Gender Detection

By

Ezz O. Alsulimani

Supervisor

Dr. Ashraf S. Huwedi

This Thesis was submitted in Partial Fulfillment of the Requirements for Master's Degree in Computer Science.

University of Benghazi

Faculty of Information Technology

2019 January

University of Benghazi **Faculty of information Technology**

Department of Computer science

Gender Detection

By
Ezz Omar Abdulali

This Thesis was Successfully Defended and Approved on **2.2.2018**

Supervisor
Dr. Ashraf Saad Huwedi

Signature**: ………………………..……………………………..**

Dr. Kenz Amhmed Bozed………………..……………..……. (**Internal examiner)**

Signature: ……………………….…………………………..

Dr. Abdelhamead M. Abdelkafy……………………….……… (**External examiner)**

Signature: ………………………………..………………….

(Dean of Faculty) **(Director of Graduate studies and training)**

Dedication

To my mother and the soul of my father...

Ezz O. Alsulimani

Acknowledgments

I begin by thanking God for all the blessings, including the accomplishment of this work. I thank my parents for their support and care. I would also like to thank and express my sincere gratitude to my supervisor Dr. Ashraf Huwedi. I thank my brothers, relatives, and friends for their participation in this journey. Thanks also to my colleagues at the Social Security Fund. Special thanks to Mrs Ainoor Tarbah and engineer Fathia Al Tabouni for their support, assistance, and encouragement.

Ezz O. Alsulimani

Table of Contents

Chapter 4 Random Forest

Chapter 5 Research Methodology

Chapter 6 Conclusion and Future work

List of Tables

List of Figures

List of Algorithms

List of Appendices

Gender Detection

By

Ezz O. Alsulimani

Supervisor

Dr. Ashraf S. Huwedi

Abstract

Today's machine learning is widely used in diverse areas. For example, fraudulent systems, recommender systems, exploited prediction and many other applications. One of these applications is being exploited in this search. This research presents an approach to detecting a person's gender through the front face image, using extraction features and classification techniques. Gender prediction can be a very useful method in HCI (Human-Computer Interaction) systems. As a very powerful method of extracting data, the classification is used here to collect class data and to classify the gender as either male or female. To extract data features, Local Binary Pattern (LBP) is used, whereas the Random Forest (RF) algorithm of classification is used to gauge the maximum accuracy. Various database models were used in this search: ORL database, FEI database, LFW database, Jaffe database, and CUHK database where Jaffe database gave a very high level of accuracy which is 99.89% in contrast CUHK database which gave a lower level of accuracy 76.25% with relative stability. Details of the prediction model and results model are reported here.

Chapter 1
Introduction

This chapter introduces background about artificial intelligence, machine learning, computer vision and introduction to gender detection, also introduces problem statement, scope, and limitation of the study, aims and objectives and motivation.

1.1 Background

1.1.1 Artificial Intelligence (AI)

Any technique that enables computers to mimic human intelligence, using logic, if-then rules, decision trees, and machine learning. See figure 1.1 for applications of AI techniques.

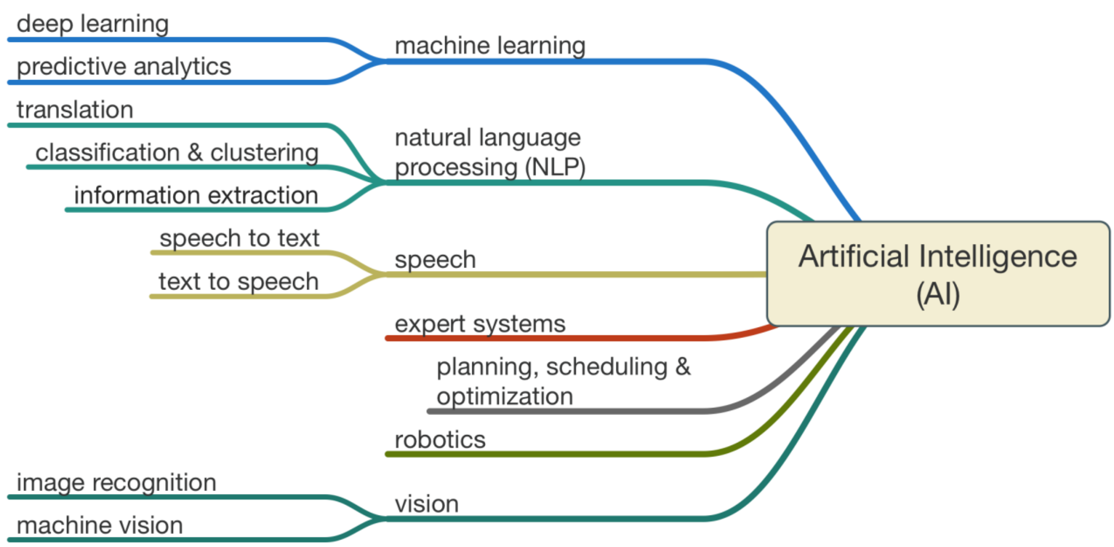


Fig. 1.1. Applications of AI Techniques

1.1.2 Machine Learning (ML)

A subset of AI that includes abstruse statistical techniques that enable machines to improve at tasks with experience. Algorithms that can learn and adapt from information to solve future problems more efficiently. See figure 1.2 for an illustration of the ML mechanism in general.

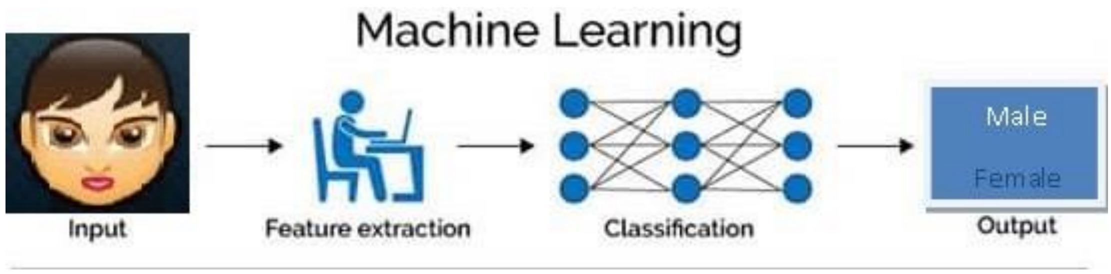


Fig. 1.2. Illustration of the ML mechanism in general

1.1.3 Computer Vision

Computer vision is the automated extraction of information from images recognition to grouping and searching image content. Sometimes computer vision tries to mimic human vision, sometimes uses a data and statistical approach, sometimes geometry is the key to solving problems. In computer vision, we are trying to describe the world that we see in one or more images and to reconstruct its properties, such as shape, illumination, and color distributions. It is amazing that humans and animals do this so effortlessly, while computer vision algorithms are so error-prone. See figures 1.3, 1.4.

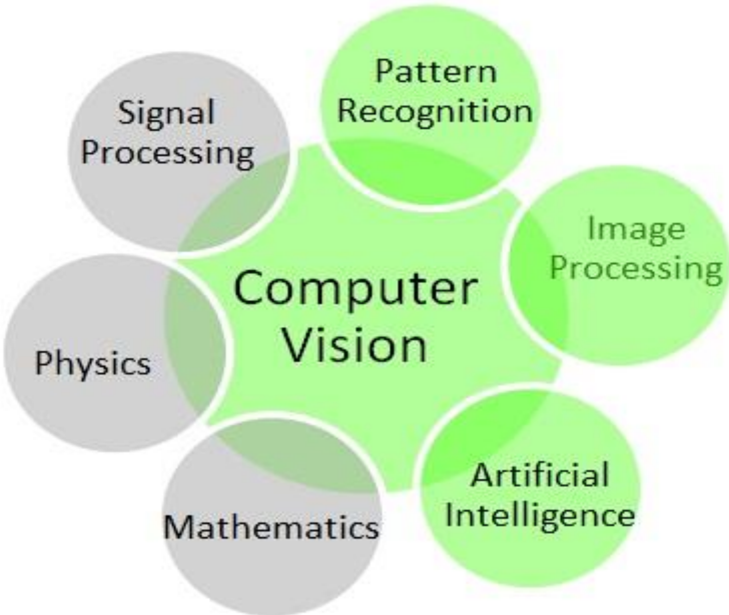


Fig. 1.3. Computer Vision and its relationship to other techniques

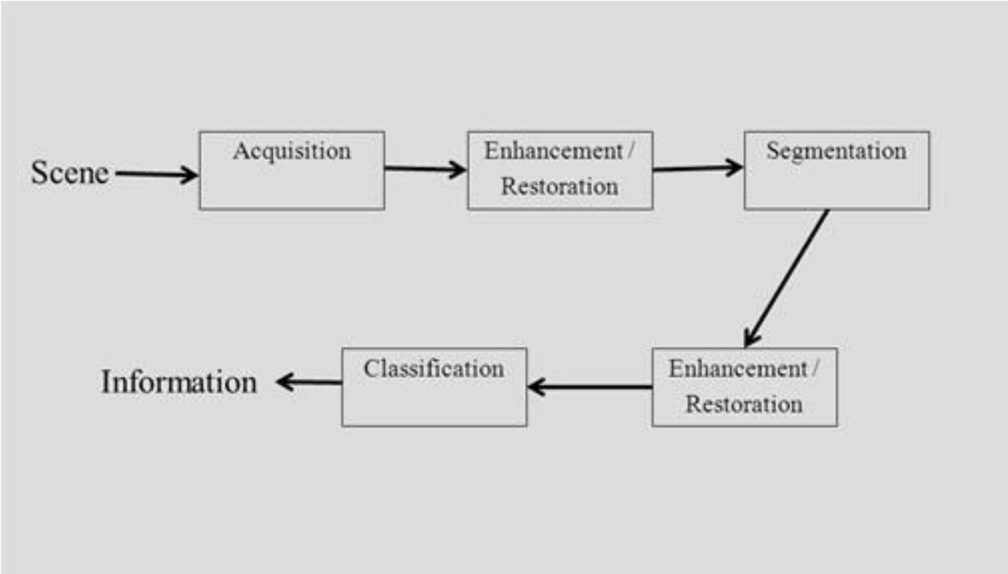


Fig. 1.4. Computer Vision Process

1.1.4 Gender Detection

A variety of attributes such as gender, age, and ethnicity, besides an individual's identity, can be deduced from face images, see figure 1.5. Over the past decades, there have been significant advances in facial image processing, especially, in a face detection area where a number of fast and robust algorithms have been proposed for practical applications. As a result, a number of research areas attempting to extend the works have been emerging, for example, face recognition, facial expression recognition, and gender recognition. Conforming to the practicality of gender prediction, see figure 1.6. It is necessary to improve the algorithms from time to time in order to achieve higher accuracy levels and build more robust and accurate systems (Gupta, 2015). Predicting gender from a face image has been actively studied in the computer vision and biometrics literature.

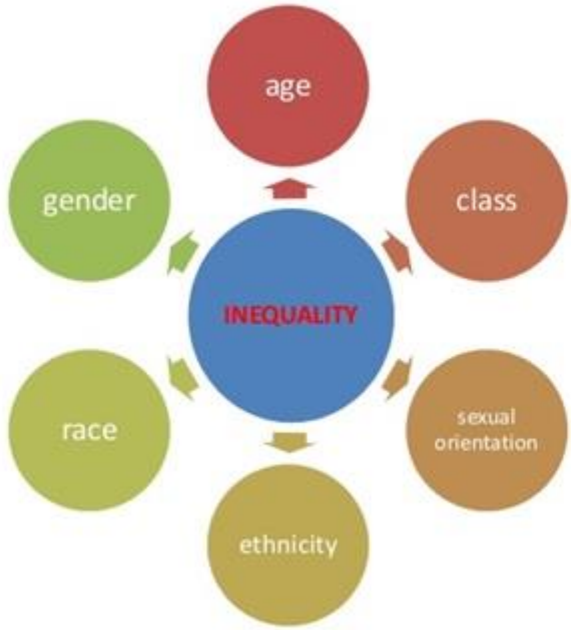


Fig. 1.5. A variety of attributes can be deduced from face images

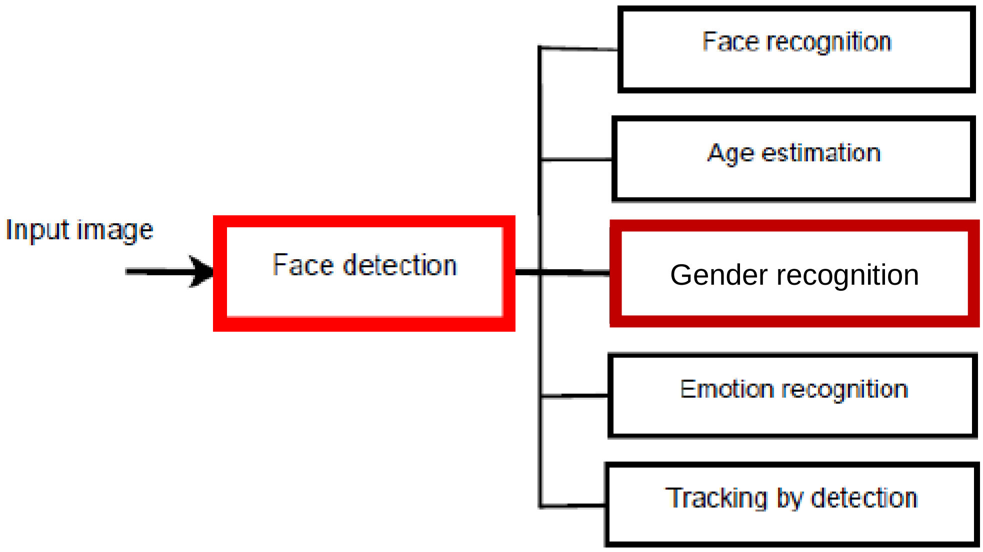


Fig. 1.6. Illustration of different stages in face processing

1.2 Problem Statement

Face localization, detection, and the identification or verification have been a challenging task due to a number of factors. The face is so non-rigid and has so many variations that no one technique can cope with all these variations. That is why in spite of a large number of algorithms and techniques a robust system is still far from real implementation.

