Fingerprint-Based Age and Gender Determination Using Support Vector Machine

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Fingerprinting is one of the most useful approaches of human identification for it is considered as one of the unique features of a human being. Thus, it has the capacity to determine human's identity. Some researchers found the use of the fingerprint for gender and age determination by using different approaches and many law enforcement employers assert its significance especially in criminal investigation. In this paper, an algorithm of Support Vector Machine (SVM) is used to classify the gender and estimate the age of a fingerprint image. A dataset of 83 different left middle fingerprint images of different gender and ages is gathered in the study. For the input data, the proponents used the Digital Persona 1.6 One Touch® for Windows SDK: Java Edition software and hardware to capture fingerprint images. The study identified six classifications: male: 1-19, female: 1-19, male: 20-35, female: 20-35, male: 36 and up, and female: 36 and up. Furthermore, the parameters used for the classification are the ridge ends (E), ridge bifurcations (B), number of white pixels (W) and ridge density ratio (R). These values were computed in the image processing phase. In this phase, it includes several procedures such as image binarization using Thresholding and image thinning using Hilditch Thinning Algorithm. The purpose of these procedures is to enhance the fingerprint image to produce clear and accurate data. Accordingly, the LIBSVM, an SVM library, is used to classify the fingerprints based on the data extracted. Before the SVM training phase, values extracted from the image processing phase was converted into LIBSVM data sets, then the training follows. After the training phase, it generates a model based on the trained data. This model was used as the basis for classification. During SVM testing phase, data extracted from the image(s) will be weighted based on the trained model and produce a predicted classification. By this, the researchers found out that SVM can produce an accuracy rate up to 34.15% using nu-CSV linear kernel. Thus, SVM shows a promising approach for the prediction of both gender and age, at the same time, through fingerprint images.

General Terms: Human unique feature

Additional Key Words and Phrases: Support vector machine, image processing, ridge end, ridge bifurcation, image binarization, image thinning, Hilditch algorithm, SVM training, SVM testing, threshold

1. INTRODUCTION

1.1 BACKGROUND OF THE STUDY

Every human being has several unique physical features; one of these is the fingerprint. It is known to be distinct because no two persons have the same fingerprint, not even twins. Specifically, they vary in breadth, density, pattern and structure of ridges. That is why fingerprint is recognized to have the ability to identify the personal identity of humans. Many researchers used the fingerprint to identifying one's identity like the identification of gender and estimation of age from the collected data of fingerprint images. Their study shows reliability and high accuracy by using different approaches such as Bayesian Theorem, Frequency Domain Analysis, Neural Networks, Discrete Wavelet Transform and Singular Value Decomposition. In their studies, variables are defined which includes ridge density, ridge and valley count, ridge width, fingerprint patterns (minutiae) and pattern types.

The proponents chose to use Support Vector Machine (SVM) as an approach for identifying gender and estimation of age through fingerprints. Image processing is used for the enhancement of the image and in getting the parameters needed. As for the SVM, this classifier will be used as it is known to help get a high accuracy rate and fastest training time. In the SVM phase, the procedure includes training phase and testing phase. In the training phase, the images will be trained by the given data sets. Finally, in the testing phase, this is where the prediction of the given particular images is to be classified by the used SVM algorithm.

Therefore, the uniqueness of fingerprint is a helpful tool for determining personal identity like identifying the gender and estimating the age of a person. There already exist solutions similar to this research problem that carry out the best results by using their preferred algorithms. In this research, the proponents have chosen Image processing for the fingerprint image extraction and Support Vector Machine (SVM) for the classification as it involves training and testing. By this proposed method, proponents desire to acquire a greater accuracy in identifying gender and estimate age, at the same time, through the selected fingerprint features.

1.2 PROBLEM STATEMENT

The proposed research sought to use SVM in determining gender and estimating the age of a person using fingerprints. The following is the questions that we consider in our study:

- What is the nature of gender determination of the fingerprint?
- What is the nature of age estimation of the fingerprint?
- What are other methods used to determine gender and estimate the age of a human using fingerprint?
- How can image processing be applied in the fingerprint gender determination and age estimation?
- How can our proposed method SVM be used to determine gender and estimate the age from the fingerprint?

1.3 RESEARCH OBJECTIVES

The main objective of the study is to determine the age and gender of human through fingerprint using image processing follows:

- Determine the nature of gender determination through fingerprint.
- Determine the nature of age estimation of the fingerprint.
- To identify what are the other methods used in gender and age determination.
- To prove that Image processing can be applied in determining the age and gender through fingerprint.
- To identify the use of Support Vector Machine in age estimation and gender identification.

1.4 SIGNIFICANCE OF THE STUDY

This study is very important since the aim is to determine the gender and estimate the age through the fingerprint using Support Vector Machine. The produced output of the research study will probably be helpful for the following:

- Investigators

  The study will definitely help the law enforcements for the investigation of the crime scenes which can help them identify the gender and age of the suspect. It will be easier for them to distinguish the identity of the person and will make their work faster for time efficiency.

- Technology Users

This study suggests to help improve the security of any technological devices such as cell phone and computers. By knowing the age and gender of a fingerprint, access to private accounts will be difficult for an unauthorized user even if they already know the password of the user.

- Company / Agencies

Fraud is a common problem in most agencies. In this way, the gender determination and age estimation may be helpful for them to distinguish one's personal identity using fingerprints.

- Future Researches

The proponent's research work will benefit future researchers especially the Information Technology and the Computer Science students since our study includes image processing and Support Vector Machine as an approach. This will help them get the idea on how these approaches work in the identification and classification.

1.5 SCOPE AND LIMIITATIONS

The variables for the research study will include the ridge bifurcation (B), ridge end (E), and ridge ratio (R) and no. of white pixels (W) of the left middle fingerprint image. The proponents gather the variables from both genders and different ages and obtain accuracy by using SVM classification. The research work will not include or use the minutiae classifier which deals with the shape of the ridge. Researchers will use image processing for the image extraction and SVM in classifying the gender and age of a human's fingerprint.

2. REVIEW OF RELATED WORK

2.1 FINGERPRINT GENDER IDENTIFICATION

Gender determination can be classified using human fingerprints. The fingerprint was used in this field since it is one of the unique features of humans. They classify gender by measuring the ridge density, ridge count, ridge thickness to valley thickness ratio (RTVTR), ridge width and fingerprint patterns and pattern types of the fingerprint of different genders. Researchers were able to classify gender of humans successfully by using their selected methods like, Baye's Theorem, Frequency Domain Analysis, Discrete Wavelet Transform and Singular Value Decomposition.

2.1.1 BAYE'S THEOREM

In the study of M.D. Nithin et al (2011), they applied Baye's theorem on the rolled fingerprints of 550 people in South India; 275 men and 275 women within the age-range of 18-65 years. And in their study, they found out that the theorem propose that a male fingerprint possesses a ridge density < 13 ridges/25 mm2 and a female fingerprint have a ridge density of >14 ridges/25 mm2 which is the same to the results of the study of Gungadin (2007) which obtained <13 ridges/25 mm2 and > 14 ridges/25 mm2 for male and female respectively. With similar results in the study of Acree (1999), in which he determines the significant difference of ridge density between male and female. Later in the study, results showed that women have a higher ridge density than men. Men have the ridge density of 11 ridges/25 mm2 and women have 12 ridges/25 mm2.

So based on these studies, it shows that the ridge density of men is different from women.

2.1.2 FREQUENCY DOMAIN ANALYSIS (FDA)

Gnanasivam&Muttan (2011) proposed a helpful topic for the investigators which is the fingerprint gender determination. This study was proposed using the Frequency Domain Analysis and was analyzed by different methods; the Fast Fourier Transform (FFT), Discrete Cosine Transform (DCT) and Power Spectral Density (PSD). The two researchers gathered 400 people (225 male and 175 female) for internal database purposes with different gender and ages. All of the collected data of fingerprints was already initialized and was tested. The accuracy of the study was seen as an accurate and reliable using the applied method giving 92.8% accuracy for the identified male and 84.85%. Variables which came from the image are used in their study; the fingerprint ridge count, ridge density, ridge thickness to valley thickness ration, ridge width and fingerprint patterns and pattern types for classifying sexes.

