



Fingerprint Based Gender Classification for Biometric Security: A State-Of-The-Art Technique

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Abstract: Fingerprint Identification and Verification are certainly the most reliable and adequate evidence till date in the court of law. There are many biometric techniques like Fingerprints, Hand Geometry, Retina Scanning, Iris Scanning, Face Recognition, DNA fingerprint, Signature, Voice, Key Stroke Pattern, Gait (Body Dynamics), etc., that play a crucial role in identification and verification. The fingerprint biometric is one among most researched and used techniques for identification and verification. Comparatively a small number of machine vision techniques have been suggested for gender recognition and classification. So identifying the gender from fingerprints is an important step in forensic anthropology to shorten the list of suspects search. Very few researchers have worked on gender classification using fingerprints and have gained competitive results. This paper presents a comprehensive evaluation of lstate-of-the-art research techniques associated with gender classification using fingerprints and it is also proposed to combines the elaborate study of various methods and strategies with their comparative measures and to forecast results. This will help the researcher to undertake a comprehensive review and to carry out further research in fingerprint-based gender classification for biometric security.

Key words: Gender classification, Minutia extraction, Image-based methods, Minutia based methods, feature classification.

I. Introduction

The science of fingerprint has generally been used for the identification or verification of a person for official documentation. There are many biometric techniques like Fingerprints, Hand Geometry, Retina Scanning, Iris Scanning, Face Recognition analysis, DNA fingerprint, Signature, Voice, Key Stroke Pattern, Gait (Body Dynamics), etc., A few of them are in the stage of research only (e.g., the odour analysis), but a significant number of techniques are already mature and commercially available.

Fingerprint Identification and Verification is certainly the most reliable and adequate evidence till date in the court of law. Basically, the skin of human fingertips consists of ridges (this does not change over the time and is unique to a person) and valleys which constitute a distinctive pattern which is composed of many ridges and furrows. The fingerprint pattern, when analyzed at different scales, exhibits different types of features called Macro-Characteristic of Fingerprints and Micro-Characteristics of Fingerprints.

The macro-characteristics are global features constituted by the ridge pattern and the singularity points. The ridge pattern characterizes the shape described by the ridge flow. The singularity points are localized in small regions where the ridge flow becomes irregular. Human fingerprint is comprised of a varied variety of ridge pattern, historically these are classified into (a) Arch (b) Tented Arch (c) Left Loop (d) Right Loop (e) Whorl. These are shown in figure-1. Core and delta points are shown for each class in this figure by circle and triangles, respectively.

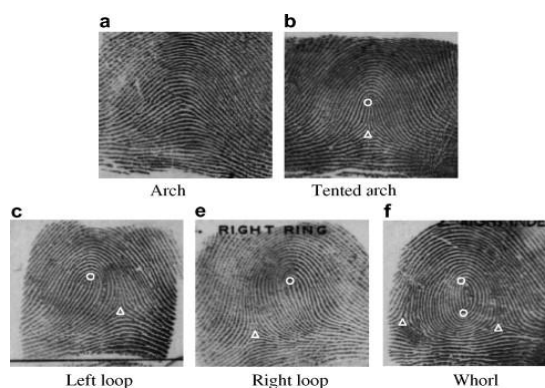


Figure-1.1 (a) Arch (b) Tented Arch (c) Left Loop (d) Right Loop (e) Whorl.

The micro-characteristics of fingerprints, or local features, are constituted by the discontinuities of the ridge lines, usually called *minutiae points*. Usually minutiae points are grouped into two types: the bifurcation and the termination of the ridge lines are shown in figure-2. The position and orientation of minutiae are claimed to be unique to each person. Therefore, they are the main features used in identification matching) process.