1.3 Scope and Limitation of the Study

The study will reveal the important aspects of different methods with respect to accuracy, speed, and suitability for specific conditions. Also, the study will provide guidelines for improving the accuracy and speed of gender detection systems. This study will help generalizing the concept for detecting other objects from still images.

1.4 Aims and Objectives

1.4.1 This study attempts to achieve the following aims:

- In the first step, a survey of different gender detection methods proposed by researchers will be done. It will help for a deep understanding of the gender detection methods their merits, demerits, and problems faced.
- A detailed study
- After a study of different methods, a suitable system is to be proposed keeping in view the requirements that it should be fast and accurate.

1.4.2 In the same context, this study has the following objectives:

- Evaluating a few techniques for image discriminating. A detailed study of Local Binary Pattern (LBP) and Random Forests (RF) will be done.
- Using face database training is perfect to produce a model for the taken best result.
- In the evaluation step, a different database of faces will be used in order of check the accuracy of the algorithm and stability.

1.5 Motivation

Gender Classification has become an area of extensive research due to its increasingly powerful applications. Automated gender classification has attracted much attention over the last ten years, since augmenting this ability with applications specific to a particular gender can provide a more user-friendly environment and human-like interaction. Till that date, the work has been emphasized on gender recognition through visual observation, but now, it has to be emphasized to the computer, to perform this task. It is observable that our behavior and social interaction are greatly influenced by the genders of people whom we intend to interact with. Hence a successful gender recognition system could have a great impact on improving human-computer interaction systems in such a way as to make them be more user-friendly and acting more human-like (Gupta, 2015).

1.6 Structure of The Thesis

This section provides a brief of the thesis structure follows:

Chapter Two: This chapter presents the introduction of gender detection, applications of gender detection, challenges of gender classification and related work.

Chapter Three: This chapter presents the introduction of local binary pattern, texture descriptor, uniform pattern, and LBP extensions.

Chapter Four: This chapter presents the introduction of classification and random forest, building a forest, random forest algorithm, advantages and disadvantages of random forest.

Chapter Five: This chapter presents research methodology in which how to preprocess the data, how to train the gender detector classifier and to choose the final model, how to test face detector framework, how to use Viola-Jones object detection framework, how to slide window technique, and results in discussion and analysis.

Chapter Six: Conclusion and future work.

Chapter 2
Gender Detection

This chapter presents the introduction of gender detection, applications of gender detection, challenges of gender classification and related work.

2.1 Introduction

The problem of gender classification from face images can be posted as a two-class problem in which the input face image is analyzed and assigned to one of two classes: male or female (Chen and Ross, 2011). Determination of the salient features from facial images is one of the most important steps in face process and recognized of it. If the extracted features do not help in discriminating between different facial images, the use of an excellent classification algorithm can lead to very bad results. The extracted feature can be subdivided into either appearance based or geometric methods. Features including the distance between eyes; size and location of the eyes, nose, mouth, and ears; the overall size of the face etc. are used in the geometric methods. In appearance-based methods, features are extracted from the whole facial image (Bebis et al., 2013). The progress of gender classification research drove many potential applications. For instance, a computer system with a function of gender recognition has a wide range of applications in fundamental and applied research areas including human-computer interaction (HCI) applications, the security and surveillance industry, demographic research, commercial development, and mobile application and video games (Long et al., 2015). Facial features can be extracted from the facial image using the Viola-Jones algorithm that returns the coordinates of various features (Viola and Jones, 2001). This work includes feature extraction methods for face recognition using Local Binary Pattern **LBP**, and classifier such as Random Forest **RF** See figure 2.1.

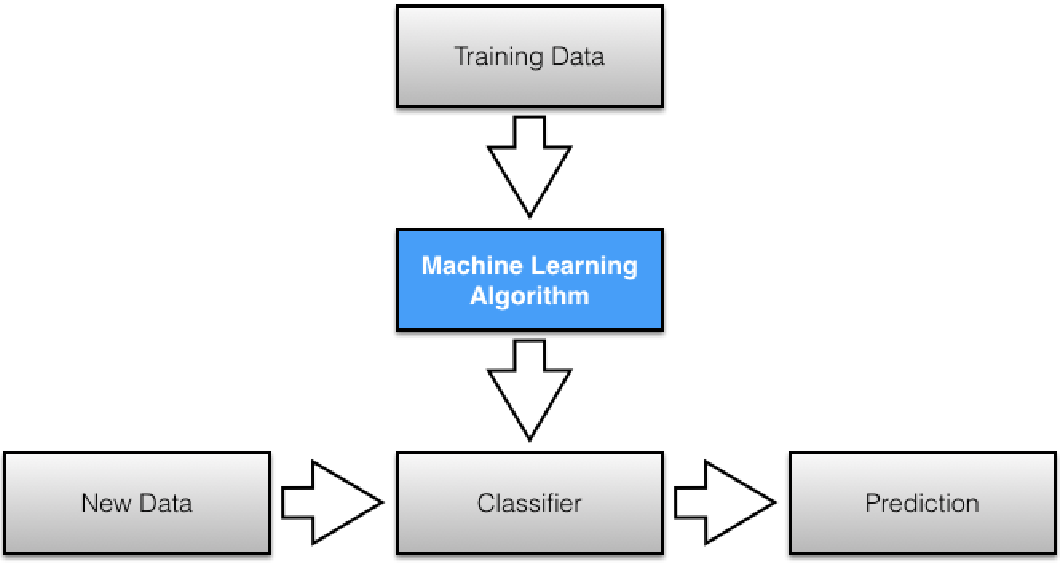


Fig. 2.1. Gender Detection

2.2 Applications of gender detection

The development and progress in gender recognition area lead to many potential uses in a large application scope because the gender classification technique can significantly improve the computer's perceptional and interactional capabilities. For example, gender classification is able to improve the intelligence of the surveillance system, analyze the customers' demands for store management, allow the robots to perceive gender, etc. To be concrete, the applications of a gender classification technique can be utilized in the following fields (Long et al., 2015):

A. Human-Computer Interaction (HCI)

In the field of HCI, the robots or computers need to identify and verify the human gender to improve the system performance based on the personalized information. By the successful determining of the gender, the system can provide more appropriate and customized service for the customer by adapting to users according to their genders.

B. Surveillance System

Classifying gender in a surveillance system for public places (e.g., airport, train station, shopping mall) can serve to enhance the security such as counting the number of males and females, whose aim is to restrict access of people entering to certain areas. Another application is to assist the intelligent security and surveillance system to track moving object and detect abnormal behaviors. In addition, this can help better evaluate the threat level for a specific gender if the gender information can be obtained in advance

C. Commercial Development

Gender classification is useful for guiding effective marketing and establishing smart shopping environment, in which the product can be directed to specific users through websites, electronic marketing, advertising, etc. For instance, in a supermarket or department store, knowing the number of male and female customers helps the store managers to make effective sales and managing decisions.

D. Demographic Research

The application of a gender classification system helps the demographic research in efficiently collecting demographic information. Automatic identification of human gender enhances the demographic statistics (e.g. gender, disability status, race definition) and population prediction. The ability to automatically detect gender information acts as a supplementary method for existing demographic research on the web or in public places.

E. Mobile Application and Video Games

Gender classification can provide supportive information to improve user experiences in mobile applications and video games. In mobile applications, some researchers seek the method to facilitate the use of the mobile Internet by distinguishing the mobile applications mainly used by a specific gender. In video games, different genders have different character features. To increase the realism of a video game, character features, like gait, can be analyzed using gender classification techniques. Applying different gait patterns to different virtual characters in the games according to their genders will apparently enhance the sense of reality.

2.3 Challenges of Gender Classification

Although some progress is reported, the gender classification is still a challenging work for the machine because of the variation in gender features, particularly the gender identities of the face, may result in difficulty of automatic detection of gender. Variation in gender information extraction occurs due to changes in illumination, pose, expression, age, and ethnicity. Similarly, during the image capturing process the factors of image quality like dithering, noise, and low resolution also make the image analysis a challenging task. On the other side, the choice of features is one of the most critical factors. The classification techniques are also affected by feature extraction and classification algorithms.

2.4 Related work

Louis and Plataniotis (2010) integrate two types of Local Binary Patterns (LBP) features in order to achieve a high detection rate with a high discriminative power face detector. First LBP feature is a novel way of using the Circular LBP, in which the pixels of the image are targeted; it is a non-computationally expensive feature extraction. The second LBP feature is the LBP Histogram, in which regions in the image are targeted; it is more computationally expensive than Circular LBP features but has a higher discriminative power.

Chen and Ross (2011) presented an Evaluation of Gender Classification Methods on Thermal and Near-infrared Face Images. Automatic gender classification based on face images is receiving increased attention in the biometrics community. Most gender classification systems have been evaluated only on face images captured in the visible spectrum. In this work, the possibility of deducing gender from face images obtained in the near-infrared (NIR) and thermal (THM) spectra is established. It is observed that the use of local binary pattern histogram (LBPH) features along with discriminative classifiers results in reasonable gender classification accuracy in both the NIR and THM spectra. Further, the performance of human subjects in classifying thermal face images is studied. Experiments suggest that machine-learning methods are better suited than humans for gender classification from face images in the thermal spectrum.

Bebis (2013) propose a Gender Recognition Using Fusion of Local and Global Facial Features. Human perception of the face involves the observation of both coarse (global) and detailed (local) features of the face to identify and categorize a person. Face categorization involves finding common visual cues, such as gender, race, and age, which could be used as a precursor to a face recognition system to improve recognition rates. In this work, they investigate the fusion of both global and local features for gender classification.

Song and et al (2013) propose a Semi-Supervised Node Splitting for Random Forest Construction. Node splitting is an important issue in Random Forest but robust splitting requires a large number of training samples. Existing solutions fail to properly partition the feature space if there are insufficient training data. In this work, they present semi-supervised splitting to overcome this limitation by splitting nodes with the guidance of both labeled and unlabeled data. In particular, they derive a nonparametric algorithm to obtain an accurate quality measure of splitting by incorporating abundant unlabeled data. To avoid the curse of dimensionality, they project the data points from the original high-dimensional feature space onto a low-dimensional subspace before estimation. A unified optimization framework is proposed to select a coupled pair of subspace and separating hyperplane such that the smoothness of the subspace and the quality of the splitting are guaranteed simultaneously. The proposed algorithm is compared with state-of-the-art supervised and semi-supervised algorithms for typical computer vision applications such as object categorization and image segmentation. Experimental results on publicly available datasets demonstrate the superiority of their method.

Wang and Kambhamettu (2013) presented Gender Classification of Depth Images Based on Shape and Texture Analysis. Gender classification of depth images is a challenging problem, most research works attempted to use shape information to solve this problem in the previous studies. In this work, they propose a new fusion scheme for gender classification using both texture and shape features. A new ensemble scheme is advocated to combine texture and shape feature at the feature level. To evaluate the performance of their algorithm, they measure their scheme on two different datasets. The final classification result is up to 93.7% using five-fold cross-validation on the whole FRGCv2 dataset, which is comparable to the classification result obtained using visible imagery.

Verma and Vig (2014) presented Using Convolutional Neural Networks to discover cognitively validated features for Gender Classification. The human visual cortex is extremely adept at distinguishing between male and female faces, or performing “Gender Classification”. While the subject of face detection and recognition has received a lot of focus, research into the features or cognitive processes that are useful for identifying gender has received relatively little attention. Researchers have attempted to extract handcrafted features like wavelet coefficients, histograms etc. on the basis of which to generate a model to classify the male and female faces. The classification results are compared with different regularization techniques and other standard classifiers, and the CNN models yield higher accuracy than both SVM and random forest classifiers.

Gupta (2015) propose a Gender Detection using Machine Learning Techniques and Delaunay Triangulation. Data mining today is being used widely in diverse areas. For example, fraudulent systems, recommender systems, disease prediction, and numerous other applications. One such application is exploited in this article. This paper presents an approach to detect the gender of a person through a frontal facial image, using techniques of data mining and Delaunay triangulation. Gender prediction can prove to be a very useful technique in HCI (Human-Computer Interaction) Systems. Classification, is a very powerful technique in data mining to group categorical data, is used here also to classify a gender as either male or female.

Santana et al (2015) presented Descriptors and Regions of Interest Fusion for Gender Classification in The Wild. Gender classification (GC) has achieved high accuracy in different experimental evaluations based mostly on inner facial details. However, these results are not generalized in unrestricted datasets and particularly in cross-database experiments, where the performance drops drastically. Analyze the state-of-the-art GC accuracy on three large datasets: MORPH, LFW, and GROUPS. They discuss their respective difficulties and bias, concluding that the most challenging and wildest complexity is present in GROUPS. This dataset covers hard conditions such as low-resolution imagery and cluttered background.

