural features. Contextual features are collected from the data outside the region of interest. Textural are the spatial distribution of gray tones which is available in the gray scale images.

Texture features gives the information about the surface with respect to the surrounding which is useful in discriminating one image from other image. Haralick et al., in their work extracted 14 types of features[1] based on homogeneity, gray-tone linear dependencies complexity, contrast, number and nature of the boundaries of the image. The textural features are easy to compute because less number of operations needed for computation. Haralick et al., is experimented the textural features of different type of images varying in resolution and its performance varies from 80% to 90%.

Tone and texture features are available in all the types of images. The image with more variation in the discrete gray tone has dominant texture features and has less variation and also good tone property in the dominant texture features. Texture features are more specific and general than tone features. It depends on angular nearest neighbour gray tone spatial-dependence matrices.

Matrices of gray tone spatial dependence frequencies are generated by measuring the angular relationship between the resolution cells. In the below figure1, the angles of the eight cells with respect to the center cell is represented in degrees. 1 and 5 are  $0^\circ$  neighbours, 2 and 6 cells are  $135^\circ$  neighbours, cell 3 and 7 are  $90^\circ$  neighbours and cell 4 and 8 are  $45^\circ$  neighbours. The neighbours cells are separated with distance 1.

6	7	8
5	.	1
4	3	2

Fig. 1: The resolution cells

Thirteen types of Haralick features extracted are angular second moment, contrast, and correlation, Sum of squares, Different inverse moment, sum average, sum moment, sum entropy, entropy, difference variance, difference entropy and Information measures of correlation. The equations from (1) to (13) are utilized for the extraction process.

Angular second moment: Homogeneity of the gray scale image focus on the gray scale distribution which is a measure termed as Angular second moment. It is denoted by the equation (1).

$$f1 = \sum_i \sum_j \{p(i,j)\}^2 \quad (1)$$

where,

$p(i,j)$  is the normalized gray tone spatial dependence matrix.

Contrast: The changes between a pixel and its neighbourhood pixels are denoted as Contrast measure which can be measured with the equation (2).

$$f2 = \sum_{n=0}^{Ng-1} n^2 \{ \sum_{i=1}^{Ng} \sum_{j=1}^{Ng} p(i,j) \} \quad (2)$$

where,

Ng Number of distinct gray levels.

Correlation: It is a measure of correlation between a pixel and the neighbourhood pixels which depends on mean and standard deviation. A flag +1 rise for positive correlation and -1 for negative correlation.

$$f3 = \frac{\sum_i \sum_j (i,j) p(i,j) - \mu_x \mu_y}{\sigma_x \sigma_y} \quad (3)$$

here  $\mu_x, \mu_y$  are the mean of the  $p_x$  and  $p_y$

$\sigma_x, \sigma_y$  are the standard deviation of the  $p_x$  and  $p_y$

$p_x, p_y$  probability matrix obtained from summing of  $i^{\text{th}}$  and  $j^{\text{th}}$  entry respectively

Sum of squares: Sum of squares is the summing up of the extracted values with respect to squaring the overall mean.

$$f4 = \sum_i \sum_j (i-\mu)^2 p(i,j) \quad (4)$$

Inverse difference moment: Analysing the homogenous of an image is vital factor for which higher value will be generated for high homogeneity.

$$f5 = \sum_i \sum_j p(i,j) \frac{1}{1 + (i-j)^2} \quad (5)$$

Sum average: Summing all the pixel values in the image ranging from Number of distinct gray levels.

$$f6 = \sum_{i=2}^{2N_g} ip_{x+y}(i) \quad (6)$$

Sum variance: Summing all the co-related pixel values in the image ranging from Number of distinct gray levels.

$$f7 = \sum_{i=2}^{2N_g} (i - f8)^2 p_{x+y}(i) \quad (7)$$

Sum entropy: The degree of unordered that occurs in the image is Entropy. The entropy value depends on co-occurrence matrix. It is large for the same co-occurrence matrix and small for different co-occurrence matrix. Sum entropy means summing the entropy values ranging from Number of distinct gray levels.

$$f8 = - \sum_{i=2}^{2N_g} p_{x+y}(i) \log\{ p_{x+y}(i) \} \quad (8)$$

Entropy: Entropy can be calculated with the pixel value and the logarithm of the pixel value.

$$f9 = - \sum_{i,j} p(i,j) \log (p(i,j)) \quad (9)$$

Difference variance: Measuring the pixel value how well it varies from the mean value of the image.