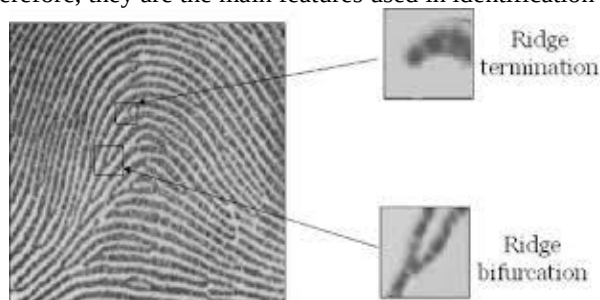


Figure-1.2: Minutiae points-Termination and Bifurcation

The performance of a fingerprint feature extraction and matching algorithm depends upon the quality of the input fingerprint image. While the 'quality' of a fingerprint image cannot be objectively measured, it roughly corresponds to the clarity of the ridge structure in the fingerprint image. Therefore, it is necessary to improve the clarity of the ridge structures of fingerprint images, maintain their integrity, avoid introduction of spurious structures or artefacts, and retain the connectivity of the ridges while maintaining separation between ridges. As the distance between minutiae is normalized by ridge frequency at each minutia, the distance variation by nonlinear deformation is minimized. The positions and ridge orientations of minutiae that are located in near region also are less affected by nonlinear deformations since they appear in some local areas and change gradually[24],[31]. Classification performance largely depends on the pre-processing steps where various ways to extract and represent distinguishable features among classes can be applied [44]. The main purpose of fingerprint classification is to facilitate the management of large fingerprint databases and to speed up the process of fingerprint matching. As the database of fingerprints increased, manual identification became tedious and automated methods became more widespread [49]. Gender classification from fingerprints is an important step in forensic anthropology in order to identify the gender of a criminal and shorten the list of suspects search. All the methods proposed in the literature are primarily based on the fingerprint ridges and have given insight about the ridge parameter mentioned about but fail to give accurate method of measuring the parameters. This may be due to the measurement made on the inked fingerprint impressions and manual measurements of the parameters where human error and recklessness is inevitable [19],[21],[36].

A. Classification of Algorithms

Fingerprint based gender classification algorithms/methods can be classified into two categories: *image-based* and *minutiae-based* and follow the general steps involved in it. These are shown in figure-1.3

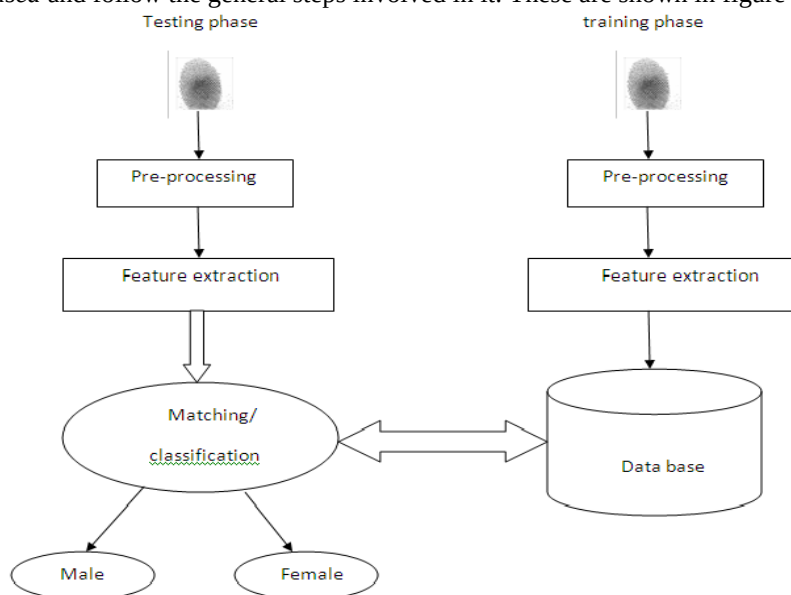


Figure-1.3: Shows the steps involved in the *image-based* and *minutiae-based* methods.

A.1 Fingerprint acquisition:

Image acquisition could be as simple as being specified in image that is already in digital form. Generally, the image acquisition steps include pre-processing, such as scaling. In digital image processing image augmentation is one of the easiest and most pleasing zones [17].

A.2. Pre-processing

After collecting fingerprint samples in different formats like .jpg, .png, bitmap, they are pre-processed for background elimination, resizing, cropping, converting colour image into binary image etc. For computer efficiency, the colour image is converted into binary image [17].

A.3. Feature Extraction

Several representations have been used to assess fingerprint similarity. Fingerprint representations can be broadly categorized into two types: global and local [11],[42],[45],[50].

The Global approaches of automatic fingerprint matching have been proposed in the literature. The most popular ones are based on the minutiae pattern of the fingerprint and are collectively called minutiae-based approaches. Although rather different from one other, most of these methods require extensive pre-processing operations (such as orientation flow estimation, ridge segmentation, ridge thinning, and minutiae detection) in order to reliably extract the minutia features. Another class of fingerprint matching approaches does not use the minutiae features of the fingerprint. They either match directly the fingerprint images or match features extracted from the image by means of certain filtering or transform operations.

The local representation consists of several components; each component typically derived from a spatially restricted region of the fingerprint. Typically, generic representations are used for fingerprint indexing and local representations are used for fingerprint matching. One of the significant global features used for fingerprints is its class or type. The overall fingerprint pattern is typically categorized into a small number of classes. Several fingerprint classification schema exist and as mentioned earlier, we will avoid delving into the details of the classification schema adopted by different automatic identification schemes. A simple fingerprint classification scheme categorizes the prints into following six major classes: whorl, right loop, left loop, arch, twin loop, and tented arch. Fingers can also be distinguished based on features such as ridge thickness, ridge separation, or ridge depths. Some examples of global representation include information about locations of critical points (e.g., core and delta) in a fingerprint. Core-delta ridge count feature, sometimes simply referred to as the ridge count, measures the number of ridges between core and delta points. All these features measure an overall property of a finger and we will refer to these similarities as global or generic features. Major representations of the local information in fingerprints are based on finger ridges, pores on the ridges, or salient features derived from the ridges [46]. The most widely used local features are based on minute details (minutiae) of the ridges which are shown in figure 1.4.