Al Mashagba (2016) presented Real-Time Gender Classification by Face. This work presents a robust method that uses global geometry-based features to classify gender and identify age and human beings from video sequences. The features are extracted based on face detection using the skin, color segmentation and the computed geometric features of the face ellipse region. These geometric features are then used to form the face vector trajectories, which are inputted to a time delay neural network and are trained using the Broyden–Fletcher–Goldfarb–Shanno (BFGS) function.

Results show that using the suggested method with our own dataset under an unconstrained condition achieves a 100% classification rate in the training set for all application, as well as 91.2% for gender classification, 88% for age identification, and 83% for human identification in the testing set.

In this research, presented Gender Detection from facial images was using the technique of extracting features Local Binary Pattern and the technique of Random Forest classification. This research is distinguished from the previous research, which stated that a different set of databases were used and compared with the different results obtained, and using the Viola Jones algorithm and the technique of Sliding Windows to reveal the face and obtain more accurate results. The results varied between 99.89% and 76.25%. We observed when using databases containing high and different facial expressions we get very high results unlike using databases containing lower facial expressions.

Chapter 3

Local Binary Pattern

This chapter presents the introduction of local binary pattern, texture descriptor, uniform pattern, and LBP extensions.

3.1 Introduction

The local binary pattern (LBP) operator, introduced by (Ojala et al.,2002) become based on the assumption that texture has locally two complementary aspects, a sample, and its power. In that paintings, the LBP became proposed as a two-level version of the texture unit to describe the local textural patterns. The LBP operator (Hadid et al., 2004) is one of the best performing texture descriptors and it has been widely used in various applications. It has proven to be highly discriminative and its key advantages, namely its invariance to monotonic gray level changes and computational efficiency, make it suitable for demanding image analysis tasks.

The idea of using LBP for face description is motivated by the fact that faces can be seen as a composition of micro-patterns which are well described by such operator.

The LBP operator was originally designed for texture description. Derived from a general definition of texture in a local neighborhood, LBP is defined as a grayscale invariant texture measure.

3.2 Texture Descriptor

The original version of the local binary pattern operator works in a 3 × 3-pixel block of an image. The pixels in this block are thresholded with the help of its center pixel value, improved by using powers of two after which summed to reap a label for the center pixel. If the result is a negative number then the pixel encoded with 0, otherwise, the pixel encoded with 1. For each pixel, a binary number is revealed by concatenating the 8 binary results to form a number in a clockwise direction, which starts with its top-left neighbor. Then, the decimal value that generated from the binary number is used for labeling the pixel. The derived binary numbers are known as LBP codes. See figure 3.1.

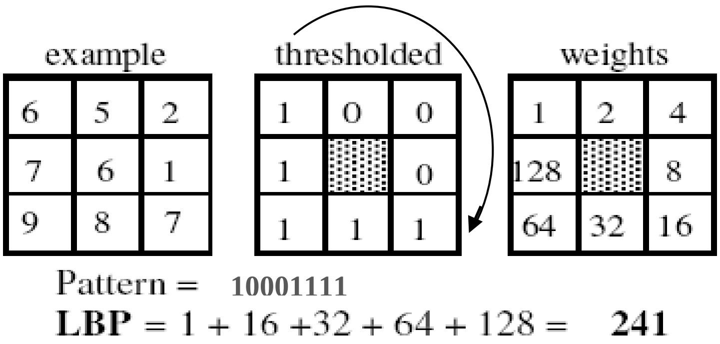


Fig. 3.1. Example of calculating LBP operator

As the neighborhood consists of 8 pixels, a total of $2^8 = 256$ different labels can be obtained depending at the relative gray values of the center and the pixels in the neighborhood (Pietikäinen et al., 2011). An instance of an LBP photo and histogram are shown in Figure 3.2 (Bebis et al., 2013).

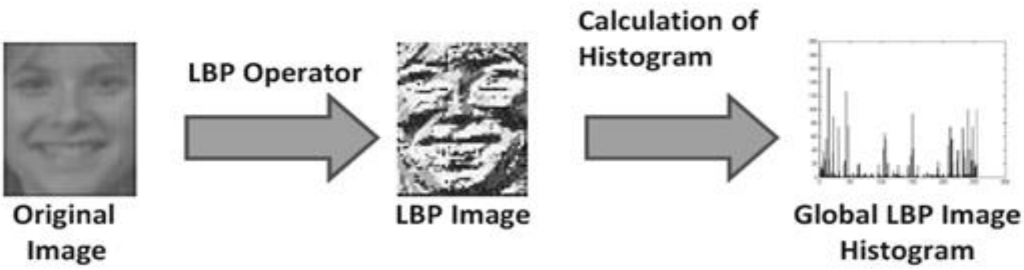


Fig. 3.2. LBP histogram calculation for the whole image

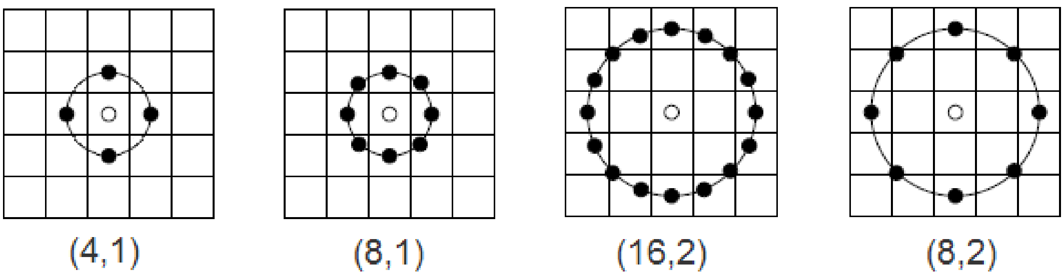


Fig.3.3. LBP different sampling point and radius examples

In the basic LBP, the number of neighbors is restricted to 3 X 3, which failed to deal with the structure of bigger and different scale images, for this reason, they generalize it to use a different number of neighbors of different sizes.

By definition, the local neighborhood is a set of sampling points evenly spaced on a circle centered at the pixel to be labeled, this allows any radius and number of sampling points. The notation (*P*,*R*) will be used for pixel neighborhoods which mean *P* sampling points on a circle of radius of *R*. See figure 3.3 for an example of circular neighborhoods and see algorithm 3.1 shows LBP algorithm.

Formally, given a pixel at(x_c,y_c), the resulting LBP can be expressed in decimal form as follows:

$$\mathrm{LBP}_{P,\,R}(x_c, y_c) = \sum_{P=0}^{P-1} s(i_P - i_c)2^P$$

Where i_c are gray level values of central pixels and i_p = (p = 0,1,2,……) is the neighborhood of i_c, are surrounding pixel values with *R* radius. Where function s(x) = s (i_p- i_c) defined as:

$$s(x) = \begin{cases} 1, & \text{if } x \geq 0 \\ 0, & \text{if } x < 0. \end{cases}$$

Algorithm 3.1. Local Binary Pattern algorithm

Define a variable:

- P: pixel neighborhoods, R: radius sampling points on a circle.
- i_c: gray level values of central pixel, i_p = (p = 0,1,2,…) is the neighborhood of i_c.
- $x = (i_p - i_c)$.

1. LBP operator works in a 3 × 3-pixel block of an image.
2. $$s(x) = \begin{cases} 1, & \text{if } x \geq 0 \\ 0, & \text{if } x < 0. \end{cases}$$
3. The neighborhood consists of 8 pixels, a total of $2^8 = 256$ to form a number in a clockwise direction, which starts from its top-left neighbor.
4. Formally, given a pixel at (x_c, y_c), the resulting LBP can be expressed in decimal form as follows:
$$\mathrm{LBP}_{P,\,R}(x_c, y_c) = \sum_{P=0}^{P-1} s(i_P - i_c)2^P$$
5. Repeat all previous steps on each image from step 1 to 4.

3.3 Uniform pattern

In many texture analysis applications, it is desirable to have features that are invariant or robust to rotations of the input image. As the $\mathrm{LBP}_{P,R}$ patterns are obtained by circularly sampling around the center pixel, rotation of the input image has two effects: each local neighborhood is rotated into other pixel location, and within each neighborhood, the sampling points on the circle surrounding the center point are rotated into a different orientation.

Another extension to the original operator uses so-called *uniform patterns* (Ojala et al.,2002). For this, a uniformity measure of a pattern is used: U (“pattern”) is the number of bitwise transitions from 0 to 1 or vice versa when the bit pattern is considered circular. A local binary pattern is called uniform if its uniformity measure is at most 2. For example, the patterns 00000000 (0 transitions), 01110000 (2 transitions) and 11001111 (2 transitions) are uniform whereas the patterns 11001001 (4 transitions) and 01010011 (6 transitions) are not. In uniform LBP mapping, there is a separate output label for each uniform pattern and all the non-uniform patterns are assigned to a single label (Pietikäinen et al., 2011).

We use the following notation for the LBP operator $LBP_{P,R}^{u2}$ The subscript represents using the operator in a (*P*,*R*) neighborhood. Superscript *u2* stands for using only uniform patterns. See figure 3.4.

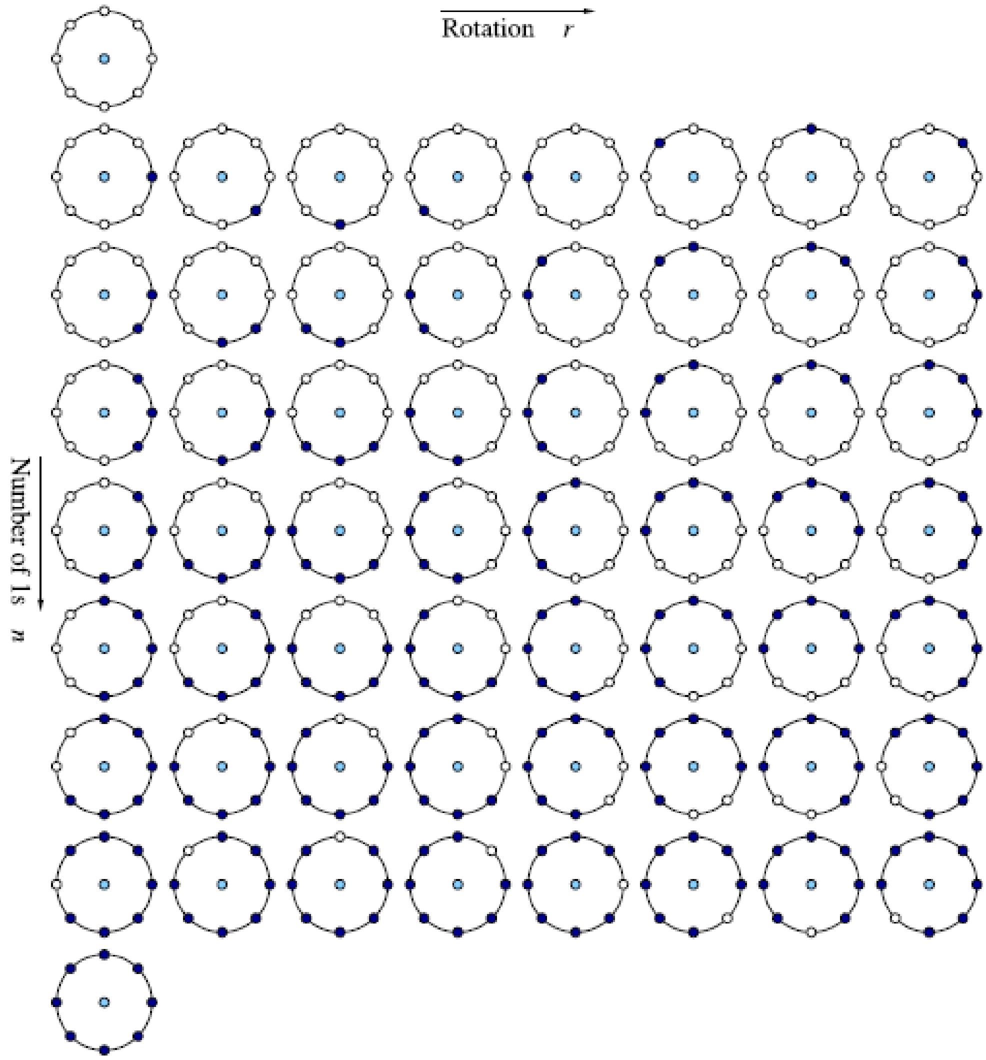


Fig. 3.4. The 58 different uniform patterns in *(*8,*R)* neighborhood

3.4 LBP Extensions

On the survey by (Huang and et al, 2011), many extensions are made of LBP, such as:

- **Improved Local Binary Pattern (ILBP):** Jin *et al.* developed the LBP operator to describe more local structure information under certain circumstances. They proposed an improved LBP (ILBP), which compares all the pixels (including the central pixel), with the mean intensity of all the pixels in the patch.