The method FDA used has found the reliability of the study by first analyzing the three transforms to identify gender; the FFT, DCT, PSD. Then, the threshold for each analysis is set and is prepared for the comparison between the transforms and the threshold for it to make the decision if it is a male or female. The output is based from the comparison of the transforms to the threshold; if the identified gender of the three comparisons has two or greater similar results, the gender is identified.

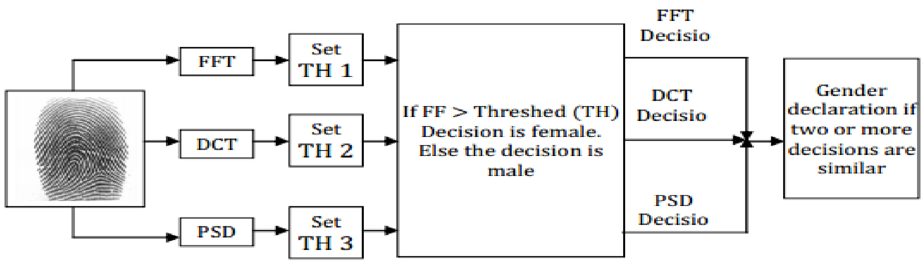


Fig. 1 Conceptual Framework made by Gnanasivam&Muttan (2012) results with 92.8% accuracy for identifying male gender and 84.85% for the female.

2.1.3 NEURAL NETWORK (NN), FUZZY C-MEANS (FCM) and LINEAR DISCRIMINANT ANALYSIS (LDA)

Badawi, et. Al (n.d.) used NN, LDA and DCM as classifiers for gender classification. The researchers used features of fingerprints such as ridge count, ridge thickness to valley thickness ratio (RTVTR), white lines count and ridge count asymmetry, and pattern type concordance as variables in the study. The result of their work discovers the accuracy of the FCM algorithm in classification with the rate of 80.39 %, LDA with 84.3 % accuracy and NN with 87.64 %. Which means these three methods are giving low classification accuracy in the study. And later in their study they concluded that “the variation among females and males in the membership of fingerprints to the different pattern types are very small, thus are statistically insignificant” and found out that the most significant features are the RTVTR and white lines count.

2.1.3 DISCRETE WAVELET TRANSFORM (DWT) AND SINGULAR VALUE DECOMPOSITION (SVD)

Gnanasivam and Muttan (2011) also found a unique way to determine the gender of human by its fingerprints using the Discrete Wavelet Transform (DWT) and Singular Value Decomposition (SVT). They consider the extraction of the sub-band energy vector and calculate the sub-band vector from the DWT and the extraction of the non-zero singular values from the SVT technique and attain 88.28% accuracy in their research. By gathering 3570 fingerprints from different genders, they obtained 91.67% accuracy for the male fingerprints and 84.69% for females.

The classification of the two genders through fingerprints is based on the pattern of their ridges. In their method, they used DWT and SVD and identified its feature vector. The fusion of the two feature vectors was concatenated for the classification of gender using K-nearest neighbor classifier.

Fig. 2 The framework formed by Gnanasivam and Muttan (2012) which produces an accuracy of 88.28%.

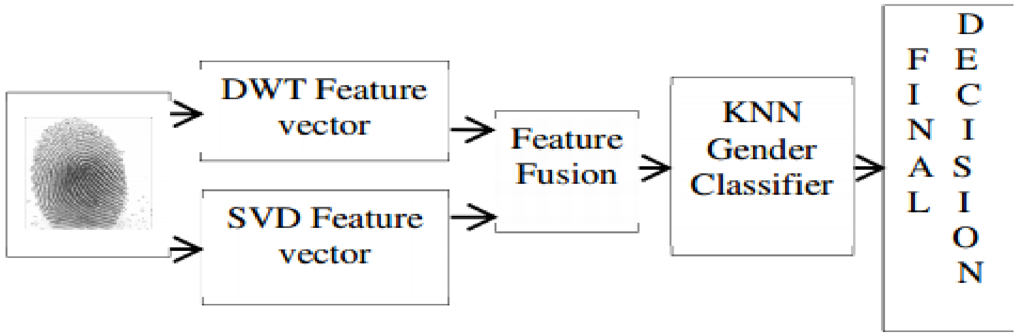


Fig. 2 The framework formed by Gnanasivam and Muttan (2012) which produces an accuracy of 88.28%.

2.1.4 SUPPORT VECTOR MACHINE

According to Gunn (1998), SVM was known to develop in solving classification problems. This method aims to separate the data and is proved to have an empirical performance in terms of specification. Support Vector Machine classifier can also get high accuracy in determining the gender of human. In the study of Jain, et. al (*n.d.*), they use Independent Component Analysis for the image representation technique and Support Vector Machine as a classifier in identifying the gender of a human through frontal facial images. The proponents tested many classifiers and differentiated the accuracy for each tested classifier. Using 200 as a training set size, the accuracy rate of the cosine classifier is 85.33%, for linear discriminant classifier it increases to 93.33% and finally, using SVM as a classifier for gender verification the accuracy rate rises to 95.67%. Therefore, in their research work, gender is identified using ICA + SVM which worked hand-in-hand to get high accuracy through facial image of human.

The process used by Jain, et. al (n.d.) goes through first by preprocessing the image and the reduction of the dimensions using the selected analysis method, the independent component. In classifying the gender, the proponents used the support vector machine and finally identify the gender of a human face with the accuracy rate of 95%.

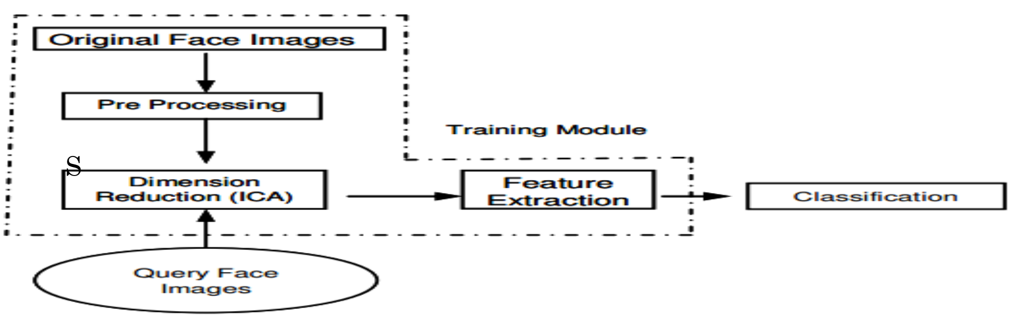


Fig 3. Framework used by Jain, et. al (n.d.)

2.2 FINGERPRINT AGE ESTIMATION

Age estimation based on fingerprint is a useful tool for investigative purposes. This study is helpful for the law enforcements in classifying the age of the suspects of the crime. The fingerprint is used because this is one of the unique features in a human being and age will be based on the pattern, count and breadth of the ridges of the fingerprint. There are also points to consider because the count of ridges on different sexes is different; the average ridge count of males is more numerous than the female. However, researchers managed to identify those and able to come up with high accuracy.

2.2.1 DISCRETE WAVELET TRANSFORM (DWT) AND SINGULAR VALUE DECOMPOSITION (SVD)

Many studies were made in this area and had proven the reliability of their studies through their selected methods. One of the researchers who entered the study of age classification are Gnanasivam&Muttan (2011), they used Wavelet Transform and Singular Value Decomposition of the fingerprint. They gathered data for their internal database, the compilation of the different strokes of fingerprints in different genders classified with their ages. They examined 1980 male fingerprints and 1590 for female and then separated it into five groups based on their ages; 12 and below, 13-19, 20-25, 26-35 and 36 and above. The accuracy of the different ages using the Discrete Wavelet Transform (DWT) and Singular Value Decomposition was different:

	12 and below	**13 – 19**	**20 – 25**	**26 – 35**	**36 and above**
Female	66.67%	63.64%	76.77%	72.41%	16.79%
Male	96.67%	71.75%	86.26%	76.39%	53.14%

Table 1 Accuracy of different genders with their ages grouped into five groups.

Their method Wavelet Transform and Singular Value Decomposition was used for feature extraction and feature vector. After the features were finalized, the Neural Network method is used for classifying the age of human by its fingerprint and will present the final output.