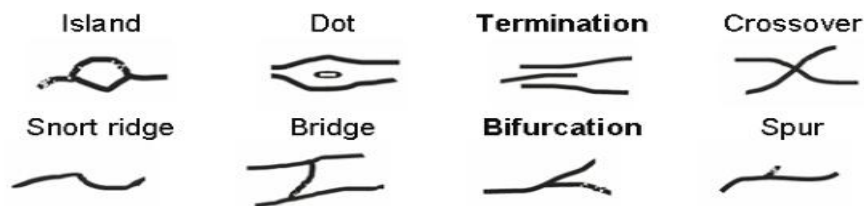


Figure-1.4: Local features of Fingerprint image

A.4. Feature Matching

Several approaches have been developed for automatic fingerprint classification. These approaches can be broadly put into four main categories:

- Knowledge-based: This classification technique that uses the locations of singular points (core and delta) to classify fingerprints.
- Structure-based: This classification technique uses the estimated orientation field in a fingerprint image to classify the fingerprints.
- Frequency-based: This classification technique uses the frequency spectrum of the fingerprints for classification.
- Syntactic: This classification technique uses a formal grammar to represent and classify fingerprints.

II. Image-Based gender classification Methods

Image-based methods include methods involving optical correlation and transform-based features [7],[15],[19],[21-23],[25],[30-32],[34],[37-39]. Very few researchers have worked on fingerprints for gender classification using these feature extractions and have obtained the competitive results.

A. Related Work of Transform-Based Image Feature Extraction for Gender Classification

Park et. al., (2004) have proposed a novel approach for fingerprint classification based on Discrete Fourier Transform and nonlinear discriminate analysis. The directional images are constructed from fingerprint images utilizing DFT. Applying directional filters in the frequency domain after the transformation by the DFT achieves effective low frequency filtering, reducing the noise effects in fingerprint images. Fast algorithm FFT for DFT speeds up the pre-processing to construct directional images. Once the transformation matrix by KDA/GSVD is computed, the classification in the reduced dimensional space saves computational complexities further. And they achieved satisfactory and competitive results [7].

Uday Rajanna et. al., (2009) have proposed a comparative study on feature extraction for fingerprint classification and performance improvements using rank-level fusion. The features were extracted like Gabor features, OM (Orientation Maps), MM (minutia Maps) and OC (orientation co-linearity). In MMs, the total rejection rate was 1.77% with 36 training samples and 35 testing samples rejected. Using OM the total rejection rate was 1.75% with 37 training images and 33 testing images rejected. Using OC the top-class accuracy was close to 77%, while the top-two classes accuracy was 93.7%. Using Gabor features the top-class accuracy was 83.86% while the top-two-classes accuracy was 96.1%. With processing time in sec for Gabor features 5.6, OM 0.03, MM 0.30 and OC 2.29 respectively [15].

Gnanaswami P, et. al., (2011) have proposed a method for gender identification using fingerprint through frequency domain analysis to estimate gender by analyzing fingerprints. The features were extracted from Fast Fourier Transform (FFT), Discrete Cosine Transform (DCT) and Power Spectral Density (PSD). A dataset of 400 persons of different age and gender is collected as internal database. Frequency domain calculations are compared with predetermined threshold and gender is determined. They obtained the results of 92.88 % and 94.85 % for male and female respectively.[19]

Naveen Kumar Jain, et. al., (2012) have proposed a real time approach to determine the gender using fingerprint. The real time processing is done using the CODE composer Studio IDE. A dataset of 300 persons of different age and gender is collected as internal database. Initially the fingerprints of the subject were tested and after the manual analysis threshold is specified. Frequency domain calculations are compared with predetermined threshold and gender is determined. Of the samples tested, 138 samples were identified exactly out of 150 female samples, and 131 samples were identified exactly out of 150 male samples [25].

Shrikant Tiwari et. al.,(2012) have proposed a method for the recognition of the newborn using Fusion of Ear and Soft-Biometrics. A dataset of the newborn includes 2100 images from 210 subjects with 10 images per person. Features extracted Principal Component Analysis (PCA), Kernel Principal Component Analysis(KPCA),Fisher Linear Discriminate Analysis (FLDA) Independent Component Analysis(ICA), Geometrical Feature Extraction(GF) and HAAR. Identification accuracy of 90.72% was obtained [40].

Gnanaswami P, et al., (2012) have proposed a method for gender classification from fingerprint based on Discrete Wavelet Transform (DWT) and Singular Value Decomposition (SVD). The feature set is obtained using DWT and SVD. This method is experimented with the internal database of 3570 fingerprints in which 1980 were male fingerprints and 1590 were female fingerprints. They obtained Finger-wise gender classification which is 94.32% for the left hand little fingers of female persons and 95.46% for the left hand index finger of male persons. Gender classification for any finger of male persons tested is obtained as 91.67% and 84.69% for female persons [21].