- **Hamming LBP**: Hamming LBP was proposed by Yang and Wang, to improve the discriminative ability of the original LBP. They reclassified nonuniform patterns based on Hamming distance, instead of collecting them into a single bin as LBP*u*2 does.
- **Extended Local Binary Pattern (ELBP):** After performs, a binary comparison between the central pixel and its neighbors, this operator encodes their exact gray-value differences (*GDs*) using some additional binary units.
- **Haar Local Binary Pattern (HLBP):** This binary feature compares bin values of Local Binary Pattern histograms calculated over two adjacent image subregions. These subregions are similar to those in the Haar masks, hence the name of the feature. They capture the region-specific variations of local texture patterns and are boosted using AdaBoost in a framework similar to that proposed by Viola and Jones.
- **A Completed Modeling of Local Binary Pattern (CLBP):** A completed modeling of the LBP operator is proposed and an associated completed LBP (CLBP) scheme is developed for texture classification.
- **Local Ternary Patterns (LTPs):** Tan and Triggs extended the original LBP to a version with 3-value codes. The LTP codes are more resistant to noise, but no longer strictly invariant to gray-level transformations.
- **Three-patch LBP (TP-LBP) and four-patch LBP (FP-LBP)**: Similar schemes to MB-LBP are proposed to compare distances between the whole blocks (patches) concerned, and any distance function can be used.
- **Volume LBP (VLBP or 3-D-LBP):** Zhao and Pietikäinen extended the LBP neighborhood from 2-D plane to 3-D space. VLBP combines motion and appearance information, and can thus be used to analyze image sequences or videos.
- **Center-Symmetric LBP (CS-LBP)**: It compares pairs of neighboring pixels, which are in the same diameter of the circle. This variation combines the LBP

operator with the scale-invariant feature transform (SIFT) definition, and thus produces fewer binary units than the original LBP does.

- **LBP histogram Fourier features (LBP-HF):** Ahonen *et al*. proposed it, they combine the LBP and the discrete Fourier transform (DFT). Unlike the existing local rotation-invariant LBP features, the LBP-HF descriptor is produced by computing an LBP histogram over the whole region, and then, constructing rotationally invariant features from the histogram with DFT.

The List of some of recent LBP variations is shown in table 3.1.

Table 3.1. List of some of recent LBP variations

Subsection	Variation	Properties	Application	Reference
A: Enhancing the discriminative ability	Improved LBP (Mean LBP)	Consider the effects of central pixels; present complete structure pattern.	Face detection	Tan and et al 2004, Solar and Qinteros 2008, Bai and et al 2008
	Hamming LBP	Incorporate non-uniform patterns into uniform pattern.	Face recognition	Yang and Wang 2007
	Extended LBP	Discriminate the same local binary patterns; cause high dimensionality.	Texture classification	Yang and et al 2006, 2007
	Completed LBP	Include both the sign and magnitude information of the given local region.	Face recognition	Guo and et al 2010
B: Improving the robustness	Local Ternary Pattern	Bring in new threshold; no longer strictly invariant to gray-level information.	Face recognition	Tand and Triggs 2007
C: Choosing the neighborhood	Three/Four Patch LBP	Encode patch type of texture information.	Face analysis	Wolf and et al 2008
D: Extending to 3D	3D LBP	Extend LBP to 3D volume data.	Image indexing	Fehr 2007, Ramel and et al 2008
E: Combining with other feature	LBP and Gabor wavelet	Combine advantages Gabor and LBP; increase time cost and cause high dimensionality.	Face recognition	Shan and Zhao 2005, Chen 2006, Yan and Tan 2007, Noore and Li 2008
	LBP Histogram Fourier	Obtain rotation invariance globally for the whole region.	Human detection	Ahonen and et al 2009

Chapter 4

Random Forest

This chapter presents the introduction of classification and random forest, building a forest, random forest algorithm, advantages and disadvantages of random forest.

4.1 Classification

In machine learning, **classification** is the problem of identifying to which of a set of categories (sub-populations) a new observation belongs, on the basis of a training set of data containing observations (or instances) whose category membership is known. An example would be assigning a given email into "spam" or "non-spam" classes or assigning a diagnosis to a given patient as described by observed characteristics of the patient (gender, blood pressure, presence or absence of certain symptoms, etc.). Classification is an example of pattern recognition. In the terminology of machine learning, classification is considered an instance of supervised learning, i.e. learning where a training set of correctly identified observations is available. An algorithm that implements classification, especially in a concrete implementation, is known as a **classifier**. The term "classifier" sometimes also refers to the mathematical function, implemented by a classification algorithm, that maps input data to a category. Terminology across fields is quite varied. In statistics, where classification is often done with logistic regression or a similar procedure, the properties of observations are termed explanatory variables (or independent variables, regressors, etc.), and the categories to be predicted are known as outcomes, which are considered to be possible values of the dependent variable. In machine learning, the observations are often known as *instances*, the explanatory variables are termed *features* (grouped into a feature vector), and the possible categories to be predicted are *classes* (*Alpaydin, 2014*).

Classification involves segregating the data into segments which are non-overlapping. Any approach to classification assumes some knowledge about the data termed as training. Training data requires sample input data, domain expertise, and classification assignment to the data. Performance of classification is measured in terms of classification accuracy (Basha and Jahangeer, 2014).

The outcome of classification can be described as:

True-positive (TP): also called hit or detection; a correctly detected face gender.
False-positive (FP): also called miss- or false-detection; detecting a face gender where there is none actually.
False-negative (FN): when missing a visible face gender.
True-negative (TN): describing missing face gender correctly.
Best Performance: TP = 100%, FP = 0%, FN = 0%, and TN = 100%. (Basha and Jahangeer, 2014).

4.1.1 Applications of Classification

- Computer vision
    - Medical imaging and medical image analysis
    - Optical character recognition
    - Video tracking
- Drug discovery and development
    - Toxicogenomics
    - Quantitative structure-activity relationship
- Geostatistics
- Speech recognition
- Handwriting recognition
- Biometric identification
- Biological classification
- Statistical natural language processing
- Document classification
- Internet search engines
- Credit scoring
- Pattern recognition
- Micro-array classification

4.1.2 Examples of classification algorithms

- Linear Classifiers
  - Fisher's linear discriminant
  - Logistic regression
  - Naive Bayes classifier
  - Perceptron
- Support vector machines
  - Least squares support vector machines
- Quadratic classifiers
- Kernel estimation
  - k-nearest neighbor
- Boosting (meta-algorithm)
- Decision trees
  - Random forests
- Neural networks
- Learning vector quantization

See figure 4.1.

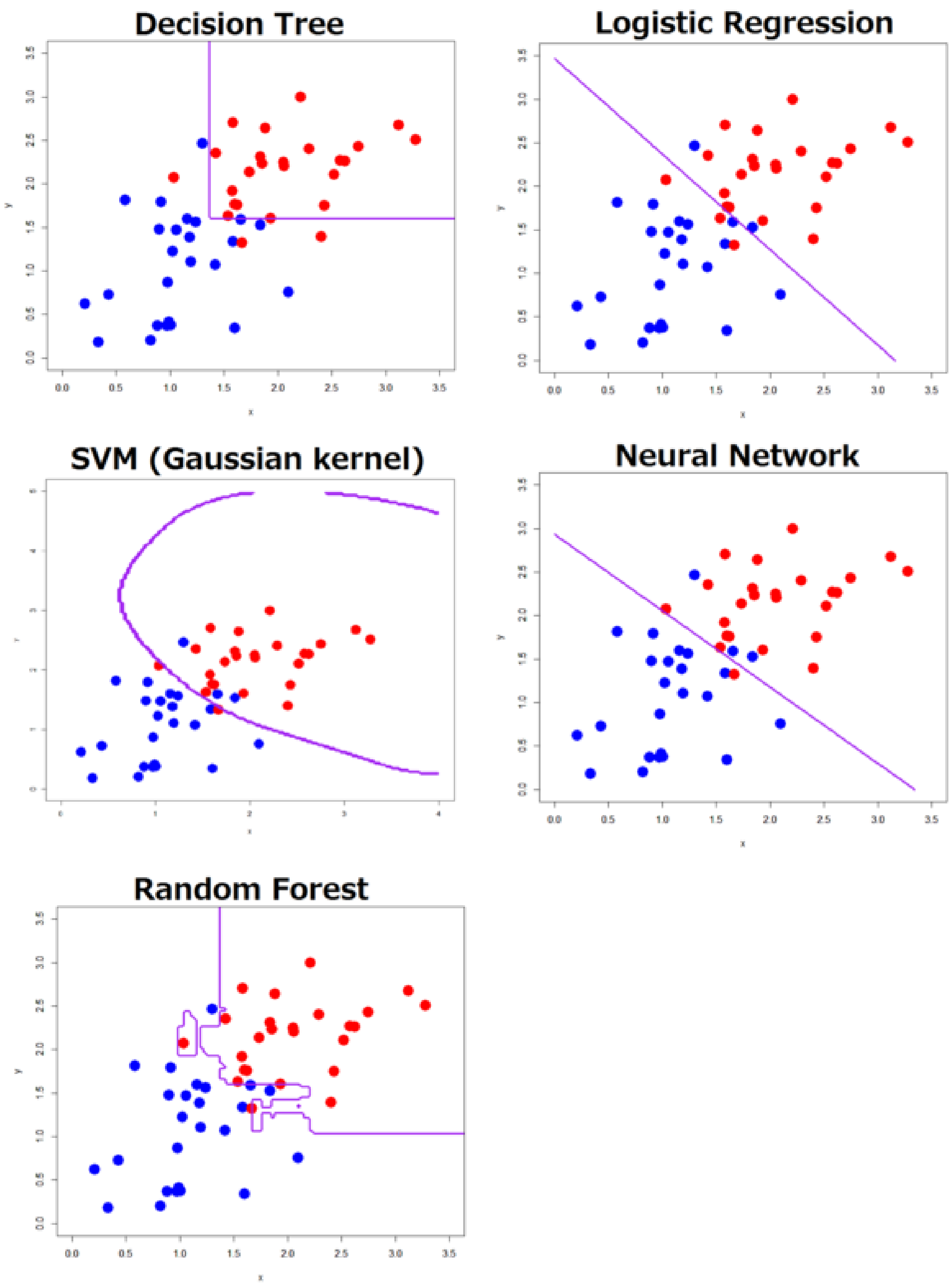


Fig. 4.1. Examples of classification algorithms

Decision Tree Algorithms

Decision tree builds classification or regression models in the form of a tree structure. A decision tree is a graphical representation of specific decision situations that are used when complex branching occurs in a structured decision process. A decision tree is a predictive model based on a branching series of Boolean tests that use specific facts to make more generalized conclusions. Decision trees build the rule by recursive binary partitioning into regions that are increasingly homogeneous with respect to the class variable. The homogeneous regions are called nodes. At each step in fitting a decision tree, an optimization is carried out to select a node, a predictor variable, and a cut-off or group of codes (for numeric and categorical variables respectively) that result in the most homogeneous subgroups for the data, as measured by the Gini index. The splitting process continues until further subdivision no longer reduces the Gini index. Such a decision tree is said to be fully grown, and the final regions are called terminal nodes. The lower branches of a fully grown decision tree model sampling error, so algorithms for pruning the lower branches on the basis of cross-validation error have been developed. A typical pruned decision tree has three to 12 terminal nodes. Interpretation of decision trees increases in complexity as the number of terminal nodes increases (LAWLER et al., 2007). See figure 4.2.

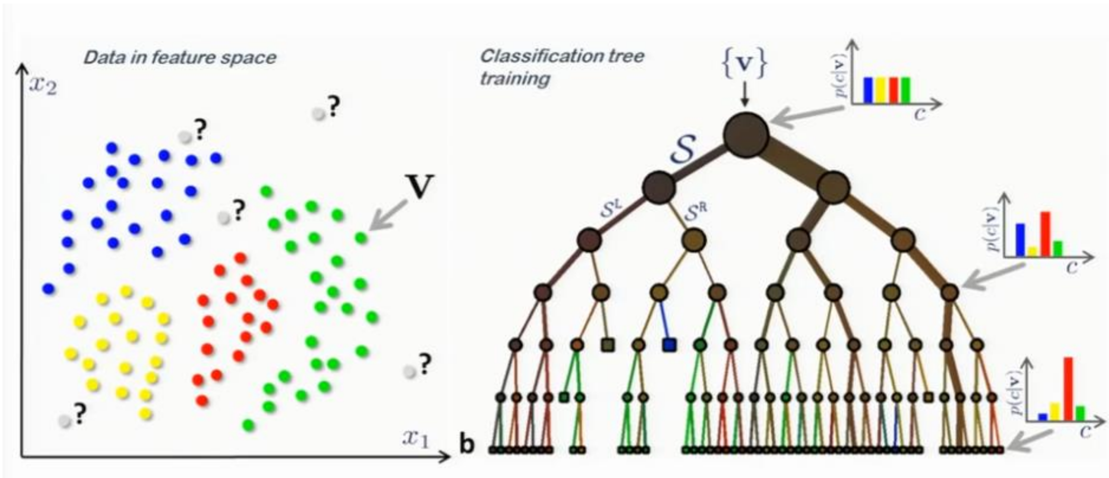


Fig. 4.2. Showes Decision tree

A generic data point is denoted by a vector $\mathbf{v} = (x_1, x_2, \cdots, x_d)$

$$\mathcal{S}_j = \mathcal{S}_j^{\mathrm{L}} \cup \mathcal{S}_j^{\mathrm{R}}$$

Logistic Regression (Predictive Learning Model):

It is a statistical method for analyzing a dataset in which there are one or more independent variables that determine an outcome. The outcome is measured with a dichotomous variable (in which there are only two possible outcomes). The goal of logistic regression is to find the best fitting model to describe the relationship between the dichotomous characteristic of interest (dependent variable = response or outcome variable) and a set of independent (predictor or explanatory) variables.

Support Vector Machine Learning Algorithm

Support Vector Machine is a supervised machine learning algorithm for classification or regression problems where the dataset teaches SVM about the classes so that SVM can classify any new data. It works by classifying the data into different classes by finding a line (hyperplane) which separates the training dataset into classes. As there are many such linear hyperplanes, SVM algorithm tries to maximize the distance between the various classes that are involved and this is referred as margin maximization. If the line that maximizes the distance between the classes is identified, the probability to generalize well to unseen data is increased.

