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Fusion of Local Binary Pattern and Local Phase Quantization features set for Gender Classification using Fingerprints

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Abstract— Gender identification of an individual is a fundamental task, as many social interactions are gender-based. The fingerprint is the most precise and reliable biometric trait for gender identification. It plays a vital role to link the suspect in a crime scene or to find an unknown person. The gender identification can significantly enhance the performance of authentication systems and reduces the search space and speed up the matching rate. Several previous studies have investigated the gender identification from fingerprints but lack's in conventional results. In this work, the authors propose gender identification based on fingerprints by using the fusion of two well-known local descriptors, such as LBP and LPQ. The proposed algorithm is evaluated on state of two datasets i.e. publically available SDUMLA-HMT fingerprint dataset and other is self-created fingerprint dataset, which embraces fingerprints of 348 individuals (10 samples from each individual) of which 183 are males and 165 are female volunteers and obtained the best classification rate of 97% accuracy using SVM classifier. The results are competitive and appreciable as compared to earlier methods.

Keywords—Gender Identification, Biometrics, Fingerprint, LBP, LPQ, KNN, and SVM.

I. Introduction

Biometrics measures individual's anatomy based on physiological or behavior-logical measurements for his or her identification; humans have many unique and distinctive features which can be used to distinguish them thus, acting as a form of credentials, as a fingerprint is one of the prominent credentials. Fingerprint identification algorithms are well established in now a day's era and are being implemented all over the world for security and even in the judiciary. Fingerprints are unvarying but its size and shape may change with age, however, a basic pattern of fingerprint remains unchanged these features make fingerprint one of the important biometrics can be considered for gender identification.[1][2][3][7][11][12][18].

Gender classification based on human characteristics such as fingerprint, palm print, face, iris etc. is becoming popular. Although many achievements have attained by these biometrics trait but human gender identification using fingerprint will be among the next most popular task in biometric technologies; especially in forensic applications and anthropology for quarried articles, for crime investigators and for reducing the rage of the suspects. Subsequently, gender classification problem using a fingerprint as a trait is matured to some extent, but there is still scope for development with the more generic and generalized algorithm [17][21][22][25].

In particular, gender identification based on any biometrics bisects the search space as human vision system is self-sufficient and quite adaptive in recognizing someone's age and gender approximately, but for the machine, it is still a hard or daunting task to distinguish between a male or female's fingerprint. In this proposed work, the objective is to examine the gender identification by fusing LBP and LPQ features on the enhancement of the enactment of the biometric system by using biometric trait i.e. fingerprints. The rest of this paper is organized as follows: In Section 2, the brief related work is reported. The feature extraction and the flow of work carried out are placed in Section 3. Experimental results are discussed in section 4 and concluding remarks are reported in Section 5.

II. Related Work

In related literature the possibility of authenticating and classifying individuals [15] and their gender from the fingerprints was studied but to limited extent. In this section, we discuss the review of studies which have been reported on fingerprint based gender identification.
Gnanasivam P et al. [3] have focused on frequency domain analysis i.e. FFT, DCT is used to extract features on a

database of 400 persons. And by PSD and threshold value accuracy of 92.88 % for male and 94.85 % for a female is attained.

Akanchha Gour et al. [4] took advantage of frequency domain transformations i.e. Discrete Cosine Transforms (DCT) and Discrete Wavelet Transforms (DWT) based features are extracted over a smaller database of 100 fingerprint images and using K-Nearest Neighbor classifier got the overall result of 90% accuracy.

S. F. Abdullah et al.[5] works on a database of 3000 fingerprints on which the local features like ridge density, ridge thickness to valley thickness ratio and white lines count was calculated and further feeded to multilayer perceptron neural network classifier and overall result with accuracy of 96.25% obtained.

A. S. Falohun et al. [6] use combinational features of discrete wavelet transformation and principal component analysis over a smaller dataset of 280 fingerprint samples by back propagation neural network accuracy of 80.0% for females and 72.86% for males correctly classified respectively. Along with gender, auxiliary information like age is also calculated from the same experimental environment.