Ritu Kaur et.al, (2012) have worked on fingerprint-based gender identification using frequency domain analysis. The feature set is extracted from Fast Fourier Transform, Discrete Cosine Transform and Power Spectral Density (PSD). A dataset of 220 persons of different age and gender is collected as internal database. Frequency domain calculations are compared with predetermined threshold and gender is determined. They obtained results of 90%, and 79.07% for female and male samples respectively [22].

Pallavi Chand et.al., (2013) have proposed a method for gender classification using DWT and SVD Techniques. The 2D-Discrete Wavelet Transformation (DWT) was used to find the frequency domain vector and Singular Value Decomposition (SVD) was implemented in order to find the spatial feature of the non-zero singular values. The K-nearest neighbour classifier is used to classify the fingerprint. The method is experimented with the internal database of 100 fingerprints of left hand index finger, 50 males and 50 females belonging to the same age group and achieved the success rate of classification that is more than 80% [32].

T Arulkumaran, et al., (2013) have proposed a method for fingerprint based age estimation which extracts the features through 2D Discrete Wavelet Transforms and Principal Component Analysis. A dataset of 400 fingerprints of the age of 12-60 was collected and the overall success rate of classification in age estimation was around 68% [27].

Rijo Jackson Tom, et al., (2013) have proposed a method for fingerprint based gender classification through frequency domain analysis to estimate gender by analyzing fingerprints using 2D Discrete Wavelet Transforms (DWT) and Principal Component Analysis (PCA).A dataset of 400 persons of different age and gender is collected as internal database. Their overall success rate in gender classification is around 70% [30].

S. S Gornale et. al.,(2013) have proposed gender identification that is carried out using frequency and spatial domain by combined features using FFT, Eccentricity and Major Axis Length. A good quality internal database of 450 male and 550 female samples of left thumb impression of each sample were considered. An optimal threshold is chosen to achieve better results. The algorithm produces accurate classification of 80% of male and 78% of female [31].

Ravi Wadhwa et.al.,(2013) have proposed a gender classification based on age and gender determination from fingerprints using RVA and DCT coefficients. The age and gender finger prints are classified on the basis of ridge to valley area, entropy and RMS value of Discrete Cosine Transform (DCT) coefficients The novelty of

the method lies in the fact that the identification of age and sex is independent of the pressure i.e. finger prints thickness or ridge/valley thickness. And they have achieved competitive results [34].

Pragya Bharti et.al.,(2014) have proposed a DWT-Neural Network based Gender Classification. The features were extracted using Discrete Wavelet Transform (DWT). Using 5-level Haar Wavelet Transform, the directional images of fingerprints are obtained. The Neural Networks are used to classify it and they achieved classification rate of 91.30% of an internal database of 300 images [37].

Samta Gupta et.al.,(2014) have proposed a method of fingerprint based gender classification using discrete wavelet transform & artificial neural network. The two methods are combined for gender classification. The first method is the wavelet transformation employed to extract fingerprint characteristics/features by doing decomposition up to 5 levels. The second method is the back propagation artificial neural network algorithm used for the process of gender identification. This method is experimented with the internal database of 550 fingerprints in which 275 were male fingerprints and 275 were female fingerprints. The overall classification rate of 91.45% has been achieved [38].

M Vadivel et.al.,(2014), have proposed a method of gender identification through fingerprint biometric using Discrete Curvelet Transform and back propagation with feed forward neural network classifier. These features were extracted from the fingerprint database utilized for learning stage of neural network. The trained network acts as automatic classifier to identify the gender from input image features. The Fast Discrete Curvelet Transform decomposes an image into different orientation wedges, details of which provide texture pattern and frequent occurrences of intensities. The orientation image represents an intrinsic property of the fingerprint images and defines invariant coordinates for ridges and valleys in a local neighbourhood. These patterns will be estimated using *haralick* or *glcm* features and can achieve better classification accuracy and low complexity in performance [39].

Image-based methods include methods involving optical correlation and transform-based features have been and still are significant in research field. Many methods have been proposed for each and every category and there are several approaches so far suggested in the literature for transform-based features. It was observed that some researchers have worked on gender classification by different approaches and predicted some promising results which are shown in Table-2.1. But still there is a scope for developing a robust algorithm using different parameters like age group, demographic characterization based on rural and urban people, and different robust features are required to be extracted for gender classification which will be more accurate and suitable for all types of applications to increase the classification rate.