Neural Network

A neural network consists of units (neurons), arranged in layers, which convert an input vector into some output. Each unit takes an input, applies an (often nonlinear) function to it and then passes the output on to the next layer. Generally, the networks are defined to be feed-forward: a unit feeds its output to all the units on the next layer, but there is no feedback to the previous layer. Weightings are applied to the signals passing from one unit to another, and it is these weightings which are tuned in the training phase to adopt a neural network to the particular problem at hand.

Random Forest

Random forests or random decision forests are an ensemble learning method for classification, regression, and other tasks, that operate by constructing a multitude of decision trees at training time and outputting the class that is the mode of the classes (classification) or means prediction (regression) of the individual trees. Random decision forests correct for decision trees' habit of overfitting to their training set.

4.2 Random Forest

Random Forest (RF) is an ensemble classifier that consists of many decision trees. Each decision tree is trained independently and successively based on a boot-strapped sampling of the training dataset. The individual learners are combined through bootstrap aggregation. Given an input feature vector, it successively moves through the individual trees in the forest. The final classification (prediction) is based on a majority voting scheme over all the trees. Recent work on the task of gender classification from infants to seniors has also shown the superiority of using Random Forest for feature selection (Chen and Ross, 2011). The following figure 4.3 is an illustration of the RF mechanism in general.

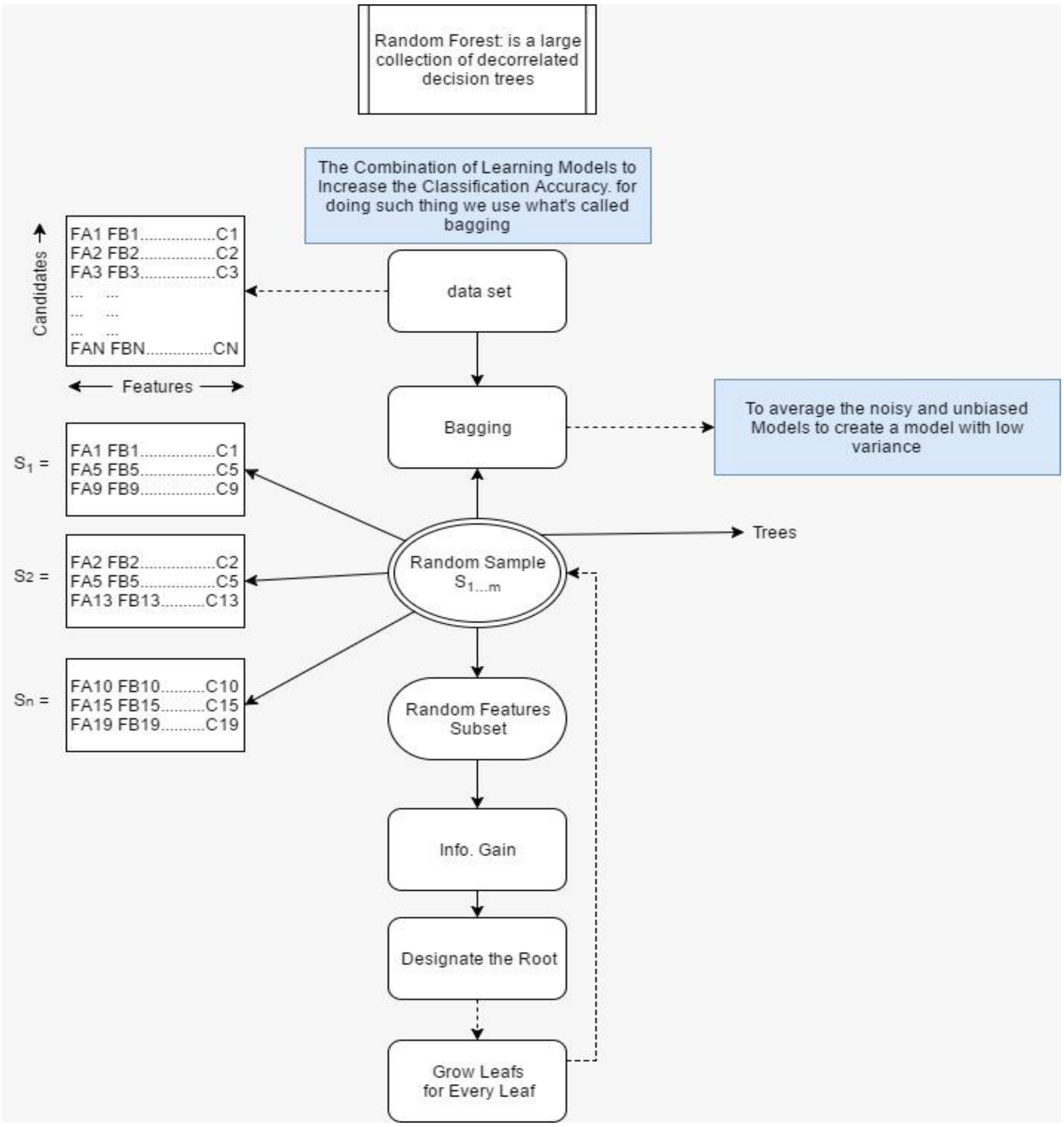
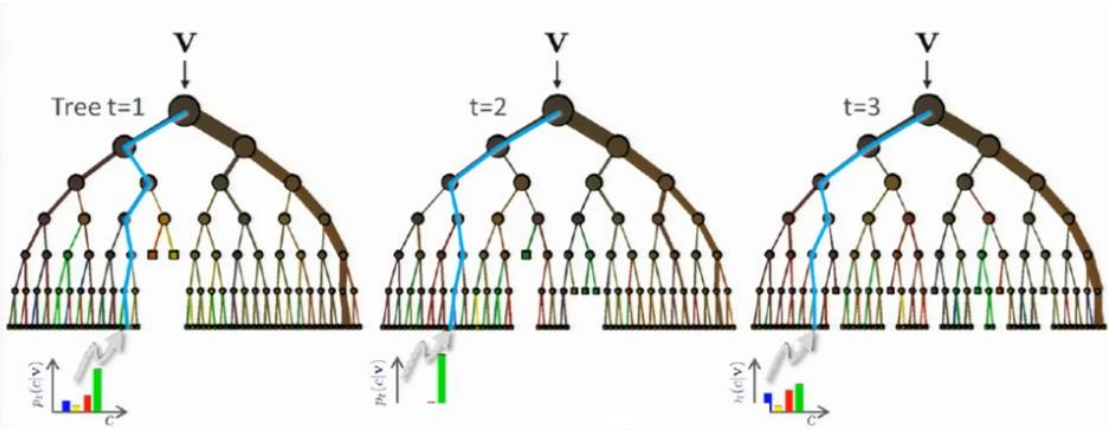


Fig. 4.3. Illustration of the RF mechanism in general

4.3 Building a forest (ensemble)

Decision Forests. A forest consists of T trees we have $t \in \{1, \dots, T\}$. A feature vector is classified by descending each tree. This gives, for each tree, a path from the root to leaf, and a class distribution at the leaf. Figure 4.4 shows how to simultaneously exploit both the hierarchical clustering implicit in the tree structure and the node class distributions. (Freitas, 2013).



$$p(c|\mathbf{v}) = \frac{1}{T}\sum_{t=1}^{T} p_t(c|\mathbf{v})$$

Fig. 4.4. Showes building a Random Forest

4.4 Random Forest algorithm

The accuracy of the classification decision is obtained by voting from the individual classifiers in the ensemble. The common element in all of these steps is that the number of b tree and a random vector (Sb) using bootstrap sample are generated independent of the past random vectors but with the same distribution, and a tree is grown using the training set and Sb. The random forests algorithm is shown in Algorithm 4.1 (Basha and Jahangeer, 2014).

Algorithm 4.1. Random Forest algorithm

Input: S: training sample
f: number of input instance to be used at each of the tree
B: number of generated trees in random forest
1) E is empty
2) for b=1 to B
3) Sb = bootstrapSample(S)
4) Cb = BuildRandomTreeClassifiers(Sb,f)
5) E=E ∪ {Cb}
6) next b
7) return E

4.5 Random Forest advantages

1. Straightforward Learning. The random sampling of features does not impose any explicit template or model. A generic algorithm learns characteristics directly from the training data.

2. Local Representation. The randomly sampled features directly analyze the image region without explicitly extracting geometric primitives such as edges.

3. Classification with Occlusion. approaches that use random forests are able to classify and detect partially occluded objects since not all the sampled regions need to be accurately classified. The voting procedure allows for a few sampled sub-windows to be falsely classified.

4. Parallelization. Because of the independent training of random trees, parallel architectures can be used to grow each tree of a random forest.

5. Fast Training Time. Breiman discusses the fast training time of random forests. As random features are selected, no computational time is spent on searching for the most discriminative attribute. Thus, at each node only a single decision criterion is instantiated.

6. Comparable Accuracy. Breiman also discusses that random forests perform favorably in comparison to adaptive boosting based approaches. This is attributed to the fact that multiple classifiers are built, each with decent classification accuracy.

7. Low Generalization Error. The generalization error tends to a limit as the number of random trees grown increases.

8. An integrated approach for tasks. Creating a collection of learned features and querying them is a part of the same framework. This factor is influential in presenting a unified approach to detection and recognition.

4.6 Random Forest disadvantages

- Random forests have been observed to over fit for some datasets with noisy classification/regression tasks.
- Unlike decision trees, the classifications made by random forests are difficult for humans to interpret.
- For data including categorical variables with a different number of levels, random forests are biased in favor of those attributes with more levels. Therefore, the variable importance scores from the random forest are not reliable for this type of data. Methods such as partial permutations were used to solve the problem.
- If the data contain groups of correlated features of similar relevance for the output, then smaller groups are favored over larger groups.

Chapter 5

Research Methodology

This chapter presents research methodology in which how to preprocess the data, how to train the gender detector classifier and to choose the final model, how to test face detector framework, how to use Viola-Jones object detection framework, how to slide window technique, and results in discussion and analysis.

Following the (chapter 2), Local Binary Pattern (LBP) was chosen for extracting features, and Random Forest (RF) was used as a classifier to build the model. As illustrated in figure 5.1, the research plan can be described as:

- Preprocessing the data.
- Training the gender detector classifier and choosing the final model.
- Testing and conclusion.

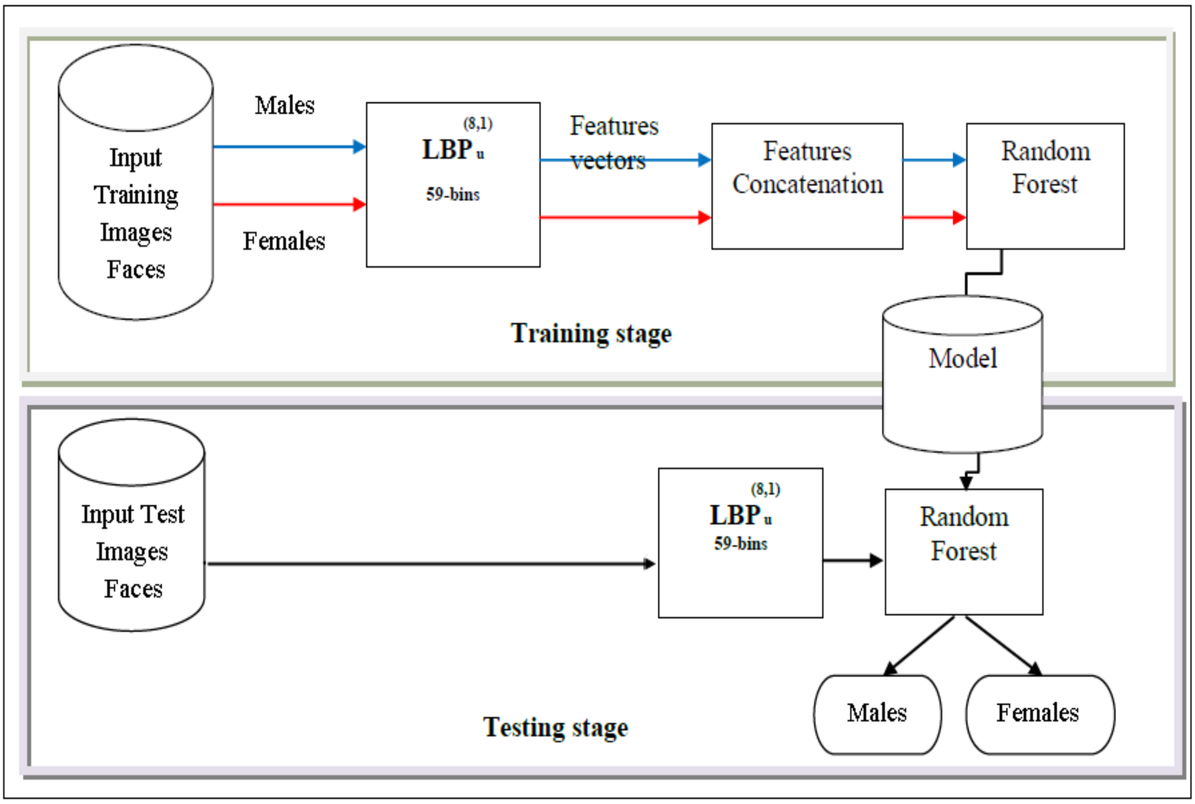


Fig. 5.1. Gender Detection scheme

5.1 Preprocessing the data

The initial process before the training begins is to transform the input training dataset into a format that can be used by the RF, the target format must be a vector of integer numbers. First of all, the images are resized to 32×32 pixels, then it is converted to a grayscale image. After that, for every single image, we extract the LBP histogram which is only 59 bins vector. The same steps are applied to male and female images. Finally, concatenate all the vectors for male and female training data in a single matrix, which is the input to the Random Forest.