Pragya Bharti et al. [8] worked on 5-level haar discrete wavelet transform (DWT) and with Neural Networks classifier over 300 images of database and an accuracy of 91.3% is obtained.

Manish Verma et al. [10] demonstrated and performed experiments by using the local features of fingerprint i.e. ridge density from a smaller database of 400 fingerprints images using SVM classifier an accuracy of 89% was obtained.

R Jackson et al. [13] extracted the features through the combination of discrete wavelet transformation using PCA on the dataset of 400 fingerprints images out of which 200 were male and 200 were female respectively. The minimum distance Classifier and Euclidean distance were used for classification and the overall accuracy rate of 70% was obtained.

Pallavi C et al. [14] took advantage of frequency domain transformations and frequency domain analysis along with a discrete wavelet transforms and discrete cosine transforms were combined, on smaller database of 100 persons, of which 50 males and 50 female’s fingerprints were collected from different age and gender using KNN classifier and obtained classification rate of 80%.

S.S Gornale et al. [16] used well-known haralick local feature descriptor based texture extractor on 740 fingerprints image dataset, which is further led to basic linear discriminant analysis and obtained an accuracy of 94%.

S.S Gornale et al. [20] had designed an approach to perform glocal features extraction i.e. discrete wavelet and Gabor wavelets features from 740 fingerprints image dataset, with a smaller self-created database and by using simple quadratic discriminant analysis accuracy of 97% result attained.

S.S Gornale et al. [21] utilized a very basic yet prevailing local descriptor for feature extraction i.e. Local binary pattern technique was utilized on 740 images database with parametric K-NN classifier, an accuracy of 95.8 % result was achieved.

Prabha et al. [22] utilized multi-resolution statistical features on a dataset of 740 fingerprint images which were further feeded to back propagation neural network classifier and obtained an accuracy of 96.6%.

Suchita Tarare et al. [24] took advantage of frequency domain transformations and frequency domain analysis along with a discrete wavelet transforms, on a smaller database of 60 fingerprints, by using KNN classifier and Euclidean distance measure obtained accuracy of 70%.

From the related literature, it is observed that still there is an extent to develop a needed and generic algorithm to categorize the gender based on the fingerprints. In view of this, the LBP and LPQ feature sets are proposed and implemented to the strengthen accuracy of algorithm.

III. PROPOSED WORK

Gender classification using fingerprint analysis generally involves three steps namely preprocessing, feature extraction and classification. The initial task is to do pre-processing and the pre-processing techniques are application dependent. In our case we have pre-processed the fingerprint images such as background elimination, cropping, converting a color image into binary image etc., to increase the computational efficiency. We employ Otsu method for binarizing and to enhance the fingerprint image and normalize the intensity values. In the feature extraction [9] a textured area in an image is characterized by a non-uniform spatial distribution of image intensities. The texture descriptor models are classified into three main classes; Pixel based models, Local feature based model and Region based model. In this work we have employed local features for the fusion of two well-known features i.e. LBP and LPQ and classification is done with support vector machine. For the best understanding the schematic representation of the proposed methodology is shown in fig 1.

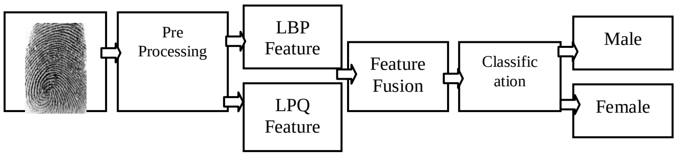

Fig.1. Proposed Methodology

A. Dataset and Evaluation Protocol

The Database contains fingerprints captured from 348 subjects out of which 183 are males and 165 are females. From each such subject, 10 left-hand thumb images were collected by giving prerequisite directions. Thus in total, we have 3480 fingerprints, from which 1830 are of females and 1650 are of males. if required, this dataset can be made available for further comparisons. Sample fingerprint images from the dataset are shown in fig 2.