SL. NO	AUTHOR & YEAR	METHOD	FEATURES	RESULTS
01	Park et.al. (2004)	Fingerprint classification based on Discrete Fourier Transform and nonlinear discriminate analysis.	FFT for DFT	Satisfactory and Competitive Results are obtained
02	Uday Rajanna et.al (2009)	Comparative study of feature extraction for fingerprint classification and performance improvements using rank-level fusion	Gabor Features OM (Orientation Maps), MM (minutia Maps) and OC (orientation co-linearity)	MMs-Rejection rate 1.77%. OM-Rejection rate 1.75%, OC -77%, and 93.7%. Using Gabor features 83.86% and 96.1%.
03	Gnanaswami P, et al., (2011)	Gender Identification Using Fingerprint through Frequency Domain Analysis	Frequency domain transform (FFT), (DCT) and (PSD)	92.88 % and 94.85 % for male and female respectively.
04	Naveen Kumar Jain, et.al., (2012)	A real time approach is proposed to determine the gender using finger-print.	The real time processing is done using the CODE composer Studio IDE.	92.00% and 87.33% for male and Female respectively,
05	Shrikant Tiwari et al.,(2012)	Recognition of the newborn using Fusion of Ear and Soft-Biometrics.	PCA, KPCA, FLDA ICA, GF and HAAR.	Identification accuracy rate of 90.72%
06	Gnanaswami P, et al., (2012)	Gender Classification from Fingerprint based on discrete wavelet transform (DWT) and singular value decomposition (SVD).	Discrete Wavelet Transform and Singular Value Decomposition	A 94.32% for the left hand for female and 95.46% male. For any finger of male 91.67% and 84.69% for female
07	Ritu Kaur et.al, (2012)	Fingerprint-based gender identification using frequency domain analysis.	FFT, DCT and Power Spectral Density (PSD).	90%, and 79.07% for female and male samples respectively
08	Pallavi Chand et.al.,(2013)	Gender Classification from Fingerprint based on discrete wavelet transform (DWT) and singular value decomposition (SVD).	Discrete Wavelet Transform and Singular Value Decomposition	K-nearest neighbour classifier is used to classify it and achieved the success rate of 80%.
09	T Arulkumaran, et. al., (2013)	Fingerprint-Based Age Estimation extracted the features through 2D, DWT and PCA	Discrete Wavelet Transform and Principal Component Analysis	The overall success rate 68.00%

10	Rijo Jackson Tom, et al., (2013)	Fingerprint Based Gender Classification through frequency domain analysis to estimate gender	Wavelet Transforms (DWT) and Principal Component Analysis (PCA)	The overall success rate in gender classification is around 70.00%
11	S. S Gornale et. al.,(2013)	Gender identification is carried out by combined features using frequency and Spatial domain techniques	FFT, Eccentricity and Major Axis Length	The overall success rate in gender classification is around 80% of male and 78% of female
12	Ravi Wadhwa et.al.,(2013)	Gender classification based on age and gender of a person from fingerprint impression.	Ridge to valley area, entropy and RMS value DCT coefficients	Satisfactory and Competitive Results are obtained
13	Pragya Bharti et.al.,(2014)	DWT-Neural Network based Gender Classification	DWT using 5-level Haar Wavelet Transform	Neural Networks are used to classify it. A Success rate of 91.3%.
14	Samta Gupta et.al.,(2014)	Fingerprint Based Gender Classification Using Discrete Wavelet Transform & Artificial Neural Network	wavelet for to 5 levels and artificial neural network	Overall classification rate of 91.45% has been achieved.
15	M.Vadivel et.al.,(2014),	gender classification through fingerprint biometric using discrete curvelet transform and back propagation	The curvelet transform wedges and frequent occurrences of intensities.	Satisfactory and Competitive Results are obtained

Table-2.1: Comparative Results of transform-based image feature extraction for gender classification

III. Minutia-Based gender classification Methods

The minutia- based Other aspects of fingerprint identification are orientation, segmentation and core point detection [5],[9],[24],[36].The most common ridge characteristics of fingerprint image are as show in figure-3.1.



Figure-3.1: Common ridge characteristics

The gender classification using minutia extraction is still significant in research field. Very few researchers have worked on fingerprints for gender classification using minutia extractions and have achieved competitive results [1-2],[8-10],[12-14],[18],[26][33]. The minutia like intersecting points, number of blobs, ridge counts and terminating points etc., were extracted and classified accordingly.

A. Related Work of Minutia-Based Image Feature Extraction for Gender Classification

Angela Bell et.al., have proposed a method in contrast to Acree's M(1991) method of comparing ridge densities. This work compares fingerprint loop ridge counts from data set of 40 male and 40 female fingerprints. The analysis revealed no significant mean difference in the loop ridge counts across gender represented by these eighty fingerprints, $F(1, 78) = .308$, $p > .05$, $MSE = 7.946$. There is no difference in the number of loop ridge counts that males have (13.18, $SD = 2.735$) and females have (13.53, $SD = 2.900$). The work concluded that there were no significant differences in loop ridge counts between male and female [1],[2].