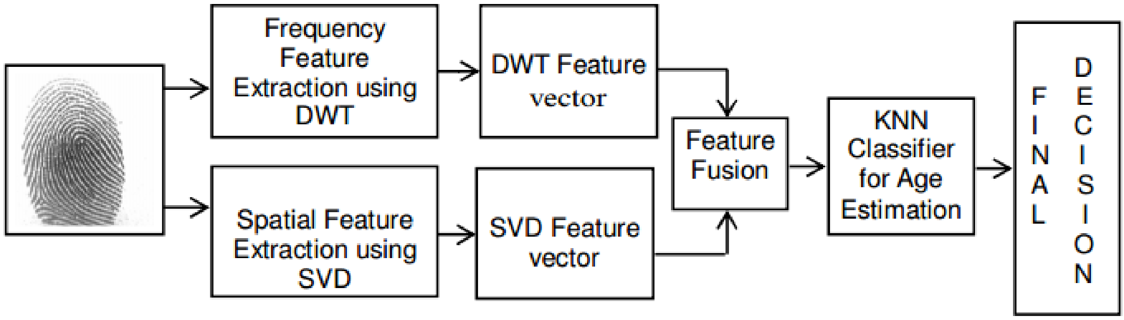


Fig 4. Conceptual Framework of Gnanasivam&Muttan (2012) in their study for fingerprint estimation of age using Discrete Wavelet Transform and Singular Value Decomposition.

2.2.2 ARTIFICIAL NEURAL NETWORKS (ANN)

Another research was conducted for age classification of fingerprints. It can be seen in the study of Ponnarasi and Rajaram (2012) in which they used Artificial Neural Networks as age classifier. And in their study, they gathered 500 people for fingerprint data gathering with ages 1-90 years old, 50% are females and 50% also are males. The flow of the process goes first through the image binarization based on the two levels of interest, the valleys and the ridges of the fingerprint. By this binarization, it will convert the image to a binary image. Next is image skeletonization, it is where the thinning of the image happens. Then, the Minutiae Extraction follows for identifying the ridge ending and the bifurcation point. Lastly, the image will undergo minutiae matching based on the template.

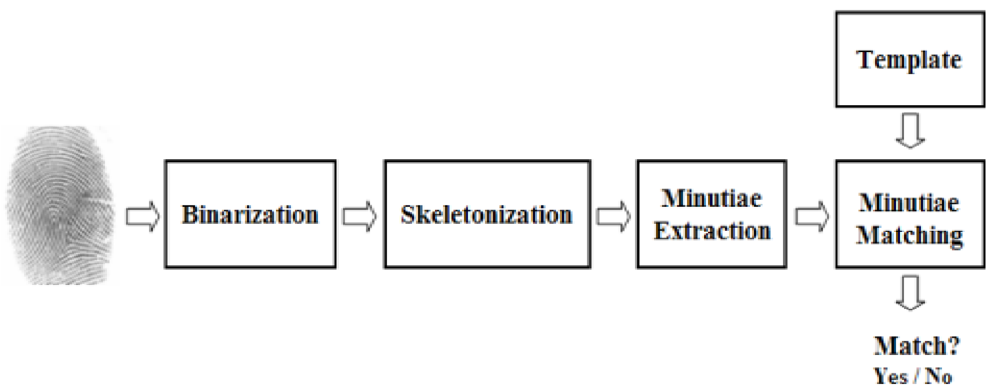
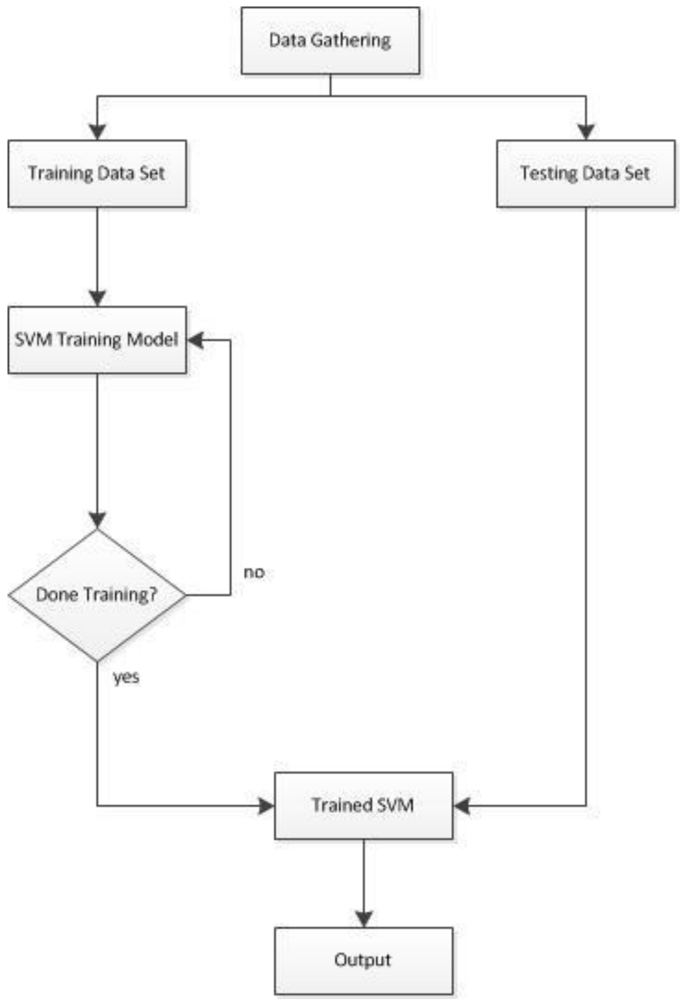


Fig 5. Conceptual Framework used by Ponnarasi&Rajaram (2012) in their study entitled Age Classification System Anchored in Fingerprint Minutiae Extraction.

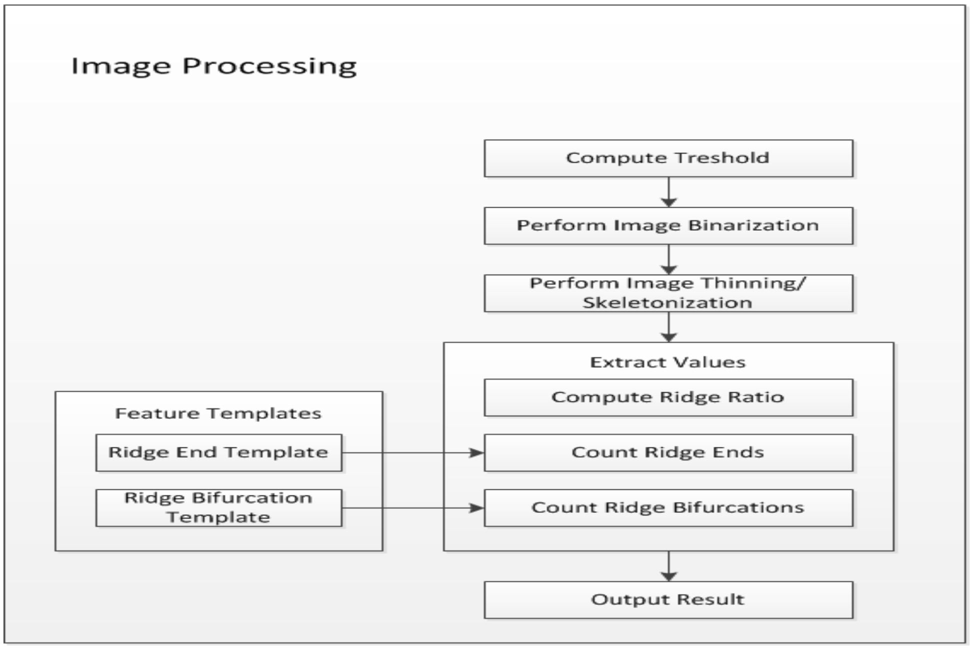
Later in the study it was proven that the method gives an accuracy rate up to 97.47%. This means that the values from image processing with the use of ANN as a classifier are good methods in age classification.Though, it gives high rate of accuracy for age classification, the problem is that they used only four age groups. Which means the probability of getting the right age group is 25 %. Therefore the realization of this study is the greater the number of range values for an age group the lesser the probability of getting the exact estimation of age