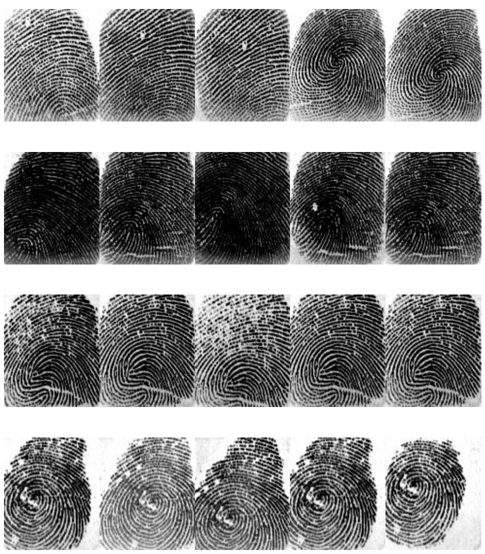

Fig.2. Sample of left thumb images from the database

B. Pre-processing

In this section, we aim to enhance the image for better feature extraction for this each image from the dataset is normalized to the size of 240 x 240 and further is binarized using Otsu method.[23]

Fig.3. (a) Input Fingerprint (b) Binarized Image (c) Scaled Image

C. Feature Extraction

In this feature extraction we have utilized two most successful local textural feature extraction methods due to their biological inspired nature perceptions and image representations; they are LBP and LPQ. However, from available literature review and empirical testing it is witnessed that fusion scheme significantly improves the gender classification accuracy and leads to promising performance.

1) Local Binary Pattern (LBP)

LBP was introduced by Ojala et al. [24] in 1996 for obtaining micro and local information from the image [14]. Figure 4 shows the working of LBP operations. After constructing all new grey value codes, the histogram will be extracted to represent the feature sets. The below equation shows the process of computing of LBP features.

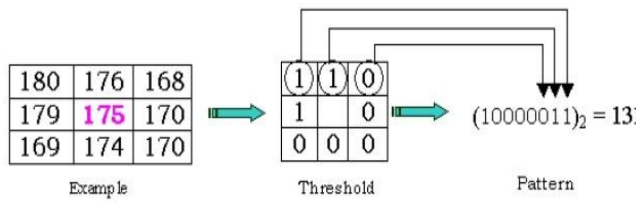

Fig.4. Working of LBP Operation

$$LBP\,(X_{p,c}) = \sum_{p=0}^{p=7} u(Xp - Xc)2P \qquad (1)$$

Where (Xp) is the represents to sample and (Xc) denotes the value of the central pixel, (p) is representing the pixels in neighborhoods. The LBP operator computes 58 features from each male and female from fingerprint images. Further, these features are used to test and train using basic classifiers with 10 folds cross-validation, Detail results of experiments are shown in the Table-1.

2) Local Phase Quantization (LPQ)

LPQ [19] originally introduced for blur texture classification additional to it can differentiate phase spectrum in image and loss of information at high frequencies. The extraction of Local phase information is done by applying local DFT to entire image linearly by considering image patch .The Local-FT $G_s(u,v)$, with s being the patch value indices obtained by applying linear filtering technique based on weighted sum of the frequency component of the image patch. For every pixel in the image, I(x, y) the phase of local-FT is calculated in M x M neighborhood. The scalar quantizer is defined by equation 2.

$$q(j)=\begin{cases}1 if\\0\end{cases}$$
$$q_j>0, otherwise \quad (2)$$

Where q(j) is the jth component of the G. The scalar quantizer results in a 2bit integer representation for a single frequency component at every point at x. The L quantized coefficient is presented at histogram according to the binary coding.

$$B=\sum_{j=1}^{L} qj^{2j-1} \quad (3)$$

This ranges between 0 and 2L-1 and describes the local textures at x.