Ahmed Badawi, et. al., (2006) have proposed a method for Gender classification from fingerprints. A dataset of 10-fingerprint images for 2200 persons of different ages and gender (1100 males and 1100 females) was analyzed. Features like ridge count, ridge thickness to valley thickness ratio (RTVTR), white lines count, and ridge count asymmetry, and pattern type concordance were extracted. Fuzzy- C Means (FCM), Linear Discriminate Analysis (LDA) and Neural Network with the most dominant features were used for the classification along with the most dominant features. They obtained results of 80.39%, 86.5%, and 88.5% using FCM, LDA, and NN, respectively [8].

Shimon K. Modi et. al., (2007) worked on Impact of Age groups on Fingerprint Recognition Performance. Features were extracted from fingerprints of different quality levels, for minutiae count, to test the performance of a minutiae-based matcher. A dataset of 18-25years, 26-39 years, 40-62 years and 62 years and above, in all 1620 samples was collected. The results confirm a difference in fingerprint image quality across age groups. The statistical result produced through the work indicates that the fingerprint image quality is not similar between age groups because the quality score was not within a reasonable tolerance to be similar [9].

Sudesh Gungadin et. al., (2007) carried out a research work whose goal is to set up a correlation among sex and fingerprint ridge density. The fingerprints were collected from 500 persons (250 males and 250 females) within the age group of 18-60 years. The parameter used by them is ridge density. By counting the ridges in the upper segment of all ten fingers and calculating the mean value, they illustrated that a fingerprint ridge of < 13 ridges/25 mm² is probably of male origin and that of > 14 ridges/25 mm² is perhaps of female origin. It has been a great achievement to sustain the hypothesis that women are likely to comprise a statistically imperative greater ridge density than men [10].

Manish Verma, et. al., (2008) proposed a method for gender classification from fingerprints. Features like ridge width, ridge thickness to valley thickness ratio (RTVTR), and ridge density were extracted. This method is experimented with the internal database of 400 fingerprints in which 200 were male fingerprints and 200 were female fingerprints Support Vector Machine (SVM) was used for the classification and 91% correct classification for male and female classes was achieved [12].

Jen feng wang, et al., (2008) worked on gender determination using fingertip features. The fingerprints from 115 normal healthy adults of which 57 were male and 58 were female have been considered for research work. They used ridge count, ridge density, and finger size features for classification. However, the ridge count and finger size features of left little fingers were also used to achieve the classification. The best classification result of 86% accuracy is obtained by using ridge count and finger size feature together [13].

Nithin et. al., (2011) have proposed a study using Baye's theorem on the rolled fingerprint images belonging to south Indian population. The objective is to identify the gender depending upon the finger ridge count contained by a definite region. A set of database of 550 persons (275 men and 275 women) belonged to the age range of 18-65 years. The experimental results illustrated that women have an appreciably greater number of ridge count than men. Furthermore, it is established that fingerprint having ridge density < 13 ridges/25 mm² is almost certainly of male origin and ridge count > 14 ridges / 25 mm² are probably of female [14].

Ramanjit and Rakesh (2011) have carried out a research work and revealed that there is a considerable variation in epidermal ridge density among males and females. The research was conducted to scrutinize ridge density variations in two North Indian populations (Sikh Jat and Bania). The experimental results revealed that 92% of Sikh Jat females comprise a mean ridge density above 13, while 76% of Sikh Jat males comprise a mean ridge density below 13, while in Bania, 100% of females possess mean ridge density above 14 and 80% of males – below 14. Hence it was concluded that there are considerable variations in epidermal ridge density amongst males and females within each of the two populations, and also considerable variations amongst the two populations [18].

S. Sudha Ponnarasi et. al., (2012) have proposed gender classification system derived from fingerprint minutiae extraction. The study was carried out over 500 people (250 male & 250 female) belonging to various age groups between 1 to 90. Features extracted were; ridge count, ridge thickness to valley thickness ratio (RTVTR), white lines count, and ridge count asymmetry, and pattern type concordance. SVM was used for the classification using the most dominant features and competitive results were achieved [24].

E.O. Omidiora et.al.,(2012) have analyzed human fingerprint texture in order to determine their Age and Gender, correlation of RTVTR, and Ridge Count on gender detection. The Features extracted were like ridge count, standard deviation, mean etc. The results were obtained for age and gender, ridge thickness to valley thickness ratio and ridge count for trained fingerprints samples and they observed that females have a higher ridge thickness to valley thickness ratio compared with males. Males have a slightly higher ridge count compared with females. There is no particular relationship between the age of the subjects and their fingerprint pattern, as it does not change (only as a result of accident or mutation)[26]

Ravi Wadhwa et.al.,(2013) have proposed a gender classification method based on age and gender of a person from fingerprint impression. The novelty of the method lies in the fact that the identification of age and sex is independent of the pressure i.e. fingerprints thickness or ridge/valley thickness. The age and gender based fingerprints are classified on the basis of ridge to valley area, entropy and RMS value of Discrete Cosine Transform coefficients. Whereby and achieved the competitive results can be achieved [34].