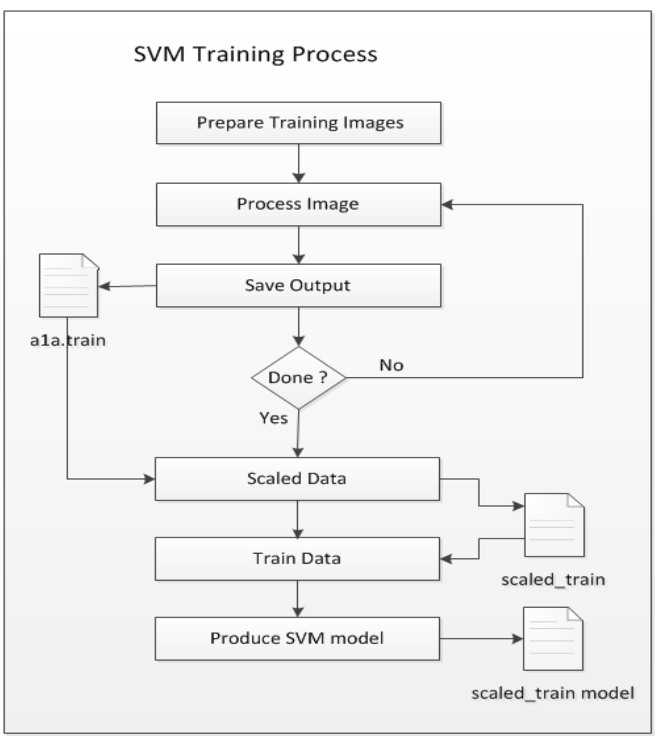
2.3 THEORETICAL FRAMEWORK

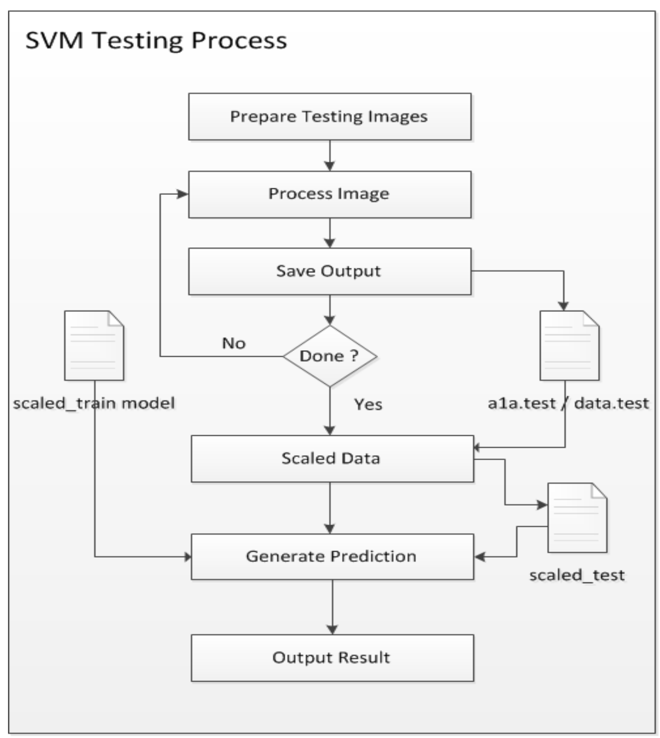


3. PROJECT DESIGN AND METHODOLOGY

3.1 CONCEPTUAL FRAMWORK







3.2 METHODOLOGY

3.2.1 PREPARE THE IMAGES

In the study, fingerprint images will be gathered from different gender and age that is classified by ranges; 1-19y.o, 20-35y.o, 36 and above. These age ranges are based on the study of Gnanasivam & Muttan (2011). Furthermore, there are six (6) classifications in the proposed study: male 1-19 y. o., male 20-35 y. o., male 36 and up, female 1-19 y. o., female 20-35 y. 0.,and female 36 and up. The proponents agreed to use the left middle fingerprints, which is based on the related study of Gnanasivam&Muttan (2011) for it is tested to produce greater classification accuracy.

The proponents will use Digital Persona 1.6 software and hardware, which is a trademark of DigitalPersona, Inc. registered in the United States and other countries, to capture fingerprint images. Furthermore, One Touch® for Windows SDK: Java Edition is used as a software developing tool for integrating fingerprint biometrics into wide set Java-based applications, services and products. Hence, Digital Persona 1.6 will be used in the study to capture images for data gathering that will be saved as *.png* file.

Then, the saved image will undergo many procedures which will happen in the image processing phase which will be used for the enhancement of the fingerprint images.

From the saved *.png* file, the image will be cropped so that the unnecessary and unknown marks from scanned image will be deleted and to achieve better presentation of the image.

3.2.2 IMAGE PROCESSING

In this phase, the images will undergo enhancement to produce a clear data which will create an accurate output. Also, image processing will generate values that will be used as parameters in the SVM phase. The parameters to be extracted from the image are the number of white pixels (W), ridge ratio (R), ridge ends (E) and ridge bifurcation (B). Furthermore, Image processing procedures are as follows:

a.) COMPUTE THRESHOLD

From the captured and cropped image, its threshold value will be computed. It will be calculated by getting the average thresholds of all grayscales per single image. Thus, different images will have different threshold values. To compute the grayscale of each pixel, the formula grayscale = 0.299*red + 0.587*green + 0.114*blue will be used. This formula is based on the research study of Jason Summers (2011), the formula of grayscale produces the possible results from an objective technical perspective. Accordingly, the average will be computed by adding all the grayscale values and dividing it to the total number of pixels.

The threshold (average grayscale) per image is equal to $\frac{\text{Sum of all grayscale values}}{\text{total no.of pixels}}$. This value will be used for image binarization. Furthermore, it serves as the borderline between lighter and darker shades of gray.

b.) IMAGE BINARIZATION

After computing the threshold value, images will be converted into a digital image that has only two possible values for each pixel (Gupta, Jacobson, & Garcia, 2006). Black region (ridges) will be represented as 1 and 0 for white (valleys) colored pixel. It will be done by letting grayscale values lesser than or equal the threshold is a white pixel and values greater than or equal to threshold values be a black pixel.

```
red = new Color(original.getRGB(i, j)).getRed();
green = new Color(original.getRGB (i, j)).getGreen();
blue = new Color(original.getRGB (i, j)).getBlue();
alpha = new Color(original.getRGB(i, j)).getAlpha();

if(( 0.299*red + 0.587*green + 0.114*blue )<= threshold)
    newPixel = 0;
else
    newPixel = 255;
```

Fig 6. Image Binarization conversion

c.) COMPUTE WHITE RATIO AND COUNT RIDGE PIXEL

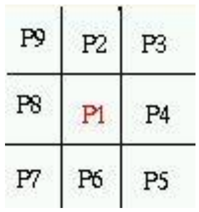
After the image binarization, white pixels will be counted and ridge ratio will be computed. It will be done by first counting the total no. of white pixels. After counting the white pixels, the ridge ratio/density will be computed by dividing the total no. of white pixels to the total no. of pixels of an image.

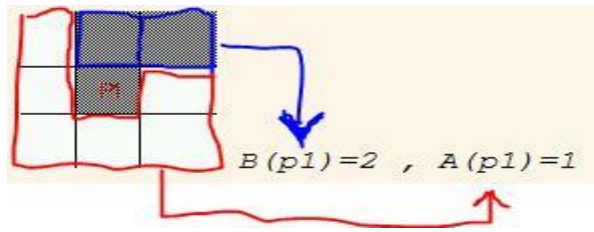
$$\text{ridge ratio} = \frac{\text{total no. of white pixels}}{\text{total no. of pixels}}$$

d.) IMAGE THINNING USING HILDITH ALGORITHM

The final image processing phase is to convert image to thinned image. Thinning algorithms are widely used as a useful method of pre-processing of image. Thinning/skeletonizing ridges of a fingerprint image is done in order to eliminate false lonely points and breaks, and count ridge-ends. According to

Danielle Azar (1997), skeletonization is the process of stripping off of a pattern as many pixels as possible without changing the original shape of the pattern. There are several thinning algorithms, but the proponents agreed to use Hilditch Algorithm. In this algorithm, it computes the gray skeleton summing the skeletons of the binary images that result from thresholding the gray scale image at each value of the gray scale. By this algorithm, it decides whether we keep the specific part or just remove it. Given the 8-neighbors of p1 in the pattern shown below, the derived functions are B (P1), as the number of non-zeroes and A (P1) as the number of zeroes patterns in the neighbors of P1.