3) Feature Fusion

In the feature level fusion technique given a fingerprint image di of size m*n, with a suitable set of the feature using say k feature extraction technique are extracted say{f1,f2…..fk} where internally fi={fi1.fi2…..fij}.j is the number of features obtained from the ith extraction technique. The features extracted using k feature extraction techniques are fused together using concatenation rule the fused features are feed to appropriate classifiers for classification.

In this work we have implicated two local feature extraction techniques i.e. LBP and LPQ descriptors, the combined feature vector is computed features from LBP operations i.e.58 features which are fused (combined) with obtained 256 features of LPQ descriptor and final feature vectors are generated by concatenation rule. The computed feature vector contains314 features obtained from each male and female fingerprint images. Further, these features are stored and are used to train and test the system to classify male and female based on the subject's fingerprints. For this, we have trained our proposed system with different parametric and non-parametric classifiers to check the performance and evaluation of earlier venerated classifying techniques.

D. Classifier

Linear Discriminant Analysis: LDA is one of the basic techniques with less computational complexity and is commonly used for dimensional reduction, the LDA classifier separates by maximizing the ratio between classes to within the class variance [3].

Quadratic Discriminant Analysis: QDA is moreover a generalization of Linear Discriminate Analysis which separates between the classes by quadratic measuring decision boundary rationally between and within of the classes variances [20].

Nearest Neighbour classifier: K-NN classifier will be classifying on measuring the distance between test and training data. KNN will be classified based on user-defined suitable K distance-value and inters which searches for the nearest neighbor and gives a label for unlabelled samples. Depending on the types of problem, different distance measures can be implemented. In the proposed method, City-block distance with K-Value equals to 3 is considered whose value is empirically fixed. Basically, K-NN shows the test data M, then finds the D distance between training sample X and testing pattern N using the following equation:

$$D_{City}(M,N)=\sum_{J=0}^{n}\left|M_J-N_J\right| \quad (4)$$

Support Vector Machine: SVM is a statistical learning based classifier which attempts to search for an optimal hyperplane which separates the classes a set of n data vectors says Yi .In the particular instance, a discriminant function:
F (X) = WT .Y − b separates each data item into two classes

$$f(x)=WT.Y_i-b\geq 1. \quad (5)$$

Here Yi is the class either +1 (male) or −1 (female) in our case.

E. Experimental Analysis

The independent performance of LBP and LPQ are separately investigated over the fingerprints respectively to test the effectiveness of the algorithm. But the overall result observed optimal by fusion of LBP and LPQ in terms which provides higher accuracy rather than using them alone: LBP gathers smaller and local appearance information while LPQ encodes global information over a broader range of scales from the images. Precision (P), Recall (R) and Accuracy (A) are computed and are represented in below equations:

$$\Pr ecision=\frac{T_P}{T_P+F_P}*100 \quad (6)$$

$$\operatorname{Re} call=\frac{T_P}{T_P+F_N}*100 \quad (7)$$

$$Accuracy=\frac{T_P+T_N}{T_P+T_N+F_P+F_N}*100 \quad (8)$$

Where T_p is True Positive, T_n is True Negative; F_p is False Positive and F_n False Negative. For the classification, we have employed four different classifiers namely Linear Discriminate Analysis, Quadratic Discriminate Analysis, K-Nearest Neighbor and Support Vector Machine Classifiers on fingerprints database. The detailed exhaustive results are shown below table-1 to table-3

Table 1 Results of Local Binary Pattern on Own Dataset

Classifier	***Precision***	***Recall***	***Accuracy***
LDA	78.36	76.27	75.5%
QDA	86.01	83.85	83.9%
KNN	82.02	88.98	87.3%
SVM	92.24	92.19	91.8%

From the Table-1, we observed that by using SVM classifier, the highest accuracy of 91.8% is achieved and lowest accuracy of 75.8 % is obtained by Linear Discriminate Analysis. K-NN with City-Block distance with a value of K=3 which is empirically fixed and has performed less than SVM and also yielded a result of 87.3% and accuracy of 83.9% is observed with QDA respectively.