Lidong Wang et al. (2014) have proposed a testing and frequency distribution analysis of African American fingerprint patterns (loop, whorl, and arch). It was shown that loops are the most common, whorls are the second most common, and arches are the least common with a very small percentage (4.33%). Most loops are ulnar loops while only 4.47% loops are radial loops. Of the total arches, 61.54% are plain arches and 38.46% are tented arches. A comparative study of gender difference in African American fingerprint patterns was conducted using a non-parametric method based on the *U* test. The *U* test results show that there is no significant gender difference in fingerprint patterns between African American males and females at the 0.05 level of significance [35].

From the above literature it is evident that the dilemma regarding minutia extraction and gender classification has been and still is a significant research field. Many methods have been proposed for each and every category and there are several approaches so far suggested in the literature for minutia extraction. Conventional methods have some shortcomings as discussed earlier. It was observed that a few researchers have worked on gender

classification by different approaches and predicted some promising results but still there is a scope for developing a robust algorithm using different parameters like age group demographic characterization based on rural, urban people. At the same time different robust features are required to be extracted for gender classification which will achieve more accurate and suitable results for all types of applications to increase the classification rate [5][21][31][33].

SL.NO	AUTHOR & YEAR	METHOD	FEATURES	RESULTS
01	Angela Bell et.al., & Acree's M (1991)	Method of comparing ridge densities.	Loop ridge count, density	Concluded that no differences in loop ridge counts between male and female
02	Ahmed Badawi, et. al., (2006)	Gender classification from fingerprints.	Ridge count, ridge thickness to valley thickness ratio (RTVTR), white lines count, and ridge count asymmetry, and pattern type	Obtained results of 80.39%, 86.5%, and 88.5% using FCM, LDA, and NN, classifier respectively
03	Shimon K. Modi et. al., (2007)	Impact of Age groups on Fingerprint Recognition Performance.	Different quality levels, minutiae count, and performance of a minutiae-based matcher.	Fingerprint image quality is not similar between age groups because the quality scores were not within a reasonable tolerance to be similar
04	Sudesh Gungadin et. al., (2007)	Finding correlation among sex and fingerprint ridge density.	Ridge density. By counting the ridges in the upper segment of all ten fingers and mean value,	women are likely to comprise a statistically imperative greater ridge density than men
05	Manish Verma, et. al., (2008)	Method for gender classification from fingerprints.	Ridge width, ridge thickness to valley thickness ratio (RTVTR), and ridge density	91% of correct classification for male and female using SVM classifier
06	Jen feng wang, et al., (2008)	Gender determination using fingertip features.	Ridge count, ridge density, and finger size	86.00% accuracy is obtained by using ridge count and finger size feature together.
07	Nithin et. al., (2011)	Study using Baye's theorem on the rolled fingerprint images belonging to south Indian population.	Finger ridge count contained by a definite region	Women have an appreciably greater number of ridge counts than men.
08	Ramanjit and Rakesh et. al.,(2011)	Proposed a research variation in epidermal ridge density among males and females	Mean value and Ridge density	Considerable variations in epidermal ridge density amongst males and females within and amongst the two population
09	S. Sudha Ponnarasi et. al., (2012)	Gender Classification System Derived from Fingerprint Minutiae Extraction.	Ridge count, ridge thickness to valley thickness ratio (RTVTR), white lines count, and ridge count asymmetry, and pattern type concordance.	Support Vector Machines (SVM) wer used for the classification using the most dominant features and achieved competitive results
10	E.O. Omidiora et.al.,(2012)	Determination of the Age and Gender, and correlation of RTVTR and Ridge Count on gender detection.	Ridge count, standard deviation, mean etc.	Males have a slightly higher ridge count compared with females, there is no particular relationship between the age of subjects and their fingerprint pattern,
11	Ravi Wadhwa et.al.,(2013)	Gender classification based on age and gender of a person from fingerprint impression.	Fingerprints thickness or ridge /valley thickness, ridge to valley area, entropy and RMS value of DCT coefficients	Achieved a satisfactory and the competitive results were predicted
12	Lidong Wang et al. (2014)	Testing and frequency distribution analysis of African American fingerprint patterns	loop, whorl, and arch	4.47% loops are radial loops. 61.54% arches are plain arches and 38.46% arches are tented arches.

Table-3.1: Comparative Results of minutia-based image feature extraction for gender classification.