5.2 Training the gender detector classifier and choosing the final model

After getting the right input format, the classifier must be trained to get the appropriate model for the testing phase. Training phase starts by entering the input training data extracted from the LBP features into RF classifier and changing the number of trees along with the number of males/females samples, where the model selection depends largely on the amount of training data, and the number of trees in the forest (classifier). Having the proper values of these parameters is essential to obtain good classification results. The model with the best TP value is the appropriate one.

5.3 Gender detector testing framework

For the purpose of the testing classifier, entering the input testing data extracted from the LBP features and also entered the database model that has been trained into RF predict classifier with changing the number of trees (100 / 50) to compare the results, thus obtaining the required classification either male or female. It should report the test results including accuracy and error rate. See figure 5.2.

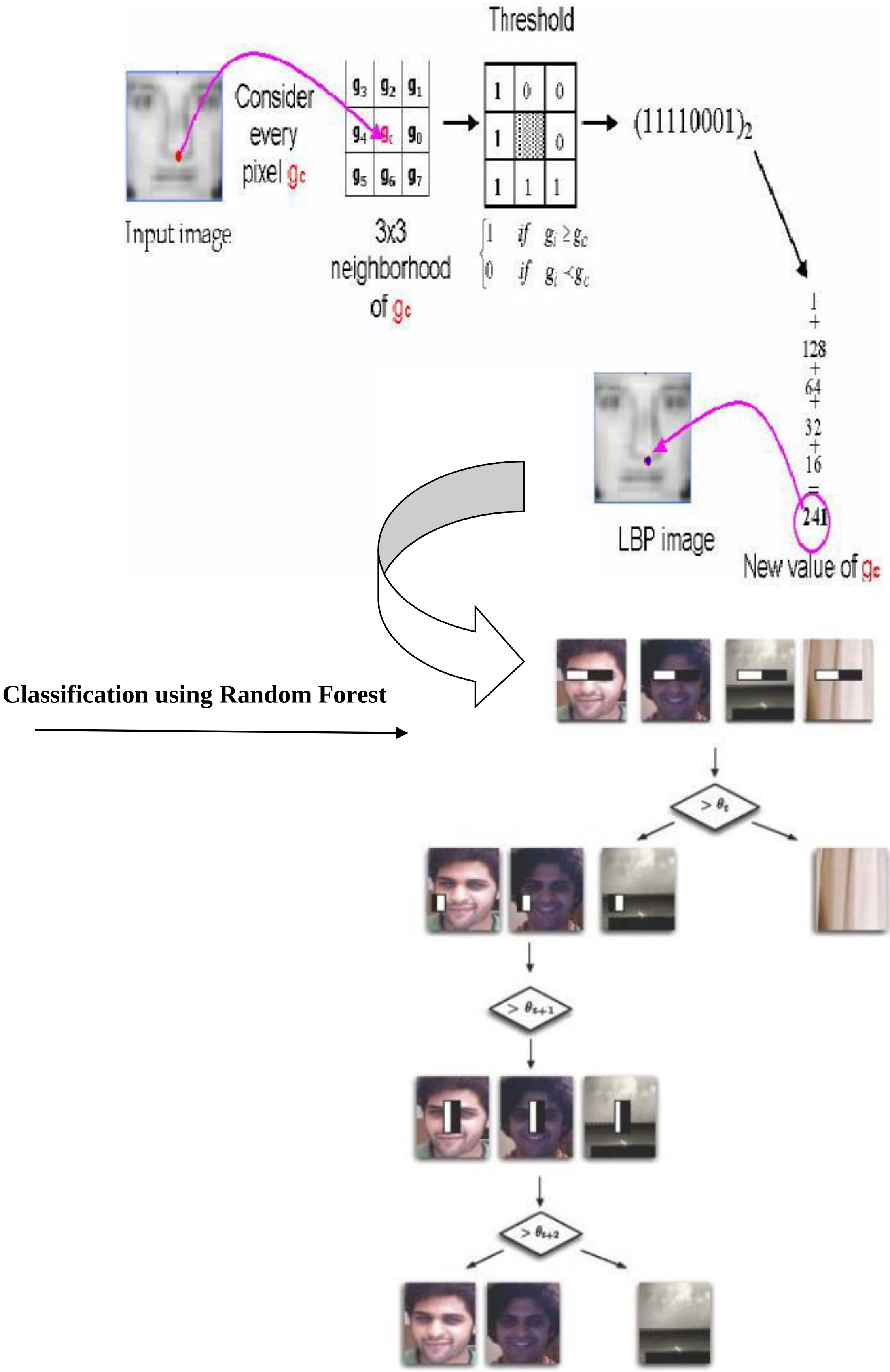


Fig. 5.2. Example of using LBP and Random Forests techniques in gender detection system

5.4 Viola-Jones object detection framework

The Viola-Jones object detection framework is the first object detection framework to provide competitive object detection rates in real-time proposed in 2001 by Paul Viola and Michael Jones. Although it can be trained to detect a variety of object classes, it was motivated primarily by the problem of face detection(Viola and Jones, 2001).

The characteristics of a Viola-Jones algorithm which make it a good detection algorithm are:

- Robust – very high detection rate (true-positive rate) & very low false-positive rate always.
- Real-time – For practical applications at least 2 frames per second must be processed.
- Face detection only (not recognition) - The goal is to distinguish faces from non-faces (detection is the first step in the recognition process).

The algorithm has four stages:

1. Haar Feature Selection
2. Creating an Integral Image
3. Adaboost Training
4. Cascading Classifiers

5.5 Sliding window technique

The input image is scanned for a face filter using a sliding window applied to different image scales. As a result, faces can be detected at different locations and degrees of images. The following parameters describe the scanning method and should be selected as a trade-off between the accuracy of the face detector and the speed of the algorithm:

Block size: A square or rectangular block that specifies the accuracy of the face detector, in my system is 32 x 32.

Moving the scan step: the number of pixels that define the sliding window step to get the analysis of each block following, which is 4.

Down-sampling rate: The scale factor down for the metering technique to reach all sites and measurements in an image is 1.

Note that when looking at high-resolution images, using a small sampling rate and a small moving step can significantly slow down the face detection algorithm. See figure 5.3.

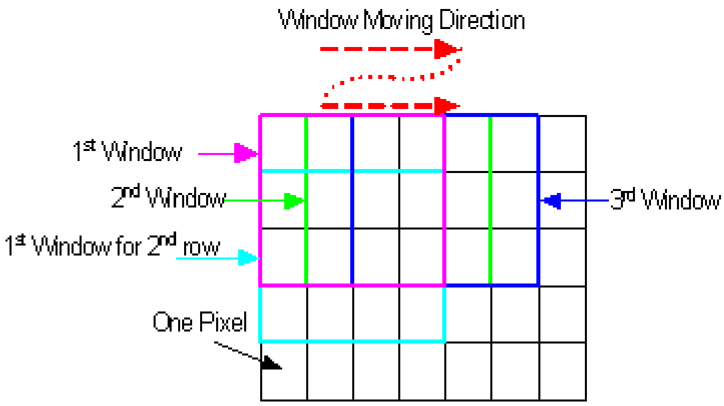


Fig. 5.3. Example of Sliding window technique

5.6 Results and Discussion

Different types of databases were used: ORL database, FEI database, LFW database, Jaffe database, and CUHK database. Each database was treated separately and obtained results, and then merged two databases with some, then three, and so on to get different results and compare them together and find out which results were better using Matlab. Some of these databases have gone through two phases. The first phase is to change the size of the images to 32 x 32 and apply the LBP and RF with changing the number of trees (100 / 50) as described in sections (5.1, 5.2, 5.3), and thus we get the results of classification (TP, FN) explained in chapter 4. The second phase is to deal with the images at their original size with use the Viola-Jones and Sliding Window algorithms and then apply the LBP and RF with changing the number of trees (100 / 50) as described in section (5.2, 5.3), and get the results required for the classification, see figure 5.4 an example of a second phase is illustrated.

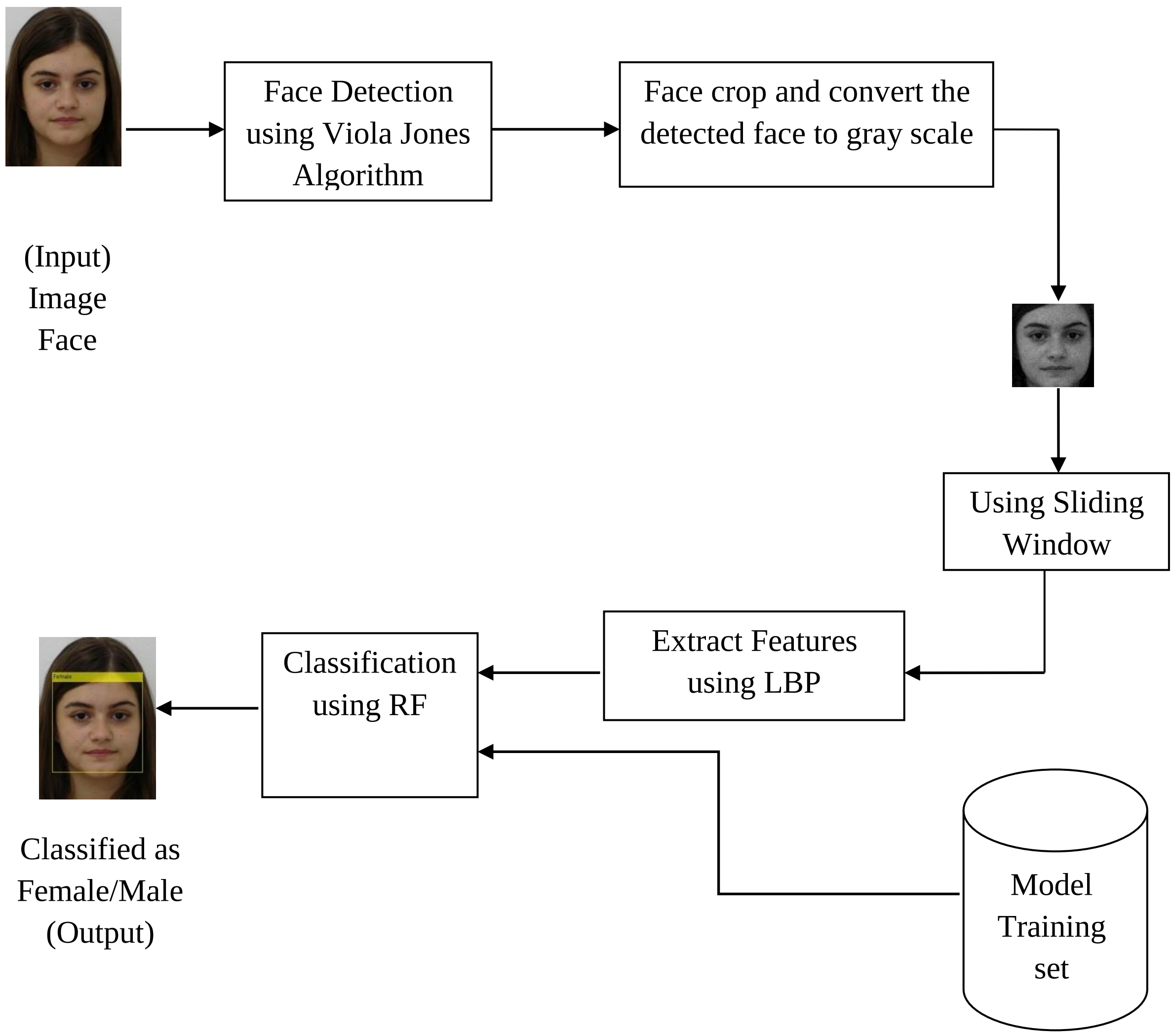


Fig. 5.4. A diagram to illustrate a face image to test for gender detection

The databases used and the mechanism of work is presented below:

- **ORL database**

contains a set of face images taken between April 1992 and April 1994 at the lab. The database was used in the context of a face recognition project carried out in collaboration with the Speech, Vision and Robotics Group of the Cambridge University Engineering Department. There are ten different images of each of 40 distinct subjects. For some subjects, the images were taken at different times, varying the lighting, facial expressions (open/closed eyes, smiling / not smiling) and facial details (glasses / no glasses). All the images were taken against a dark homogeneous background with the subjects in an upright, frontal position (with tolerance for some side movement). A preview image of the Database of Faces is available. The files are in PGM format, and can conveniently be viewed on UNIX (TM) systems using the 'xv' program. The size of each image is 92x112 pixels, with 256 grey levels per pixel. See figure 5.5

Fig. 5.5. ORL database samples

The following are the phases in which images were applied:

Phase one: Images size 32 x 32 and the following table 5.1 shows the results we have obtained, as well as the time which is taken to implement, with changes in the number of trees.

Table 5.1. Test results for different males/females samples ORL database

Models	Training data		Testing data		No. of trees	TP	FN
	No. of Males +	No. of Females times	No. of Males +	No. of Females times			
ORL database	180	30	180	10	100	95.79	0.04
	LBP/2.73 seconds		LBP/2.35 seconds				
	RF/4.16 seconds		RF/1.29 seconds				
ORL database	180	30	180	10	50	95.79	0.04
	RF/ 1.66 seconds		RF/0.77 seconds				

Phase two: Images at their original size with the use of Viola Jones and Sliding Window algorithms, the next table 5.2 shows the results that we have obtained, as well as the time is taken to implement, with changes in the number of trees.