Table 2 Results of Local Phase Quantization on Own Dataset

Classifier	***Precision***	***Recall***	***Accuracy***
LDA	83.60	84.48	83.3%
QDA	62.15	65.05	61.4%
KNN	90.87	93.95	92.1%
SVM	95.51	95.99	**95.8%**

From the table-2, we have perceived that using SVM cubic classifier, the highest accuracy of 95.5 % is achieved and the lowest accuracy of 61.4% is obtained by using QDA. KNN has performed similarly to SVM and has yielded a result of 92.1% and LDA obtained 83.3% the accuracy respectively.

Table 3 Result analysis of Fusion i.e. LBP and LPQ on Own Dataset

Classifier	***Precision***	***Recall***	***Accuracy***
LDA	86.33	85.49	85.1%
QDA	74.20	70.47	70.1%
KNN	91.80	94.17	92.7%
SVM	97.10	96.78	**97%**

From Table-3, we have noted the best accuracy of 97% achieved with support vector machine (Cubic-SVM) classifier. K-NN Classifier yielded efficient accuracy of 92.7% following similar tends with QDA classifier as poorest accuracy of 70.1% is obtained and with LDA 85.1% efficiency is noted respectively.

In this section, the proposed method is evaluated on SDUMLA-HMT standard dataset which is publically available [25]. The dataset includes real multimodal data from 106 individuals. For the fingerprint dataset images are acquired with FT-2BU sensors, the database includes fingerprint images captured from thumb, index finger and middle finger of both hand. By providing proper directions to volunteer the fingerprint images were captured of 6 fingers. SDUMLA-HMT is a multimodal dataset but for this experiment we are considering only fingerprint images acquired with FT-2BU sensors. Our basic objective of evaluating the proposed algorithm on SDUMLA-HMT fingerprint dataset is to check and generalize robustness of the proposed system. Likewise, the detailed exhaustive results are demonstrated from table-4 to table-6.

Table 4 Results of Local Binary Pattern on SDUMLA Dataset

Classifier	***Precision***	***Recall***	***Accuracy***
LDA	81.16	79.70	78.0
QDA	76.94	80.07	76.5
KNN	82.88	79.64	**78.7**
SVM	80.00	76.00	74.8

From the Table-4, we observed that by using KNN classifier with City-Block distance with a value of K=3 which is empirically fixed and have performed, the highest accuracy of 78.7% and achieved and lowest accuracy of 74.8% by SVM classifier. Linear Discriminate Analysis performed less than to KNN and have yielded a result of 78.3% and 76.5% accuracy is observed with QDA respectively.

Table 5 Results of Local Phase Quantization on SDUMLA Dataset

Classifier	***Precision***	***Recall***	***Accuracy***
LDA	79.15	79.1	76.7
QDA	73.05	75.48	71.8
KNN	86.61	85.59	**84.4**
SVM	80.33	78.21	76.6

From the table-5 further, we have perceived that using KNN highest accuracy of 84.4 % is achieved and lowest accuracy of 71.8% is obtained by QDA. SVM have performed lesser as compared to KNN and have yielded an accuracy of 76.6% and with LDA 76.7% result is observed respectively.

Table 6 Result analysis of Fusion i.e. LBP and LPQ on SDUMLA Dataset

Classifier	***Precision***	***Recall***	***Accuracy***
LDA	77.79	77.92	75.3
QDA	69.49	77.79	71.2
KNN	87.11	85.24	**84.13**
SVM	80.33	80.67	77.9

From Table-6, we have noted the best accuracy of 84.13% achieved with K-NN Classifier. Support vector machine (Cubic-SVM) classifier yielded efficient accuracy of 77.9% follows similar tends with QDA classifier as poorest accuracy of 71.2% is obtained and with LDA 75.3% efficiency is noted respectively.