These functions are then used to determine whether to change the black (1) pixel to white (0) pixel if and only if it satisfies the following conditions:

1. 2 <= B (P1) <= 6
2. A (P1) = 1
3. P2.P4.P8 = 0 or A (P2) != 1
4. P2.P4.P6 = 0 or A (P4) != 1

The first condition definitely ensures that the endpoint pixel and isolated parts are not deleted and that the pixel is the boundary pixel. Then, the second means that if A (P1) is greater than one then it should not be removed or changed to white (0) pixel to remain the connected pixels. A third condition ensures that the 2-pixel wide vertical lines are not ruined by the used algorithm. While the fourth condition ensures the 2-pixel horizontal lines are not ruined also by the algorithm. Therefore, the Hilditch thinning algorithm is useful for clarifying the patterns of an image by changing the black pixel to white pixel. Furthermore, image thinning can only be converted if the image to be converted is already binarized.

e.) FEATURE EXTRACTION

After thinning the image, fingerprint features such as ridge ends and ridge bifurcations, will be computed. The concept of the Crossing Number (CN) is used in the feature extraction. CN is calculated by investigating the 8-neighborhood of each central pixel (p) in order to determine the count of crossover occurrences.

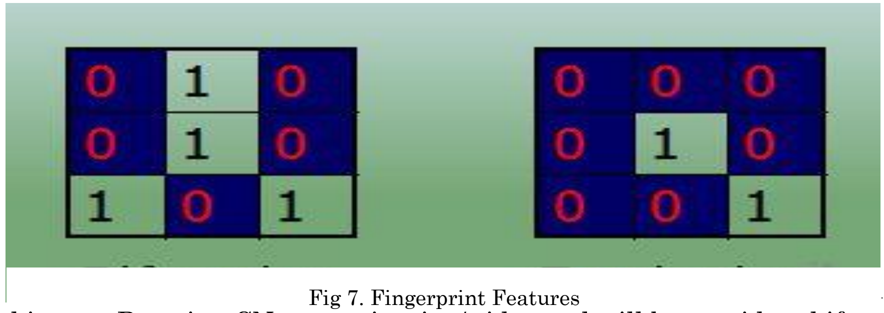


Fig 7. Fingerprint Features

e thinned image. By using CN, a termination/ ridge end will be considered if and only if there is only one (1) concurrence/ white pixel of a central pixels' neighborhood.

Different consideration will be done to counting ridge bifurcations. Ridge bifurcation is basically the point in the fingerprint where a particular ridge is divided to form two ridges. A ridge bifurcation is first considered if there are exactly three (3) concurrences/ white pixels of a central pixels' neighborhood. After considering three concurrences, patterns of these three pixels will be regarded. Patterns to be judged are the following:

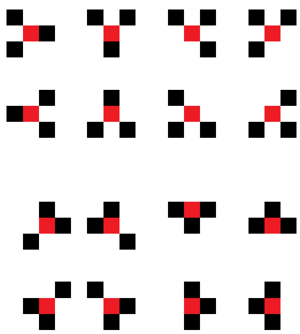


Fig 8. Accepted Patterns

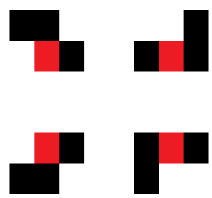


Fig.9 Not Accepted Patterns

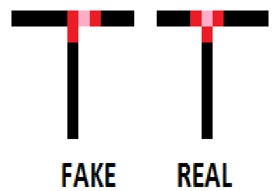


Fig. 10. Fake and Real Bifurcation

Figure's 8 and 9 shows patterns of a central pixel with three neighboring concurrences. Figure 3 shows all the accepted patterns that can be considered as a bifurcation. These acceptable patterns are based on the stated definition. Figure 4 shows some of the unacceptable patterns, the reason is shown in Figure 5, in which it shows the difference between fake and real bifurcation.

After extracting all necessary values of a fingerprint image, it will be saved to a file.

3.2.3 SVM CLASSIFICATION

After extracting all values needed, it is will be prepared for SVM Classification. SVM is conceptualized by using decision planes. According to the article of StatSoft (n.d), a decision plane separates a set of objects based on their classification of memberships.

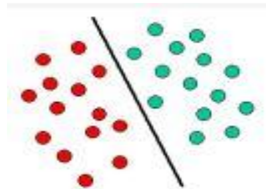


Fig. 11. Classifications separated by hyperplane

SVM is a classifier algorithm that executes classification by creating hyperplanes in a multidimensional space which separates objects of different class labels.

The SVM classification involves the training and testing process. It employs an iterative training algorithm that is useful in minimizing error functions.

The classification involves four SVM models which give a different error rate: C-SVM classification, nu-SVM classification, one-class SVM, epsilon-SVM regression and the nu-SVM regression. And each classification has different kernel types:

```
kernel_type : set type of kernel function (default 2)
     0 -- linear: u'*v
     1 -- polynomial: (gamma*u'*v + coef0)^degree
     2 -- radial basis function: exp(-gamma*|u-v|^2)
     3 -- sigmoid: tanh(gamma*u'*v + coef0)
     4 -- precomputed kernel (kernel values in training_set_file)
```

Before proceeding to SVM training and testing phase, converting results to data sets will be performed first. The format used in converting the results to a LIBSVM data set file for training is *1-6* 1: a 2: b 3: c 4: d per image. Every value is classified as:

1-6 --> classifiers
1:a --> a as the no. of white pixels
2:b --> b as the ratio of the image
3:c --> c as the no. of ridge ends
4:d --> d as the no. of ridge bifurcations

Fig. 12. Classification of the training data set variables

After converting datasets to LIBSVM format, it will be then converted to LIBSVM scaled data. To convert data to scaled LIBSVM data, the SVM - scaling algorithm will be used. In order to obtain better performance for the SVM, the training data should be scaled first by entering the specific command for scaling: **svm-scale -s train.range train.dat > train.dat.scl.** The main advantage of this is to avoid features in numeric ranges dominating those smaller numeric ranges. It also avoids numerical difficulties during the calculation of the Kernel values which depends on the inner products of the feature vectors.

3.2.3.1 SVM TRAINING PROCESS

SVM-train is a function used to train the support vector machine classifier. It is described as a constructor of SVM classifier. SVM training basically functions to check the input parameters, the values that are listed as data sets.

To train training data sets, the LIBSVM software package will be used. In training, training data sets will be tested to two different SVM types – C-SVM and NU-SVM using the four different Kernel types. With this training, it will generate a model which would be used for SVM testing and for computing accuracy.

3.2.3.2 SVM TESTING PHASE

The function SVM-predict will be used to return a vector of predictions using the trained model of SVM which is the SVM-train model. The output of this function is the vector of labels of the predicted values. If the value of the classification is true then the vector obtains the decision values attribute which contains $p \times c$ matrix, p as the number of predicted values and c for the number of classifiers. The formula for the number of classifiers is $c \times (c-1)/2$ where c is referred as the number of classes.

The command used to test is svm-predict.exe *filename*.test *filename*.train.model *filename*.out, and then the output shows the accuracy rate of the classification of the data sets. Finally, the output result is shown when the process is ready then the prediction of the image is then generated.

4.THEORETICAL BACKGROUND

4.1 SUPPORT VECTOR MACHINE

SVM is a machine learning algorithm used to provide the classification of functions from the trained data sets of the process where it can generate the accurate result of the problem. SVM can also be used for regression where it maintains the general features that maximize the margin of the used algorithm.

Advantages of SVM are to be considered because of its effectiveness in high dimensional spaces, effectiveness will not deteriorate when the dimensions are greater than the number of samples, its efficiency can be witnessed because it uses a subset and it also shows versatility, because of the Kernel functions that can be specified custom kernels and common kernels are also provided which makes it flexible (Scikit-learn Developers, n.d.).

4.2 CLASSIFICATION

Support Vector Machine Classification is a common approach used by many researchers. This type of case method is for the classification of data. It separates the training data sets from testing data sets and vice versa. In training the data sets, for an each instance, there contains a target value which has numerous attributes. The objective of this learning method is to predict and produce an accurate result of the given data; by the given test data variables we will now be able to acquire the result of the classification.