$$f10 = \text{variance of } p_{x-y} \quad (10)$$

Difference entropy: The neighbouring values of the pixel values are different on account of entropy.

$$f11 = \sum_{i=0}^{2N_g-1} p_{x-y}(i) \log\{ p_{x-y}(i) \} \quad (11)$$

Information measures of correlation: To extract more information from the pixel value, additional to the measurement of p(i,j) the other dimension of two set of discrete value p<sub>x</sub>(i) and p<sub>y</sub>(j) are also considered for trapping a new feature. Information measures of correlation can be retrieved from the following equations (12) and (13).

$$f12 = \frac{HXY-HXY1}{MAX(HX,HY)} \quad (12)$$

$$f13 = (1 - \exp[-2.0(HXY2-HXY)]) / 2 \quad (13)$$

where,

*HX and HY are entropies of p<sub>x</sub> and p<sub>y</sub>*  
*p<sub>x</sub>(i) ith entry in the marginal-probability matrix obtained by summing the rows of p(i,j).*  
*p<sub>y</sub>(j) jth entry in the marginal-probability matrix obtained by summing the rows of p(i,j).*

$$HXY = - \sum_{i,j} p(i,j) \log (p(i,j))$$

$$HXY1 = - \sum_{i,j} p(i,j) \log \{ (p_x(i)p_y(j)) \}$$

$$HXY2 = - \sum_{i,j} p_x(i)p_y(j) \log \{ (p_x(i)p_y(j)) \}$$

Haralick et al., extracted the above features from satellite images and classified different classes by means of piecewise linear distinction function. The maximum accuracy achieved for the satellite images[1] in their work was 83.5%.

### 3.2 EFT AND MAVFT

The FRS works much better when added with additional features. Here frequency components Energy of Fourier Transformed vectors (EFT) and MAVFT(Mean Absolute Value of Fourier Transformed vectors) are extracted and effectively utilized with Haralick features to equip the FRS for better accuracy.

Energy of Fourier Transformed vectors (EFT): The Fast Fourier is used to convert actual pixel values in to frequency vectors. Energy evolves by summing the real and imaginary values of the Fourier coefficients.

MAVFT(Mean Absolute Value of Fourier Transformed vectors): Mean value calculated for the shifted Fast Fourier Transform(FFT) for all rows and columns of the image.

## IV. EXPERIMENTS AND RESULTS:

The experiments and evaluation are performed with the different permutation of the extracted heterogeneous features from the popular public ORL face database[22] that is shown in the figure 2 which includes Frequency dc components, Mean Absolute Value, Energy of FFT and thirteen Haralick features [20].

The ORL database[22] of AT&T Laboratories Cambridge consists of 400 faces of 40 persons with 10 different sample faces for each subject which are with different pose, lighting, facial expressions, accessories and illumination shown in figure 2. The images available are in 256 grey levels per pixel PGM format and it is of size 92x112 pixels. The data base has 40 subjects and each subject hold one separate folder. The subject folder named with s alphabet followed by a number 1 to 40.

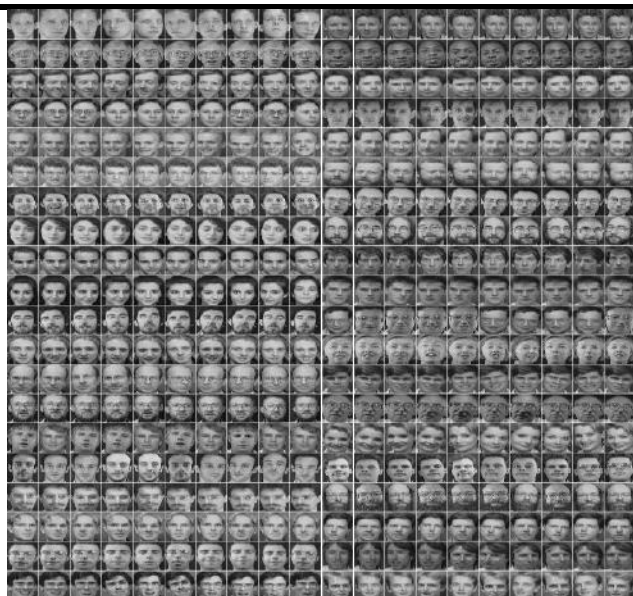


Fig. 2: ORL dataset

The tuples of features collected are appended with a unique class label for each type class. The dataset is partitioned so that one part is for training and other for testing. Cross validation method with five folds is used to construct the model for training and testing. In the proposed work, 400 tuples are collected from 400 face images of 40 individuals from the ORL dataset. The total 400 tuples were divided into 5 parts since five folds cross validation technique is considered for the proposed task. Among the five parts, 4 parts of the dataset are used for training to create a model and the remaining one part for testing. This process repeated for 5 times by changing the testing dataset with training dataset.