IV. COMPARATIVE ANALYSIS

In this section, we have compared proposed work with similar works found in the reviewed literature. In [3] authors have used fast Fourier transformation and discrete cosine transformation on 400 fingerprints database out of which 200 are males and 200 are females and threshold based Singular value decomposition accuracy is a 94.8%. Akanchha Gour et al [4] have implemented and combined Discrete Wavelet and Discrete Cosine Transformation based extraction technique over a very few images of 100 fingerprints by utilizing KNN classifier and obtained accuracy of 90%. S. F. Abdullah et al [5] implemented extracted ridge density, ridge thickness to valley thickness ratio and white lines count features from relatively larger dataset of 1430 males fingerprints and 1570 females fingerprints which are further been trained and feeded to multilayer perceptron neural network classifier and overall accuracy of 96.25% is obtained. A. S. Falohun et al [6] developed a system which is implemented on 280 fingerprints images using discrete wavelet transformation which are trained by back-propagation neural network and obtained 80% classification accuracy. Pragya Bharti et al. [8] have recognized and implemented 5 levels of Haar decomposition over smaller dataset of 300 fingerprint images which have been classified using neural network and an accuracy of 91.3 % is yielded. Manish Verma et al. [10] employed ridge based density feature for experimentation on an internal database of 400 fingerprints using SVM classifier and 89% accuracy is attained. Similarly, R Jackson et al. [13] have combined Discrete Wavelet transformation based on principal component analysis technique over a smaller database of 400 fingerprint images, which managed to obtain a result of 70%. Pallavi C et al [14] have combined FDA and 2D DWT on a smaller dataset of 100 fingerprint images, by using KNN classifier achieved classification rate of 80%. S.S Gornale et al. [16] used a Haralick texture descriptor on a dataset consisting 740 fingerprint images and performance of the system is noted to be 94%. S.S Gornale et al. [23] used discrete wavelet transformation and gabor wavelets on a dataset consisting 740 fingerprint images and took advantage of basic quadratic classifier and obtained an accuracy of 97%. Further S.S Gornale et al. [24] utilized Local binary pattern on a dataset consisting of 740 fingerprint images using KNN classifier and obtained an accuracy of 95.8%. Similarly Prabha et al.[25] have used multi-resolution statistical features on 740 fingerprint database images and obtained 96.6% accuracy by using back-propagation neural network.

The drawback of the prior reported works is that they were implemented and experimented on a very compact and limited dataset; a few of these datasets were unavailable for the further comparison. But our method has outperformed those methods by fusing of LBP with LPQ based texture analysis with SVM classifier on a relatively large dataset consisting of 3480 fingerprints of males and females, which yielded the better efficiency of 97.0% accuracy. Besides our proposed method is also immune to noise and low-resolution effects.

Table 7 Comparative Analysis

Author	***Feature Used***	***Dataset***	***Classifier***	***Results***
Suchita T et al. [2]	Discrete wavelet transformation	30 Male and 30 female	KNN classifier	70%
Gnanasivam P et al.[3]	Fast Fourier Transformation, Discrete Cosine Transformation	200 males and 200 females	Threshold-based Singular value decomposition	94.8%
Akanchha G et al.[4]	Discrete Cosine Transforms and Discrete Wavelet Transforms	100 Fingerprint images	K-Nearest Neighbour	90%
S. F. Abdullah et al.[5]	Ridge Density, Ridge Thickness to Valley Thickness Ratio and White Lines Count	1430 males and 1570 females	Multilayer Perceptron Neural Network	96.25%
A. S. Falohun et al [6]	Discrete wavelet transformation based on principle component analysis	140 males and 140 Females	Back Propagation Neural Network	80%
P Bharti et al [8]	Haar Discrete Wavelet Transform	300 Fingerprint images	Neural Network	91.3%
Manish V et al, [10]	ridge density	200 Male and 200 females	Support vector machine	89%
R Jackson et al.[13]	Discrete wavelet transformation based on principle component analysis	200 Male and 200 females	Minimum distance classifier	70%
Pallavi C et al.[14]	Fourier Descriptor and Discrete Wavelet Transformation	50 male and 50 Female	KNN classifier	80%
S.S Gornale et al.[16]	Haralick Descriptor	370 male and 370 female	Linear Discriminant analysis	94%
S.S Gornale et al.[20]	Discrete wavelet transformation and Gabor Wavelet	370 male and 370 female	Quadratic Discriminant analysis	97%
S.S Gornale et al.[21]	Local Binary Patterns	370 male and 370 female	KNN Classifier	95.8
Prabha et al.[22]	Multi-resolutional Statistical	370 Male and 370 Female	Back Propagation Neural Network	96.6%
Proposed Method	Fusion of Local binary pattern and Local phase quantization	1650 males and 1830 Female	Support Vector Machine	97%