4.2.1 LINEARLY SEPARABLE BINARY CLASSIFICATION

The SVM has the learning methods for the classification; one of the two classifications is the Linearly Separable Binary Classification. This method simply defines that by the training points of this applied method where each of the inputs has attributes. By applying this algorithm, it simply means that we can draw lines in the graph by separating two classes. Fletcher (2009) further elaborates Linearly Separable Binary Classification as:

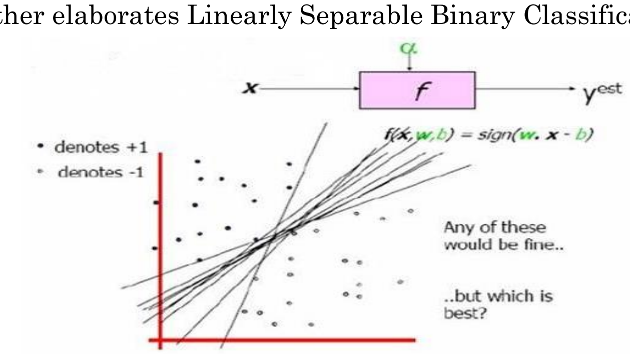


Fig 13. Linearly Separable Binary Classification

Support Vectors are the examples closer to the separating hyperplane and the aim of Support Vector Machines (SVM) is to orientate this hyperplane in such a way as to be as far as possible from the closest members of both classes.

By following the process of this learning method of classification, it can obtain the variables that define the separation of the hyperplane's optimal orientation. By defining the margin of the hyperplane, SVM will be able to classify data clearer. This margin of hyperplane could be increased by before hitting a datapointt.

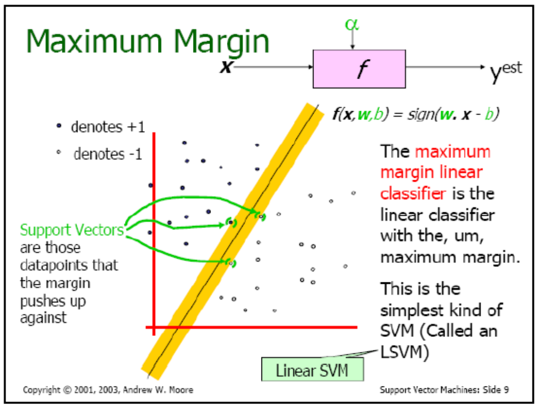


Fig 14. Maximum Margin

4.2.2 NONLINEAR BINARY CLASSIFICATION

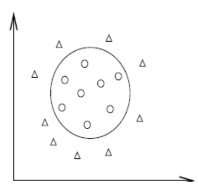


Fig 15. Shows SVM on non linear classifier

This type of classification in Support Vector Machine is a classification of the data that is not yet Linearly Separable. In this manner, it relaxes the constraints from the Linearly Separable Classification to permit the unidentified data points (Fletcher, 2009). It allows training errors.

$$\min_{\mathbf{w},b,\xi} \quad \frac{1}{2}\mathbf{w}^T\mathbf{w} + C\sum_{i=1}^{l}\xi_i$$
$$y_i((\mathbf{w}^T\mathbf{x}_i) + b) \geq 1 - \xi_i,$$
$$\xi_i \geq 0, \ i = 1, \ldots, l$$

Fig 16. Formula for training error

The problem with this as defined by Cortes and Vapnik (1995):

$$\min_{\mathbf{w},b,\xi} \quad \frac{1}{2}\mathbf{w}^T\mathbf{w} + C\sum_{i=1}^{l}\xi_i$$
$$\text{subject to} \quad y_i(\mathbf{w}^T\phi(\mathbf{x}_i) + b) \geq 1 - \xi_i, \quad \xi_i \geq 0, \ i = 1, \ldots, l.$$

Fig 17. Non linear classification error problem

5.RESULTS AND DISCUSSION

5.1 DATA GATHERING

In gathering data, the proponents used the Digital Persona 1.6 One Touch® for Windows SDK: Java Edition fingerprint scanner software and hardware to capture the fingerprint image and save it as a *.png* file. To use this scanner, the proponents simply place the left middle finger to the scanner and it automatically captures the image of the fingerprint.

Figure 17: Captured Image

Figure 18: Cropped Image

Figure 17 shows a sample of the captured and saved image of a fingerprint. The problem with this image is that unnecessary and unknown marks will be included in the image processing phase. That's why the proponents decided to crop these unnecessary marks. Figure 18 shows the cropped image of the sample captured image. With this type of image, it can now be seen that the excessive and unwanted marks are deleted. Thus, the image is ready for image processing.

The proponents gathered a total no. of 83 fingerprints; 52 for female and 31 for male classified in different age ranges; 1-19 years old, 20-34 years old and 35 years old and above.

Then, the cropped image undergoes image processing phase. In which after the image processing, data were listed in a file (*final_train. train/ final_test. test/ data. test*) together with its extracted parameters (ridge ends, ridge bifurcations, the black and white pixels and the ratio of the image). The file is then ready for the next algorithm, the Support Vector Machine. SVM is now used to train and test the data gathered and will finally generate the output.

5.2 IMAGE PROCESSING PHASE

The procedure in the image quality processing phase will go on through the binarization and image thinning by using a particular algorithm. By this process, it gives the fingerprint image a good and clear quality which will be easy for the next procedure which is the main algorithm technique that will be used in age and gender determination, the Support Vector Machine.

5.2.1 IMAGE BINARIZATION

Image binarization is used for separating the values into two, which are the 0 and 1 values or also known as a single bit. 0 represents the white pixel of an image while 1 values are the black pixels. In our study, we used the grayscale averaging for the process of getting the threshold. By using a histogram, it will restrict the region of the searched as a minimum to assure that it will specify the portion of an image to be black or white pixel (single bit). Histogram averaging simply smoothen the image and increases the localization accuracy and the separation of the ends or the peaks of the captured image. The output shown below is the sample conversion of the proponents program from the original image to the binarized image.

Fig 19. Original Image

Fig 20. Binarized Image

5.2.2 IMAGE THINNING

P9	P2	P3
P8	P1	P4
P7	P6	P5

Fig 21. 8-neighborhood

Image thinning is basically a process which removes selected pixels from the binary image. Thinning is a type of topological skeleton which is computed as a mathematical morphology. This morphology only functions on the binarized image and then applies a method called “hit-and-miss” to the binarized image and is diminished to the result of the binarized image. The method is repeated until a wider linear pixel is visible enough in representing the image. The image still is identical to the original though it is processed in thinning method. In our study, we used a particular algorithm for image thinning which is called Hilditch thinning. Hilditch thinning is particular mainly in pre-processing image. The Hilditch algorithm uses five conditions to reach the final result. The example in the figure 21; supposing that p_i are pixels of an image, this set of 8-neighborhood is defined. The purpose of this algorithm is to whether to keep a central pixel or delete it from the image by investigating (through some conditions) one by one if they are necessary to the image. Furthermore, the image shown below is the proponents conversion of the binarized image to thinned image using the Hilditch thinning algorithm.

Fig 22. *Binarized*

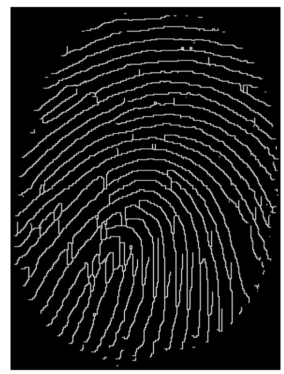


Fig 23. Thinned

5.3 FEAUTURE EXTRACTION

In this procedure, it counts the ridge ends and ridge bifurcations which are used in this study as the variables in determining the age and gender of humans through fingerprint. The concept used in the feature extraction is the concept of crossing numbers (CN). CN is computed by investigating the 8-neighborhood of each central pixel to determine the count of crossover occurrences. By using the thinned image, the proponents can already get the values that are needed in the study; the white pixels, pixels, white ratio, ridge ends and bifurcations.