The training and testing is done with the KNN classifier. KNN rule (K-Nearest Neighbour Rule) usually uses the similarities among the feature vectors for grouping the similar classes. This rule is very effective for FRS systems. M. Ezoji K. Faez[7] and Randa Atta et al[2] used this KNN rule in their FRS to improve its performance. The extracted features are classified with nearest neighbour rule with different subset of features from the collected heterogeneous set and the performance of the FRS measured with accuracy metric [21]. Accuracy is other words known as recognition rate in pattern recognition. A test dataset used for accuracy measurement is a new dataset that is not trained. The correctly classified test dataset improves the accuracy rate and it can be obtained by the equation (14) given below.

$$Accuracy = \frac{\text{Number of tuples correctly classified}}{D} \quad (14)$$

Where,

D is the total number of tuples in the testing dataset.

The different permutation of the features gives the different accuracy rate. The training is done carefully and

the feature set with best accuracy is recorded obviously which is shown in the table 1 and figure 3.

Table.1: Diverse Permutation of Facial Features versus Accuracy

Feature set	Facial Features	Accuracy %
1	All the 13 Haralick features	86.30%
2	EFT, MAVFT and selective Haralick features(3,5-8,13)	91.80%
3	EFT, MAVFT and selective Haralick features(2,3,5,6,7,13)	92.00%
4	EFT, MAVFT and selective Haralick features(3-8,13)	92.30%
5	EFT, MAVFT and selective Haralick features(3,5,6,7,13)	92.50%

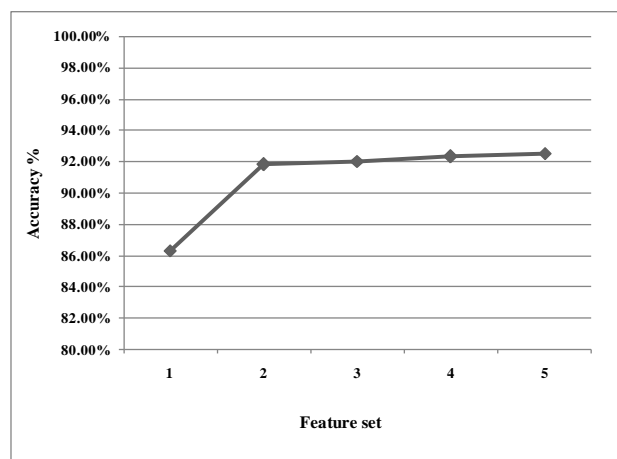


Fig. 3: Diverse Permutation of Facial Features versus Accuracy

The obtained results were compared with the existing systems like PCA, DCT and DWT [2] with the accuracy metric in the table 2 and shown in figure 4.

Table: 2 Facial Feature methods versus Accuracy

Facial Features methods	Accuracy with ORL%
PCA	87.50%
DCT	88.80%
DWT	91.10%
Proposed dataset	92.50%



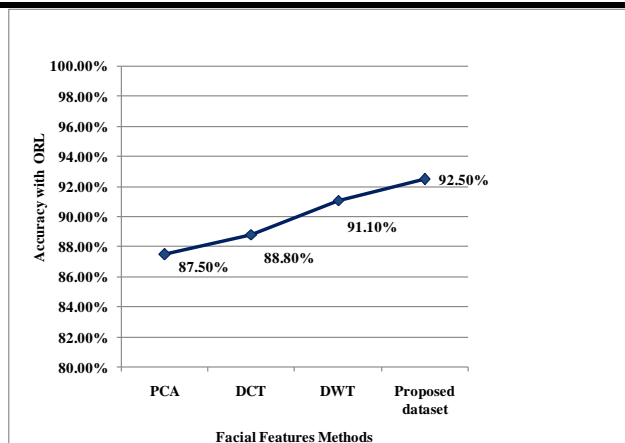


Fig. 4 Facial Feature methods versus Accuracy

The haralick features are spatial features which are significant in all types of images. The following table3 depicts the performance of haralick features on Satellite images and face images. Finally the added features with the selective haralick features are for better by its accuracy rate which is recorded in table3 and depicted in figure 5.