V. CONCLUSION

With the growth of functional biometrics devices the use of number of new datasets is increased by researchers, who creates their own datasets and tests their respective algorithms, In this way we also explore the performance of gender identification on the basis of state of two datasets i.e. on our own created database and other one is the publically available SDUMLA-HMT fingerprint dataset. Author implimented fusion of two well-known local texture representations i.e. LBP and LPQ based features which give better performance rather than using them alone. Our basic objective is to develop a generic system that can differentiate between a male and a female subject efficiently based on the fingerprints. With support vector machine classifier we managed to enact appreciable result of 97% on a relatively larger database of 3408 fingerprint images (Own Dataset) compared to other methods from the literature.

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REFERENCES

[1] Anil K. Jain, Karthik Nandakumar, Xiaoguang Lu, and Unsang park, "Integrating Faces, Fingerprints, and Soft Biometric Traits for user Recognition." Proceedings of Biometric Authentication Workshop, LNCS 3087, pp.**259-269**, **PRAGUE**,-May 2004.

[2] Suchita T, Akhile Anjikar and Hemant Thakur, "Fingerprint-Based Gender Identification using DWT Transformation", International Conference on Computing Communication Control and Automation,(ICCCA-2015), Pune , India, 2015.

[3] Gnanasivam .P, and Dr. Muttan S, "Fingerprint Gender Classification Using Wavelet Transform and Singular Value Decomposition", International Journal of Computer Science Issues, Vol. **9**, Issue **2**, No **3**, March **2012**.

[4] Akanchha Gour and Dharmendra Roy," Increasing Accuracy of Age and Gender Detection by Fingerprint Analysis Using DCT ", International Journal of Innovative Research in Computer and Communication Engineering, Vol **9**, Issue **5**, May **2016**.

[5] S. F. Abdullah, A. F. N. A. Rahman, Z. A. Abas and W. H. M. Saad," Multilayer Perceptron Neural Network in Classifying Gender using Fingerprint Global Level Features", Indian Journal of Science and Technology, Vol **9**, March **2016**.

[6] A. S. Falohun, O.D.Fenwa, F. A. Alala," A Fingerprint-based Age and Gender Detector System using Fingerprint Pattern Analysis ", International Journal of Computer Applications (0975 – 8887) Vol.**4**, pp.**136 –140**, February 2016.

[7] M vadivel , T Arulkumaran "Gender Identification from FingerPrint Images Based on a Supervised Learning Approach", PASJ International Journal of Computer Science (IIJCS), Volume **2**, Issue **7**, July **2014**.

[8] Pragya Bharti, Dr. C. S. Lamba," DWT-Neural Network based Gender Classification", International Journal of Digital Application & Contemporary research, Volume **2**, Issue **8**, March **2014**.

[9] Vikas Humbe, S S Gornale , K V Kale, R. R. Manza', "Mathematical Morphology Approach for Genuine Fingerprint Feature Extraction", *International Journal of* Computer *Science and Security*, ISSN: **1985-1533** Vol. **1** Issue **2**, pp **53-59-2007.**

[10] Manish Verma and Suneeta Agarwal.'' Fingerprint Based Male - Female Classification. '' in Proceedings of the international workshop on computational intelligence in security for information systems (CISIS'08), **Genoa, Italy**, pp.**251 – 255, 2008**.