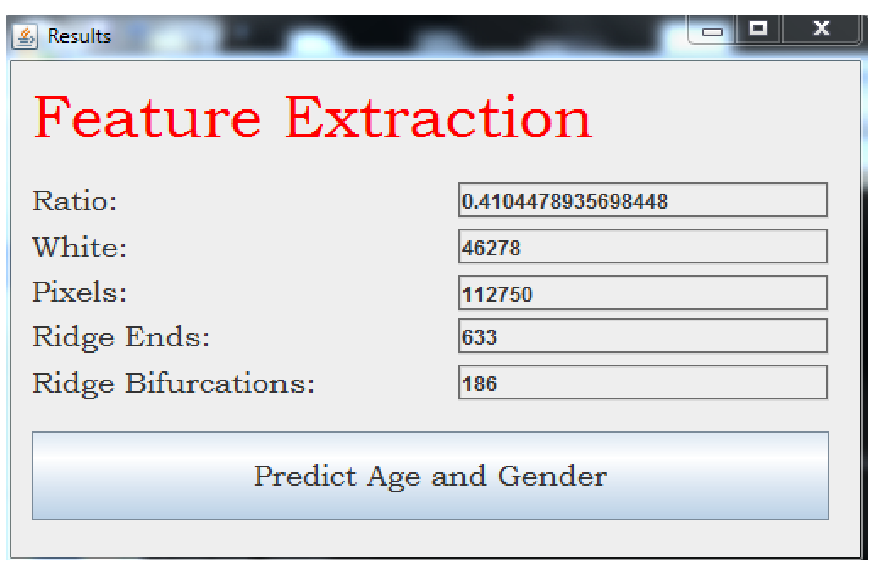
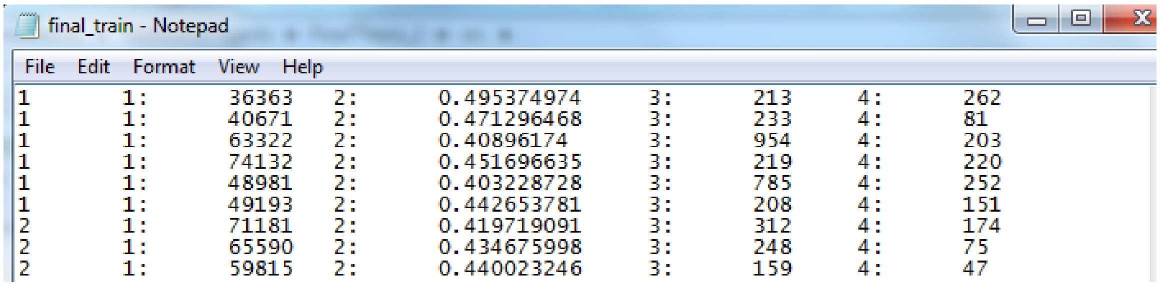


Fig 24. Output of Feature Extraction

5.4 CONVERTING TO DATA SETS

Using LIBSVM, we are able to convert the results to datasets needed for the training and testing.

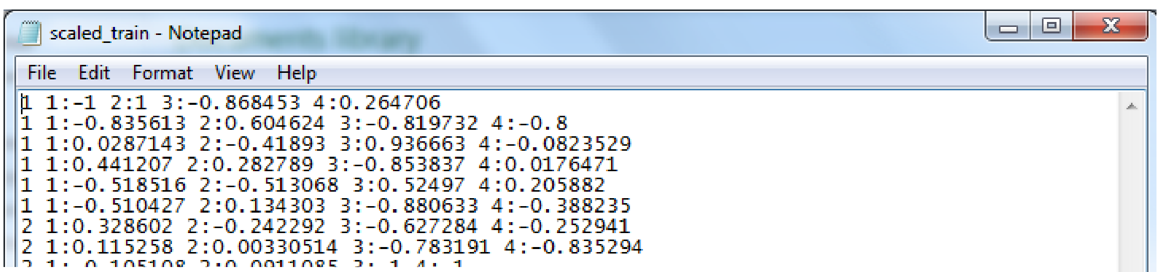
In classifying the gender, we used a specific format which will be used for the training and testing, 1-6 1: no. of white pixels, 2: ratio of the image, 3: no. of ridge ends, 4: no. of ridge bifurcations and will be used per data or fingerprint image.




```
1	1:	36363	2:	0.495374974	3:	213	4:	262
1	1:	40671	2:	0.471296468	3:	233	4:	81
1	1:	63322	2:	0.40896174	3:	954	4:	203
1	1:	74132	2:	0.451696635	3:	219	4:	220
1	1:	48981	2:	0.403228728	3:	785	4:	252
1	1:	49193	2:	0.442653781	3:	208	4:	151
2	1:	71181	2:	0.419719091	3:	312	4:	174
2	1:	65590	2:	0.434675998	3:	248	4:	75
2	1:	59815	2:	0.440023246	3:	159	4:	47
```

The above image shows a sample of a converted LIBSVM dataset format. After the conversion of conventional data to LIBSVM dataset format, it is converted to scaled LIBSVM data. The command: svm-scale –s range [train_data_set] > [scaled_data_set] is used to scale training dataset. On the other hand, svm-scale –r range [test_data_set] > [scaled_data_set] is used to scale testing dataset.

.




```
1 1:-1 2:1 3:-0.868453 4:0.264706
1 1:-0.835613 2:0.604624 3:-0.819732 4:-0.8
1 1:0.0287143 2:-0.41893 3:0.936663 4:-0.0823529
1 1:0.441207 2:0.282789 3:-0.853837 4:0.0176471
1 1:-0.518516 2:-0.513068 3:0.52497 4:0.205882
1 1:-0.510427 2:0.134303 3:-0.880633 4:-0.388235
2 1:0.328602 2:-0.242292 3:-0.627284 4:-0.252941
2 1:0.115258 2:0.00330514 3:-0.783191 4:-0.835294
```

Fig 25. Scaled sample dataset

After the conversion, it is now ready for SVM training or testing. The proponents decided to have three train-test ratios (TTR) of the datasets. These are 80-20, 50-50 and 30-70. It means that 80 % of the dataset is for training and 20 % is for testing, so as 50-50 and 30-70 correspondingly.

5.5 SVM TRAINING AND TESTING

In the SVM training phase, the proponents tested the two SVM types: c – SVC and nu – SVC using different kernel types. The command: svm-train [options] training_set_file [model_file] is used to train datasets. Options are represented by –s [for SVM type] and –t [for kernel type]. It is presented by –s [0-1] –t [0-3]. The default SVM type is C-SVC and kernel type is RBF.

After training, it outputs the image below:

```
C:\Users\siena\Documents\NetBeansProjects\FinalThesis_2\src>svm-train -t 1 scale
d_train
*
optimization finished, #iter = 14
nu = 0.838710
obj = -24.447004, rho = -0.975651
nSV = 26, nBSV = 26
Total nSV = 26
```

From the image above, obj is the optimal objective value of the dual SVM problem. Rho is the bias term in the decision function sgn (w^Tx rho). nSV and nBSV are number of support vectors and bounded support vectors (i.e., alpha_i = C). Nu-svm is a somewhat equivalent form of C-SVM where C isreplaced by nu. Nu simply shows the corresponding parameter.

After training, it produces a model that is saved as [*scaled_train.model*].

```
svm_type nu_svc
kernel_type linear
nr_class 6
total_sv 42
rho -0.697596 -0.298867 -7.60004 0.685771 0.356652 -0.425373 2.28372 1.18446 2.35187 0.778514 0.587099 0.93716 -4.62256
label 1 2 3 4 5 6
nr_sv 6 6 4 10 6 10
SV
0 0 20204.95863598922 0 0 1:-1 2:1 3:-0.868453 4:0.264706
0.7365024932917152 0 134140.7831771745 4219.69419917983 14.58476895295438 1:-0.835613 2:0.604624 3:-0.819732 4:-0.8
1.210690316677835 2.312862914824881 204569.7206580184 5868.927081294377 18.49420385824763 1:0.0287143 2:-0.41893 3:0.93
1.94719280996955 2.312862914824881 258681.4072073161 4375.872092877678 25.72439173997861 1:0.441207 2:0.282789 3:-0.853
0 1.156431457412441 215254.4545662998 3142.287870531244 18.36981066875522 1:-0.518516 2:-0.513068 3:0.52497 4:0.205882
1.94719280996955 0 201874.3045844664 0 25.72439173997861 1:-0.510427 2:0.134303 3:-0.880633 4:-0.388235
```

The above image shows that the SVM type used is no-SVC, and kernel type used is linear. It has six (6) classifications and a total of 42 trained datasets. The rho values represent all biased terms of the decision function. The label represents the label of each classification and nr_sv represents the no. of training datasets per classification.

After generating the trained model, its accuracy is tested based on the scaled test dataset. The command: svm-predict scaled_test scaled_train.model output.out is used to get the accuracy rate of the trained SVM.

Results		
Unscaled Data		
Train-Test Ratio	Result	Accuracy
80-20	4/15	26.67%
50-50	10/41	24.39%
30-70	15/58	25.86%

Result 1

Result 1 shows the accuracy rate of an unscaled trained data using the default SVM type and kernel.