Table.3: Performance comparison between satellite images and face images

Haralick features extracted Data base	Accuracy%
Satellite database	83.00%
ORL face database	86.30%
Proposed dataset	92.50%

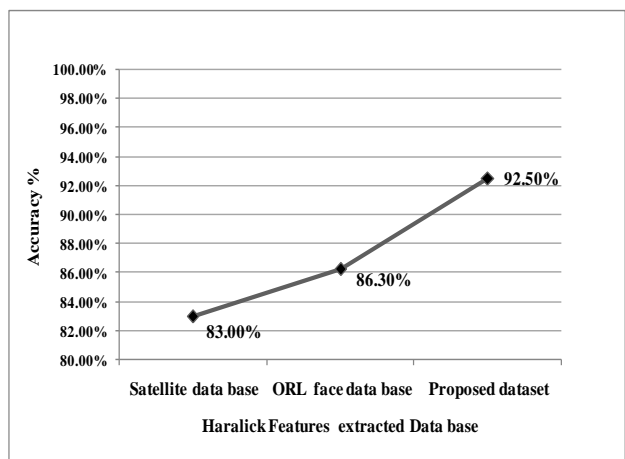


Fig.5: Performance comparison between satellite database and face database

Sensitivity and specificity across a range of cutoffs can be exposed with the ROC(Receiver operating characteristic) curve which has true negative values in the horizontal axis and true positive values in the vertical axis. Trained model of the FRS can be analysed with AUC(Area Under Curve) which is under the ROC curve which is shown in below figure 6. Ideal model achieve 1 and below 0.6 not

appreciable. The proposed dataset with cross validation model and KNN classifier produced 1 for AUC.

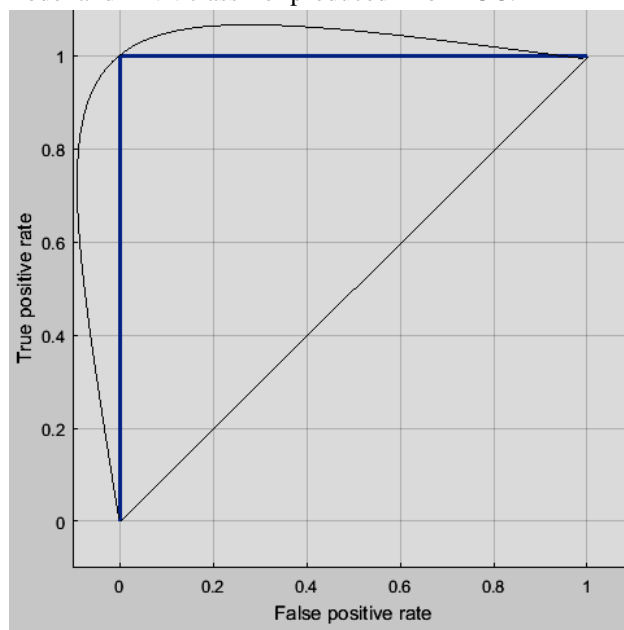


Fig.6: ROC curve for the proposed dataset

## V. CONCLUSION

Among several psychological characteristics face attracts the researchers by its uniqueness, genuinity and ease of availability. The acquisition of face need less cost, since, it can be acquired with the any type of available camera. In the proposed FRS, selective Haralick features with frequency vectors of ORL database gives the accuracy of 92.5%. Diverse features with low correlation vectors are further identified and analysed in future to improve the FRS system. The new era of Bigdata and IoT also enhance the utility of Face recognition system in the security and privacy applications by means of effective storage and dense distribution.

## ACKNOWLEDGEMENTS

I sincerely record my thanks to the Management of Francis Xavier Engineering College for their continuous moral, monetary and technical support.