IV. Fusion of fingerprint with soft biometrics.

Basically, biometric techniques are classified into soft biometrics and hard biometrics.[16] Soft Biometric traits are physical, behavioural or adhered human characteristics providing categorical information about people such as age, beard, gender, glasses, ethnicity, eye/hair /skin colour, length of arms and legs, height, weight, gait and gestures, accent, ear shape, etc. soft biometric traits instances are created in a natural way and are used by humans to distinguish their peers. Soft Biometrics inherits a main part of the advantages of Biometrics and furthermore endorses its own assets. Some of the advantages include non obtrusiveness, the computational and time efficiency and human compliance. Furthermore they require neither enrolment, nor the consent nor the cooperation of the observed subject. Hard biometrics, which include face, fingerprint, retina, iris, voice etc., are generally unique and permanent personal characteristics, soft biometrics provide some vague physical or behavioural information which is not necessarily permanent or distinctive. Such soft biometric traits are usually

easier to capture from a distance and often do not require cooperation from the subjects. Whilst they cannot provide robust authentication, they can be used for improving the verification performance of biometric recognition systems [16],[29],[41].

There are very few researchers who have fused the fingerprint with soft biometrics for identification and classification for gender. Again, these methods are also based on image-based and minutiae-based feature extraction. As per the study of earlier work no algorithm finds the perfect gender classification. [4],[6],[20],[28].

V. Current Issues and Challenges

Many methods are used for identification and classification of gender of fingerprints based on *image-based* and *minutiae-based* feature extraction. As per the study of earlier work no algorithm finds the perfect gender classification. There are numerous challenging problems in fingerprint recognition and classification system; they are:

- The tip of the finger is a small area from which taking measurements and ridge pattern can be affected by cuts, dirt, or even wear and tear. Acquiring high-quality images of distinctive fingerprint ridges and minutiae is a complicated task.
- People with no or few minutia points (surgeons, as they often wash their hands with strong detergents, builders, and people with special skin conditions) cannot enrol or use the system. The number of minutia points can be a limiting factor for security of the algorithm. Results can also be confused by false minutia points (areas of obfuscation that appear due to low-quality enrolment, imaging, or fingerprint ridge detail).
- Another open issue is the lack of robustness against image quality degradation. The performance of a fingerprint recognition system is heavily affected by fingerprint image quality. Several factors determine the quality of a fingerprint image: skin conditions (e.g., dryness, wetness, dirtiness, temporary or permanent cuts and bruises) sensor conditions (e.g., dirtiness, noise, size), user cooperation, etc. Poor quality images result in spurious and missed features, thus degrading the performance of the overall system. Therefore, it is very important for a fingerprint recognition system to estimate the quality and validity of the captured fingerprint images [47],[48]
- Fingerprint technology has been under development from nearly half a century, new challenging issues are yet to be deployed in it. These include Extraction of level 3 features (all dimensional attributes of the ridge such as ridge path deviation, width, shape, pores, edge contour, and other details, including incipient ridges, creases, and scars), aliveness detection, and automated latent fingerprint identification.

Therefore, it is very important for a fingerprint recognition system to estimate the quality and validity of the captured fingerprint images [3],[6][16][29],[43].

VI. Conclusion and Future Challenges:

This paper presents a comprehensive evaluation of state-of-the-art research techniques associated with gender classification using fingerprints. In this paper it is proposed to combine the elaborate study of various methods and strategies with their comparatives measures to forecast results. Following are the conclusions which were made from the literature.

- The Gender classification methods broadly classified into Image-based methods include methods involving optical correlation and transform-based features.
- Image-based methods include methods involving optical correlation and transform-based features has been still is significant research filed. Many methods have been proposed for each and every category and there are several approaches so for suggested in the literature for transform-based features.
- The dilemma regarding minutia extraction, gender classification has been and still is a significant research filed. Many methods have been proposed for each and every category and there are several approaches so for suggested in the literature for minutia extraction.
- Conventional methods have some shortcomings as discussed earlier. It was observed that some researchers have worked on gender classification by different approaches and predicted some promising results but still there is a scope for developing a robust algorithm using different parameters like age group demographic characterization based on rural, urban people but different robust features are required to be extracted for gender classification which will bring greater accuracy and will be suitable for all types of applications to increase the classification rate.

In future, many problems and open challenges will be posed for forthcoming young technocrats, they are;

- Robust features will be investigated for gender estimation from large scale fingerprint image data sets and compared with existing estimation techniques.
- Minutiae extraction finds diplomat features; therefore a strong as well as computationally efficient minutiae extraction algorithm should be developed.
- Building a hybrid biometric system for gender classification that uses the face and fingerprint as the primary characteristics and ethnicity, height, skin colour, hair colour etc., and other parameters as the soft biometric parameters.

- The Classification rate may be increased by extracting the features using wavelets, wavelet packets and multi-wavelets and also by using some standard classifiers like SVM, K-NN, Neural Networks, Fuzzy Sets, etc.,
- As there is no standard database for male and female fingerprints, a separate database may be created using some standard technical and non technical specifications.
- The efforts along with the capability to automatically extract behavioural traits may be necessary for developing surveillance and many large scale identification applications.

Hence, an attempt has been made to put just another small brick into the wall of research on gender classification using fingerprints. So it is an important step in forensic anthropology to shorten the list of suspects search.

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