Scaled Data				
	svm-type (-s)	kernel-type (-t)	Result	Accuracy
80-20	default	default	4/15	26.67%
[67 training datasets	0	0	3/15	20.00%
[15 testing datasets]	0	1	4/15	26.67%
	0	2	4/15	26.67%
	0	3	5/15	33.33%
	1	0	4/15	26.67%
	1	1	1/15	6.67%
	1	2	1/15	6.67%
	1	3	1/15	6.67%
50-50	default	default	10/41	24.39%
[42 training datasets	0	0	9/41	21.95%
[41 testing datasets]	0	1	5/41	12.20%
	0	2	10/41	24.39%
	0	3	10/41	24.39%
	1	0	14/41	34.15%
	1	1	10/41	24.39%
	1	2	6/41	14.64%
	1	3	11/41	26.83%
30-70	default	default	14/58	24.14%
[25 training datasets	0	0	10/58	17.24%
[58 testing datasets]	0	1	13/58	22.41%
	0	2	14/58	24.14%
	0	3	11/58	18.97%
	1	0	12/58	20.69%
	1	1	16/58	27.57%
	1	2	14/58	24.14%

Result 2

Result 2 shows the accuracy rate of all scaled data of different TTR, SVM types and kernel types.

BOTH						
variables	svm-type	kernel-type	train-result (/24)	train-accuracy	test-result(/59)	test-accuracy
wreb	1	1	24	100.00%	8	13.56%
wreb	1	0	19	79.17%	13	22.03%
reb	1	1	21	87.50%	15	25.42%
web	1	1	20	83.33%	14	23.73%
web	1	3	16	66.67%	16	27.12%
wrb	1	1	20	83.33%	9	15.25%
wrb	0	3	12	50.00%	11	18.64%
wre	1	2	22	91.67%	10	16.95%
wre	1	0	17	70.83%	13	22.03%
wr	1	2	20	83.33%	14	23.73%
wr	0	1	10	41.67%	15	25.42%
eb	1	2	15	62.50%	10	16.95%
eb	0	1	9	37.50%	12	20.34%

Result 3 Results using different variables

Result 3 shows all highest accuracy rate of both training and testing using the same datasets. Based on the results, it shows that using the four variables (W-white, R-ratio, E-ends, and B-bifurcations), it can produce a training accuracy up to 100% (WREB), and testing accuracy up to 27.12 % (WEB).

GENDER						
variables	svm-type	kernel-type	train-result (/24)	train-accuracy	test-result(/59)	test-accuracy
wreb	1	1	22	91.67%	37	62.71%
wreb	1	2	20	83.33%	37	62.71%
reb	1	2	20	83.33%	32	54.24%
web	1	1	23	95.83%	30	50.85%
AGE						
variables	svm-type	kernel-type	train-result (/24)	train-accuracy	test-result(/59)	test-accuracy
wreb	1	1	22	91.67%	27	45.76%
reb	1	1	21	87.50%	20	33.90%
reb	1	3	15	62.50%	23	38.98%
web	1	1	21	87.50%	22	37.29%
web	1	2	20	83.33%	26	44.07%

Result 4 Results on Gender and Age alone

Result 4 shows all highest accuracy rates of both training and testing using the same datasets on different classifications. Based on the results of gender classification, by using WEB, it can produce a training accuracy rate up to 95.83 % and up to 62.71 % testing accuracy rate using WREB. On the other hand, based on the results on age classification, by using WREB, it can produce up to 91.67 % training accuracy and 45.76 % testing accuracy.

Double- WREB						
classification	svm-type	kernel-type	train-result (/48)	train-accuracy	test-result(/96)	test-accuracy
both	1	1	37	77.08%	30	31.25%
both	1	2	37	77.08%	31	32.29%
gender	1	1	42	87.50%	67	69.79%
gender	1	2	46	95.83%	65	67.71%
age	1	1	37	77.08%	47	48.96%
age	1	2	40	83.33%	49	51.04%

Result 5 Experimental Data

Result 5 shows all highest accuracy rate of both training and testing using a dataset that has two different copies of each fingerprints. Based on the result, the highest training and testing accuracy rate of both gender and age classification is 77.08 % and 32.29 %. While using gender-only classification, it can give training and testing accuracy rate up to 95.83 % and 69.79 %. And while using age-only classification, it can give training and testing accuracy rate up to 83.33 % and 51.04 %.

Truth data

Classifier results		Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Classification overall	Producer Accuracy (Precision)
	Class 1	2	2	1	0	2	1	8	25%
	Class 2	2	4	1	0	0	1	8	50%
	Class 3	0	3	0	0	1	0	4	0%
	Class 4	5	3	1	3	1	2	15	20%
	Class 5	2	0	0	0	5	1	8	62.5%
	Class 6	3	5	1	2	1	2	14	14.286%
	Truth overall	14	17	4	5	10	7	57	
	User Accuracy (Recall)	14.286%	23.529%	0%	60%	50%	28.571%		

Result 6 Confusion Matrix of the six classifications

Class 1		Class 2		Class 3	
2	6	4	4	0	4
12	7	13	6	4	19
AC	33.33%	AC	37.04%	AC	70.37%
TP	36.84%	TP	31.58%	TP	82.61%
FP	75.00%	FP	50.00%	FP	100.00%
TN	25.00%	TN	50.00%	TN	0.00%
FN	63.16%	FN	68.42%	FN	17.39%
P	53.85%	P	60.00%	P	82.61%

Result 7 Confusion Matrix summary for classes 1, 2, and 3

Class 4		Class 5		Class 6	
3	12	5	3	2	12
2	10	5	14	5	8
AC	48.15%	AC	70.37%	AC	37.04%
TP	83.33%	TP	73.68%	TP	61.54%
FP	80.00%	FP	37.50%	FP	85.71%
TN	20.00%	TN	62.50%	TN	14.29%
FN	16.67%	FN	26.32%	FN	38.46%
P	45.45%	P	82.35%	P	40.00%

Result 8 Confusion Matrix summary for classes 4, 5, and 6

Result 7 and 8 are the summaries of the confusion matrix for classes 1 – 6. The accuracy (AC) is the proportion of the total number of predictions that were correct. The recall or true positive rate (TP) is the proportion of positive cases that were correctly identified. The false positive rate (FP) is the proportion of negatives cases that were incorrectly classified as positive. The true negative rate (TN) is defined as the proportion of negative cases that were classified correctly. The false negative rate (FN) is the proportion of positives cases that were incorrectly classified as negative. And precision (P) is the proportion of the predicted positive cases that were correct. Based on the results, classes 3 and 5 has the highest AC which is 70.37%, class 4 has the highest TP which is 83.33%, class 3 has the highest FP which is 100%, class 5 has the highest TN which is 62.50%, class 2 has the highest FN which is 68.42% and class 3 has the highest P.

6. CONCLUSIONS AND RECOMMENDATIONS

From the given results, the proponents did not come up to a perfect accuracy by using the SVM algorithm in classifying gender and estimating the age range by using the given data, the fingerprint images. It shows that SVM is may not be a good classifier when both gender and age are classified at the same time. Based on the result of the above images, the algorithm produces at most 34.15 % accuracy rate using 50-50 TTR, nu-SVC SVM type and linear kernel type. These are the proponents' theories about how did they come up with that result:

1. Based on the study of Gnanasivam, & Muttan (2011), the accuracy rate of age classification is about 60 – 70 % in average. This means that age prediction accuracy rate is quite high.

2. Based on the studies of some researchers, such as M.D. Nithin (2011) in which they gather up to 550 fingerprints, and Gnanasivam and Muttan (2012), up to 3570 fingerprints, no. of datasets are somewhat far from the gathered data of 83 fingerprints.

3. There might be a little significant relationship between the age and gender of human fingerprints.

4. The use of white pixels, ratio, ridge ends and bifurcations might not be enough, however significant to the studies of some researchers, to classify both gender and age at the same time.

5. SVM cannot classify the given data well.

By these, the proponents recommend for the future researchers is to use more data fingerprints when classifying both gender and age at the same time. Furthermore, the proponents suggest that to pursue this kind of project, the future researchers might find another or an additional feature of a fingerprint such as minutiae patterns as variables of the study that would probably help pull (higher) the accuracy of the study. And lastly, the proponents also recommends for future researchers to investigate more about human biometrics or fingerprints on how each pattern relate to the status of a person before pursuing this kind of study.

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