## REFERENCES

- [1] Robert Haralick, Shanmugam and Dinstein, "Texture features for Image classification", IEEE Transactions on System, man and Cybernetics VOL. 3, NO. 6, November 1973.
- [2] Randa Atta and Mohammad Ghanbari, Fellow, IEEE," Low-Memory Requirement and Efficient Face Recognition System Based on DCT Pyramid", IEEE Transactions on Consumer Electronics, Vol. 56, No. 3, August 2010.
- [3] Emdad Hossain and Girija Chetty, "Person Identity verification based on face-gait fusion", IJCSNS

- International Journal of Computer Science and Network security, Vol 11 No 6 June 2011.
- [4] N. Sudha, Senior Member, IEEE, A. R. Mohan, Student Member, IEEE, and Pramod K. Meher, Senior Member, IEEE, "A Self-Configurable Systolic Architecture for Face Recognition System Based on Principal Component Neural Network", IEEE Transactions on Circuits and Systems for Video Technology, Vol. 21, NO. 8, August 2011.
- [5] Anissa Bouzalmat et al, "Face detection and recognition using BPNN and Fourier Gabor Filter", Signal Processing an International Journal (SIPIJ) Vol 2 No3 September 2011.
- [6] Harin Sellahewa and Sabah A. Jassim, "Image-Quality-Based Adaptive Face Recognition", IEEE Transaction on Instrumentation and Measurement, Vol. 59, NO. 4, April 2010.
- [7] M. Ezoji K. Faez, "Use of matrix polar decomposition for illumination-tolerant face recognition in discrete cosine transform domain", IET Image Processing 2011, Vol. 5, Issue. 1, pp. 25–35.
- [8] Escuela Politecnica Superior et al. "Discriminative multimodal biometric authentication based on quality measures", Elsevier November 2004.
- [9] Amina Khatun and md.A1-Amin Bhuiyan,"Neural Network based face Recognition with Gabor filter", IJCSNS Vol.11 No.1 January 2011.
- [10]Mohammad Abdul Kashem, md.Nasim Akhter, Shamim Ahmed and md.Mahbub alam, "Face Recognition System on PCA with BPNN", Canadian Journal on Image Processing and computer Vision Vol2, No 4, April 2011.
- [11]Qian Tao and Raymond Veldhuis, "Biometric Authentication System on Mobile Personal devices", IEEE Transaction on Instrumentation and Measurement Vol 59, No 4, April 2010.
- [12]Yin Zhang and Zhi-Hua Zhou, Senior Member, IEEE," Cost-Sensitive Face Recognition", IEEE Transactions on Pattern Analysis and Machine Intelligence, VOL. 32, NO. 10, October 2010
- [13]Jatin Garg and Neelu Jain, "Analysis of Different databases using improved PCA face recognition approach", International Journal of Communication Engineering Applications IJCEA Vol2 Issue 04 July 2011.
- [14]Shan Du, Student Member, IEEE, and Rabab K. Ward, Fellow, IEEE," Adaptive Region-Based Image Enhancement Method for Robust Face Recognition under Variable Illumination Conditions", IEEE Transactions on Circuits and Systems for Video Technology, Vol. 20, No. 9, September 2010.
- [15] Jiashi Feng, Bingbing Ni, Dong Xu, Member, IEEE and Shuicheng Yan, Senior Member, IEEE, "Histogram Contextualization", IEEE Transactions on Image Processing, Vol. 21, No. 2, February 2012.
- [16] Shih-Ming Huang and Jar-Ferr Yang, Fellow, IEEE, "Improved Principal Component Regression for Face Recognition Under Illumination Variations", IEEE Signal Processing Letters, Vol. 19, NO. 4, April 2012
- [17] Ping-Han Lee, Szu-Wei Wu, and Yi-Ping Hung, "Illumination Compensation Using Oriented Local Histogram Equalization and Its Application to Face Recognition", IEEE Transactions on Image Processing, Vol. 21, No. 9, September 2012.
- [18] Jiwen Lu, Yap-Peng Tan, Gang Wang, "Discriminative Multimanifold Analysis for Face Recognition from a Single Training Sample per Person", IEEE Transaction on pattern Analysis and Machine intelligence Vol. 35, No.1, January 2013.
- [19] Anjali Patel and Ashok Verma, "IOT based Facial Recognition Door Access Control Home Security System", International Journal of Computer Applications (0975 – 8887), Volume 172 – No.7, August 2017.
- [20] [http://shodhganga.inflibnet.ac.in/bitstream/10603/20682/14/14\\_chapter%205.pdf](http://shodhganga.inflibnet.ac.in/bitstream/10603/20682/14/14_chapter%205.pdf)
- [21] Jiawei Han and Micheline Kamber, "Data Mining Concepts and Techniques" Second Edition, Elsevier, Reprinted 2008.
- [22] [http://www.cl.cam.ac.uk/research/dtg/attarchive/face\\_database.html](http://www.cl.cam.ac.uk/research/dtg/attarchive/face_database.html)