[11] A. Badawi, M. Mahfouz, R. Tadross, and R. Jantz "Fingerprint-based gender classification" The International Conference on Image Processing, Computer Vision, and Pattern Recognition,(CVPR-2006) in June **2006**.

[12] Naveen Kumar Jain, Sunil Sharma, Anurag Paliwal., A Real-Time Approach To Determine The Gender Using Fingerprints", IJAIR ISSN: **2278-7844**, pp:**229-233**, **2012.**

[13] Rijo Jackson Tom, T. Arulkumaran, "Fingerprint-Based Gender Classification Using 2D Discrete Wavelet Transforms and Principal Component Analysis", International Journal of Engineering Trends and Technology, Vo. **4**, Issue **2**,**2013**

[14] Pallavi Chand, Shubhendu Kumar Sarangi, "A Novel Method for Gender Classification Using DWT and SVD Techniques", International Journal of Computer Technology & Applications, Vol **4** (3),pp.**445-449**, May-June **2013.**

[15] Ritu Kaur and Susmita Ghosh Mazumdar, Mr. Devanand Bhonsle, "A Study On Various Methods of Gender Identification Based on Fingerprints", International Journal of Emerging Technology and Advanced Engineering, ISSN **2250-2459,** Vol.**2**, Issue **4**, April **2012.**

[16] S. S. Gornale, Mallikarjun Hangarge, Rajmohan Pardeshi, Kruthi R" Haralick Feature Descriptors for Gender Classification Using Fingerprints: A Machine Learning Approach ",IJARCSSE Vol. **5**,Issue **9**,September-**2015**.

[17] S. S. Gornale, Geetha D, Kruthi R "Analysis of a fingerprint image for gender classification using spatial and frequency-domain analysis", American International Journal of Research in Science, Technology, Engineering and Mathematics",ISSN **2328-3491**, ISSN:**2328-3580**, ISSN (CD-ROM): **2328-3629**, pp.**46-50**, **2013**.

[18] S. S. Gornale, "Fingerprint-Based Gender Classification for Biometric Security: A State-Of-The-Art Technique",International Journal of Research in Science, Technology, Engineering & Mathematics ISSN **2328-3491**, pp. 39-49 Dec-**2014.**

[19] V. Ojansivu and J. Heikkilä, "Blur insensitive texture classification using local phase quantization," in Image and Signal Processing. Heidelberg: Springer, 2008, pp. **236-243**.

[20] Shivanand Gornale, Abhijit Patil and Veersheety C. "Fingerprint-Based Gender Identification Using DWT and Gabor Filters", International Journal of Computer Applications Vol.**152** Issue **4**, pp.**34-37**.**2016**

[21] Shivanand Gornale, Basavana M, and Kruti R, "Fingerprint-Based Gender Classification Using Local Binary Pattern", International Journal of Computational Intelligence and Research Vol.**13** Issue **2**, pp. **261-272,2017**.

[22] Prabha,S Jitendra, and P Rajmohan,"Fingerprint-based Automatic Human Gender Identification", International Journal of Computer Applications ISSN **0975 – 8887**, Vol-**170** Issue-**7**, July **2017** .

[23] Otsu, Nobuyuki. "A threshold selection method from gray-level histograms", IEEE Transactions on systems, man, and cybernetics Vol.**9** **,**Issue **1**,pp.**62-66**. **1979**

[24] Timo Ojala, Matti Pietikainen, and David Harwood, "A comparative study of texture measures with classification based on feature distributions", Pattern Recognition Vol.**29** Issue **1**, pp.**51-59**, **1996.**

[25] Yilong Yin, Lili Liu, and Xiwei Sun," SDUMLA-HMT: A Multimodal Biometric Database", The 6th Chinese Conference on Biometric Recognition (CCBR **2011**), LNCS **7098**, pp. **260-268,** Beijing, China, **2011.**

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