Table 5.2. Test results for different males/females samples ORL database with use sliding window& Viola Jones algorithms

Models	Training data		Testing data		No. of trees	TP	FN
	No. of Males +	No. of Females times	No. of Males +	No. of Females times			
ORL database	2880	480	2880	160	100	95.9	0.04
	LBP/18.46 seconds RF/25.16 seconds		LBP/15.16 seconds RF/2.44 seconds				
ORL database	2880	480	2880	160	50	95.8	0.041
	RF/16.48 seconds		RF/1.79 seconds				

- **FEI database**

The FEI face database is a Brazilian face database that contains a set of face images taken between June 2005 and March 2006 at the Artificial Intelligence Laboratory of FEI in Sao Bernardo do Campo, Sao Paulo, Brazil. There are 200 images individuals, a total of 2800 images. All images are colorful and taken against a white homogenous background in an upright frontal position with profile rotation of up to about 180 degrees. The scale might vary about 10% and the original size of each image is 260x360 pixels. All faces are mainly represented by students and staff at FEI, between 19 and 40 years old with a distinct appearance, hairstyle, and adorns. That consists of 60 female and 140 male, colored frontal facial images, with each subject. See figure 5.6.

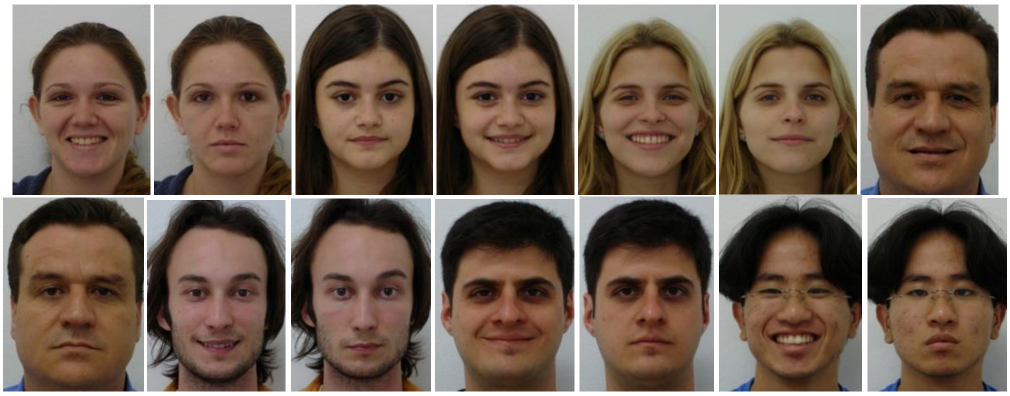


Fig. 5.6. FEI database samples

The following are the phases in which images were applied:

Phase one: Images size 32 x 32 and the following table 5.3 shows the results we have obtained, as well as the time, which taken to implement and changes in the number of trees.

Table 5.3. Test results for different males/females samples FEI database

Models	Training data		Testing data		No. of trees	TP	FN
	No. of Males +	No. of Females times	No. of Males +	No. of Females times			
FEI database	70	50	70	10	100	85	0.15
	LBP/ 1.72 seconds		LBP/1.29 seconds				
	RF/ 2.59 seconds		RF/ 1.11 seconds				
FEI database	70	50	70	10	50	83.75	0.16
	RF/1.88 seconds		RF/0.78 seconds				

Phase two: Images at their original size with the use of Viola Jones and Sliding Window algorithms, the next table 5.4 shows the results that we have obtained, as well as the time is taken to implement, with changes in the number of trees.

Table 5.4. Test results for different males/females samples FEI database with use sliding window& Viola Jones algorithms

Models	Training data		Testing data		No. of trees	TP	FN
	No. of Males +	No. of Females times	No. of Males +	No. of Females times			
FEI database	4060	2900	4060	580	100	77.3	0.22
	LBP/47.76 seconds RF/81.36 seconds		LBP/32.31 seconds RF/5.26 seconds				
FEI database	4060	2900	4060	580	50	76.9	0.23
	RF/41.42 seconds		RF/3.44 seconds				

- **LFW database**

Labeled Faces in the Wild (LFW) database, the database contains more than 13,000 images of faces collected from the web. Each face has been labeled with the name of the person pictured. 1680 of the people pictured have two or more distinct photos in the data set. In this research, a total of 983 images were taken from the total number of images randomly and was used a cropped LFW (CLFW) database, then each face is aligned to fill 32 × 32 in training and testing stages, see figure 5.7.

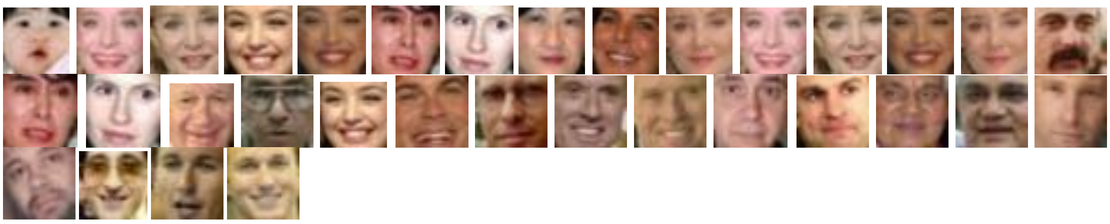


Fig. 5.7. LFW database samples

The following table 5.5 shows the results we have obtained, as well as the time, is taken to implement, and changes in the number of trees.

Table 5.5. Test results for different males/females samples LFW database

Models	Training data		Testing data		No. of trees	TP	FN
	No. of Males +	No. of Females times	No. of Males +	No. of Females times			
LFW database	431	122	400	30	100	93.02	0.07
	LBP/7.43 seconds RF/ 5.70 seconds		LBP/5.43 seconds RF/1.33 seconds				
LFW database	431	122	400	30	50	93.02	0.07
	RF/3.45 seconds		RF/ 0.82 seconds				

- **Japanese Female Facial Expression (JAFFE) Database**

The database contains 213 images vary between 20 and 23 facial expressions posed by 10 Japanese female models. The size of each image is 256x256 pixels, with 256 grey levels, see figure 5.8.

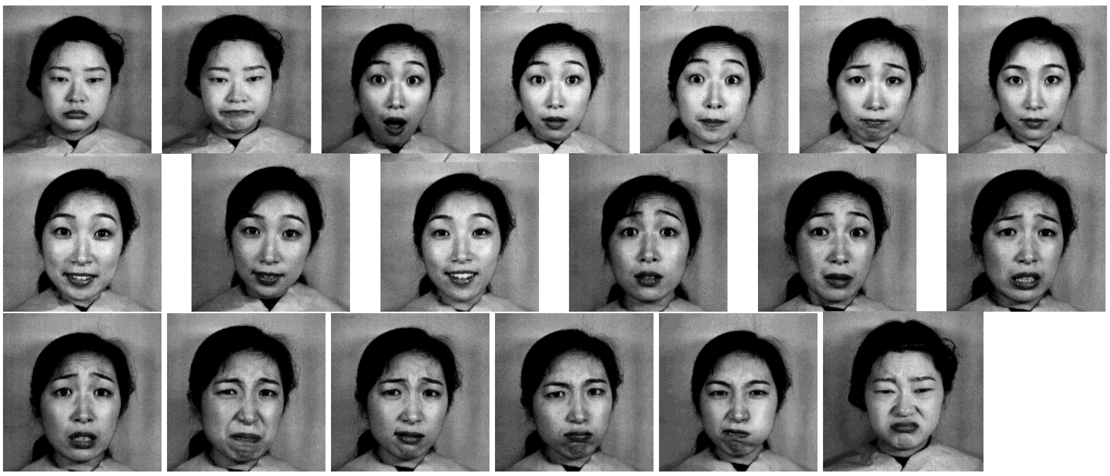


Fig. 5.8. Jaffe database samples

The following tables (5.6, and 5.7) show the results we have obtained by using the second phase which is to deal with images at their original size with the use of Viola Jones and Sliding Window algorithms, as well as the time is taken to implement, with changes the number of trees.

Table 5.6. Test results for different males/females samples Jaffe + ORL database with use sliding window& Viola Jones algorithms

Models	Training data		Testing data		No. of trees	TP	FN
	No. of Males +	No. of Females times	No. of Males +	No. of Females times			
Jaffe +ORL database	2880	2280	2880	2280	100	99.81	0.0019
	LBP/29.42 seconds RF/39.89 seconds		LBP/28.53 seconds RF/2.82 seconds				
Jaffe +ORL database	2880	2280	2880	2280	50	99.83	0.0017
	RF/25.48 seconds		RF/2.16 seconds				

Table 5.7. Test results for different males/females samples Jaffe + FEI database with use sliding window& Viola Jones algorithms

Models	Training data		Testing data		No. of trees	TP	FN
	No. of Males +	No. of Females times	No. of Males +	No. of Females times			
Jaffe + FEI database	4060	2280	4060	2280	100	99.89	0.0011
	LBP/43.63 seconds RF/60.54 seconds		LBP/48.89 seconds RF/4.04 seconds				
Jaffe + FEI database	4060	2280	4060	2280	50	99.87	0.0012
	RF/35.36 seconds		RF/2.55 seconds				

- **CUHK Face Sketch database**

Is for research on face sketch synthesis and face sketch recognition. It includes 188 faces from the Chinese University of Hong Kong (CUHK) student database. the original size of each image is 200 x 250 pixels, see figure 5.9.

Fig. 5.9. CUHK database samples

The following table 5.8 shows the results we have obtained by using the second phase that deals with images at their original size with the use of Viola Jones and Sliding Window algorithms, as well as the time is taken to implement, with changes the number of trees.

Table 5.8. Test results for different males/females sample CUHK database with use sliding window& Viola Jones algorithms

<table>
<tr><th rowspan="2">Models</th><th colspan="2">Training data</th><th colspan="2">Testing data</th><th rowspan="2">No. of trees</th><th rowspan="2">TP</th><th rowspan="2">FN</th></tr>
<tr><th>No. of Males +</th><th>No. of Females times</th><th>No. of Males +</th><th>No. of Females times</th></tr>
<tr><td rowspan="2">CUHK database</td><td>2408</td><td>1376</td><td>3440</td><td>860</td><td rowspan="2">100</td><td rowspan="2">76.25</td><td rowspan="2">0.237</td></tr>
<tr><td colspan="2">LBP/29.97 seconds
RF/37.99 seconds</td><td colspan="2">LBP/35.08 seconds
RF/3.45 seconds</td></tr>
<tr><td rowspan="2">CUHK database</td><td>2408</td><td>1376</td><td>3440</td><td>860</td><td rowspan="2">50</td><td rowspan="2">76.18</td><td rowspan="2">0.238</td></tr>
<tr><td colspan="2">RF/19.84 seconds</td><td colspan="2">RF/2.22 seconds</td></tr>
</table>

The following tables (5.9, 5.10,5.11, and 5.12) explain how to merge some databases together and compare results:

Table 5.9. Test results for different males/females samples LFW + ORL database size 32x 32

Models	Training data		Testing data		No. of trees	TP	FN
	No. of Males +	No. of Females times	No. of Males +	No. of Females times			
LFW + ORL databases	611	152	580	40	100	93.09	0.07
	LBP/ 8.98 seconds RF/7.03 seconds		LBP/8.77 seconds RF/1.53 seconds				
LFW + ORL databases	611	152	580	40	50	93.2	0.07
	RF/ 4.05 seconds		RF/0.83 seconds				

Table 5.10. Test results for different males/females samples LFW + FEI database size 32x 32

Models	Training data		Testing data		No. of trees	TP	FN
	No. of Males +	No. of Females times	No. of Males +	No. of Females times			
LFW + FEI databases	501	172	470	40	100	90.98	0.09
	LBP/7.86 seconds RF/6.87 seconds		LBP/ 7.41 seconds RF/1.58 seconds				
LFW + FEI databases	501	172	470	40	50	90.98	0.09
	RF/3.87 seconds		RF/0.80 seconds				

Table 5.11. Test results for different males/females samples ORL + FEI database size 32x 32

Models	Training data		Testing data		No. of trees	TP	FN
	No. of Males +	No. of Females times	No. of Males +	No. of Females times			
ORL+FEI databases	250	80	250	20	100	90	0.10
	LBP/4.23 seconds		LBP/ 3.38 seconds				
	RF/4.27 seconds		RF/1.33 seconds				
ORL+FEI databases	250	80	250	20	50	90	0.10
	RF/2.31 seconds		RF/ 0.76 seconds				

Table 5.12. Test results for different males/females samples LFW + ORL + FEI database size 32x 32

Models	Training data		Testing data		No. of trees	TP	FN
	No. of Males +	No. of Females times	No. of Males +	No. of Females times			
LFW + ORL+FEI databases	681	202	650	50	100	93	0.07
	LBP/12.00 seconds		LBP/9.43 seconds				
	RF/8.74 seconds		RF/1.55 seconds				
LFW + ORL+FEI databases	681	202	650	50	50	92	0.08
	RF/4.69 seconds		RF/0.95 seconds				

5.7 Results and analysis

The results obtained from the databases used in this study were based on performance evaluation criteria, explained in detail in chapter 4, (No. of trees, TP, FN), as shown in section 5.6 in the tables from table 5.1 to table 5.12. Each standard is explained in detail below:

- **No. of trees**

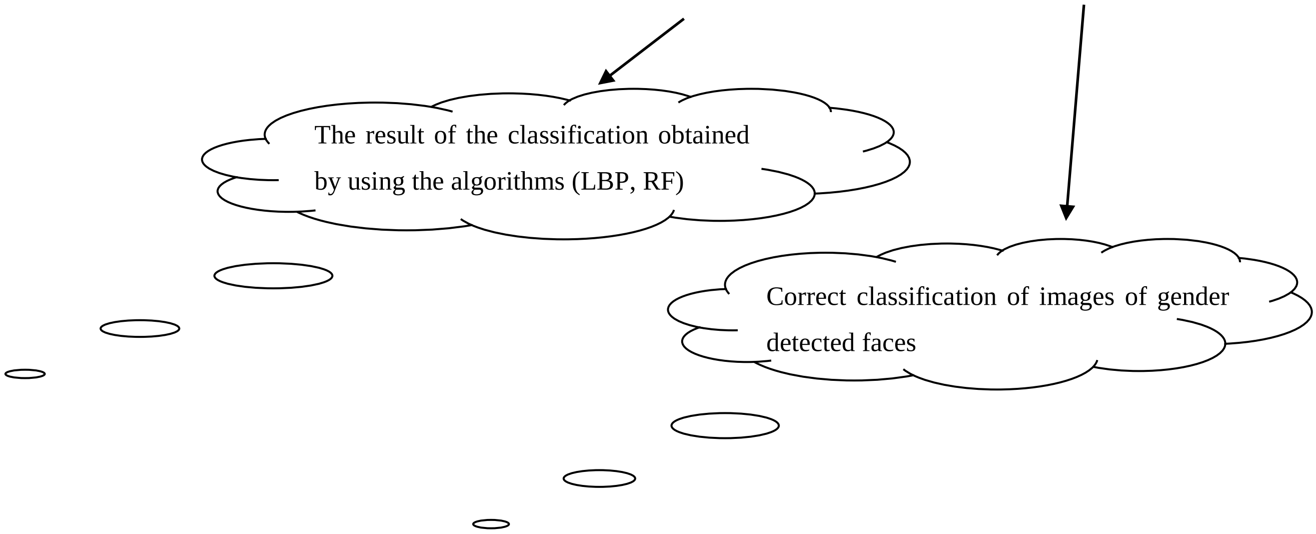
Random forest is a collection of decision trees that classification depends primarily on the number of trees and thus increase or decrease their number affects the results. In most of the databases we used in this research, the greater the number of trees the better results are given as shown in section 5.6 in tables: 5.2, 5.4, 5.7, 5.8, 5.12. In some databases, the fewer trees, the better results are also shown in section 5.6 in tables: 5.3, 5.6, 5.9. And some of the databases are getting the same result with the same number of trees, as shown in section 5.6 in tables: 5.1, 5.5, 5.10, 5.11.

- **FN (Fouls Negative)**

To measure the wrong classification of the image of gender detected faces. The closer the result to zero, the better.

Were measured using the following equation:

Error rate = length (find (predictedClass ~= classX)) / length (classX)



For a detailed explanation, see table 5.3 in Section 5.6. Note that when the number of males + females images in the test data = 80, and the number of trees = 100, was the result of the error ratio = 0.15, and when the number of trees = 50, the result was 0.16.

- **TP (True Positive)**

To measure the correct classification of gender detected faces. The closer the result to the 100 the better.

Were measured using the following equation:

Correct rate = (X) / length (featuresVectorX) * 100

The number of images of faces that have been classified correctly

The total number of testing images of gender detection

X = length(featuresVectorX) - X_Errors

The number of images of faces that have been

X_Errors = length(featuresVectorX) * Error rate

See table 5.3 in section 5.6 and following is an example that explains in detail how to get **TP**.

featuresVectorX = 80

No. of trees = 100

Error rate = 0.15

X_Error = 80 * 0.15 = 12

X = 80 – 12 = 68

Correct rate = (68 / 80) * 100 = 0.85 * 100 = 85 %

Chapter 6

Conclusion and Future work

6.1 Conclusion

In this research, the best suggestions were offered to detect a person's gender through the front face image. The technique of extracting LBP features and RF classification was used, as well as the technique of Viola-Jones and the sliding window to reveal the face, get the results and compare them. These techniques were applied to different databases: ORL database, FEI database, LFW database, Jaffe database, and CUHK database. We obtained different results from TP, FN, these databases have gone through two phases: The first phase without using Viola-Jones and sliding window and the results were as follows: The ORL database gave the best accuracy at 95.79% and the lowest error rate is 0.04 followed by the LFW database where it gave 93.02% accuracy and error rate is 0.07, FEI with 85% accuracy and 0.15 error rate. The second phase using Viola Jones and sliding window, the results were as follows: The Jaffe database gave the best accuracy 99.89% and the lowest error rate is 0.0011 followed by the ORL database where it gave 95.9% accuracy and 0.04 error rate, FEI database at 77.3% accuracy and 0.22 error rate, CUHK database at 76.25% accuracy and 0.237 error rate.

6.2 Future work

In future work, first of all, creating a database for the research, using the camera to develop work on video data, and using different classification techniques. Also using another programming language such as Python. Moreover, the techniques used in the research can also be used to detect age through the same frontal face image as used in gender detection. Also apply the Viola Jones algorithm to capture a group image (multi-faces) and determine the number of males and females. Finally, this study helps to generalize the detection concept to other objects of still images.

REFERENCES

1. Ahonen, T., Matas, J., He, C., & Pietikäinen, M. (2009, June). "Rotation invariant image description with local binary pattern histogram Fourier features". In *Scandinavian Conference on Image Analysis* (pp. 61-70). Springer, Berlin, Heidelberg.
2. Al Mashagba, E. F. (2016). "Real-Time Gender Classification by Face". *INTERNATIONAL JOURNAL OF ADVANCED COMPUTER SCIENCE AND APPLICATIONS*, *7*(3), 332-336.
3. Alpaydin, E. (2014). *Introduction to machine learning*. MIT press.
4. Bai, G., Zhu, Y., & Ding, Z. (2008, May). "A hierarchical face recognition method based on local binary pattern". In *Image and Signal Processing, 2008. CISP'08. Congress on* (Vol. 2, pp. 610-614). IEEE.
5. Basha, A. F., & Jahangeer, G. S. B. (2014). "Exploring a novel method for face image gender Classification using Random Forest and comparing with other Machine Learning Techniques". *International Journal of Computer Science Issues (IJCSI)*, *11*(6), 8.
6. Castrillón-Santana, M., Lorenzo-Navarro, J., & Ramón-Balmaseda, E. (2017). "Descriptors and regions of interest fusion for in-and cross-database gender classification in the wild". *Image and Vision Computing*, *57*, 15-24.
7. Chen, C., & Ross, A. (2011, October). "Evaluation of gender classification methods on thermal and near-infrared face images". In *Biometrics (IJCB), 2011 International Joint Conference on* (pp. 1-8). IEEE.
8. Cutler, D. R., Edwards, T. C., Beard, K. H., Cutler, A., Hess, K. T., Gibson, J., & Lawler, J. J. (2007). "Random forests for classification in ecology". *Ecology*, *88*(11), 2783-2792.
9. Fehr, J. (2007). "Rotational invariant uniform local binary patterns for full 3D volume texture analysis". In *Finnish signal processing symposium (FINSIG).*
10. Freitas, N. D. (2013, February). " Machine learning - Random forests". UBC, Computer Science, CPSC 540.
11. Guo, Z., Zhang, L., & Zhang, D. (2010). "A completed modeling of local binary pattern operator for texture classification". *IEEE Transactions on Image Processing*, *19*(6), 1657-1663.

12. Gupta, S. (2015). "Gender Detection using Machine Learning Techniques and Delaunay Triangulation". *International Journal of Computer Applications*, *124*(6).
13. Hadid, A., Pietikainen, M., & Ahonen, T. (2004, June). "A discriminative feature space for detecting and recognizing faces". In *Computer Vision and Pattern Recognition, 2004. CVPR 2004. Proceedings of the 2004 IEEE Computer Society Conference on*(Vol. 2, pp. II-II). IEEE.
14. He, L., Zou, C., Zhao, L., & Hu, D. (2006, January). "An enhanced LBP feature based on facial expression recognition". In *Engineering in Medicine and Biology Society, 2005. IEEE-EMBS 2005. 27th Annual International Conference of the* (pp. 3300-3303). IEEE.
15. Huang, D., Shan, C., Ardabilian, M., Wang, Y., & Chen, L. (2011). "Local binary patterns and its application to facial image analysis: a survey". *IEEE Transactions on Systems, Man, and Cybernetics*, *Part C (Applications and Reviews)*, *41*(6), 765-781.
16. Huang, D., Wang, Y., & Wang, Y. (2007, November). "A robust method for near-infrared face recognition based on extended local binary pattern". In *International Symposium on Visual Computing* (pp. 437-446). Springer, Berlin, Heidelberg.
17. Huang, Y., Wang, Y., & Tan, T. (2006, September). "Combining Statistics of Geometrical and Correlative Features for 3D Face Recognition". In *BMVC* (pp. 879-888).
18. Jin, H., Liu, Q., Lu, H., & Tong, X. (2004, December). "Face detection using improved LBP under Bayesian framework". In *Image and Graphics (ICIG'04), Third International Conference on*(pp. 306-309). IEEE.
19. Jones, M. J., & Viola, P. (2001, February). "Robust real-time object detection". In *Workshop on statistical and computational theories of vision* (Vol. 266, p. 56).
20. Lei, Z., Liao, S., He, R., Pietikainen, M., & Li, S. Z. (2008, September). "Gabor volume based local binary pattern for face representation and recognition". In *Automatic Face & Gesture Recognition, 2008. FG'08. 8th IEEE International Conference on*(pp. 1-6). IEEE.
21. Liu, X., Song, M., Tao, D., Liu, Z., Zhang, L., Chen, C., & Bu, J. (2013, June). "Semi-supervised node splitting for random forest construction".

In *Computer Vision and Pattern Recognition (CVPR), 2013 IEEE Conference on* (pp. 492-499). IEEE.

22. Louis, W., & Plataniotis, K. N. (2010, September). "Frontal face detection for surveillance purposes using dual Local Binary Patterns features". In *Image Processing (ICIP), 2010 17th IEEE International Conference on* (pp. 3809-3812). IEEE.
23. Mirza, A. M., Hussain, M., Almuzaini, H., Muhammad, G., Aboalsamh, H., & Bebis, G. (2013, July). "Gender recognition using a fusion of local and global facial features". In *International Symposium on Visual Computing* (pp. 493-502). Springer, Berlin, Heidelberg.
24. Ojala, T., Pietikainen, M., & Maenpaa, T. (2002). "Multiresolution gray-scale and rotation invariant texture classification with local binary patterns". *IEEE Transactions on pattern analysis and machine intelligence*, *24*(7), 971-987.
25. Paulhac, L., Makris, P., & Ramel, J. Y. (2008, June). "Comparison between 2D and 3D local binary pattern methods for characterization of three-dimensional textures". In *International Conference Image Analysis and Recognition* (pp. 670-679). Springer, Berlin, Heidelberg.
26. Pietikäinen, M., Hadid, A., Zhao, G., & Ahonen, T. (2011). "Local binary patterns for still images". In *Computer vision using local binary patterns* (pp. 13-47). Springer London.
27. Ruiz-del-Solar, J., & Quinteros, J. (2008). "Illumination compensation and normalization in eigenspace-based face recognition": A comparative study of different pre-processing approaches. *Pattern Recognition Letters*, *29*(14), 1966-1979.
28. Shan, S., Zhang, W., Su, Y., Chen, X., & Gao, W. (2006, August). "Ensemble of piecewise FDA based on spatial histograms of local (Gabor) binary patterns for face recognition". In *Pattern Recognition, 2006. ICPR 2006. 18th International Conference on* (Vol. 3). IEEE.
29. Singh, R., Vatsa, M., & Noore, A. (2008). "Integrated multilevel image fusion and match score fusion of visible and infrared face images for robust face recognition". *Pattern Recognition*, *41*(3), 880-893.
30. Tan, X., & Triggs, B. (2007, October). "Enhanced local texture feature sets for face recognition under difficult lighting conditions". In *International*

Workshop on Analysis and Modeling of Faces and Gestures (pp. 168-182). Springer, Berlin, Heidelberg.

31. Tan, X., & Triggs, B. (2007, October). "Fusing Gabor and LBP feature sets for kernel-based face recognition". In *International Workshop on Analysis and Modeling of Faces and Gestures* (pp. 235-249). Springer, Berlin, Heidelberg.
32. Verma, A., & Vig, L. (2014, September). "Using convolutional neural networks to discover cognitively validated features for gender classification". In *Soft Computing and Machine Intelligence (ISCMI), 2014 International Conference on* (pp. 33-37). IEEE.
33. Wang, X., & Kambhamettu, C. (2013, December). "Gender classification of depth images based on shape and texture analysis". In *Global Conference on Signal and Information Processing (GlobalSIP), 2013 IEEE* (pp. 1077-1080). IEEE.
34. Wu, Y., Zhuang, Y., Long, X., Lin, F., & Xu, W. (2015). "Human gender classification": A review. *arXiv preprint arXiv:1507.05122*.
35. Wolf, L., Hassner, T., & Taigman, Y. (2008, October). "Descriptor based methods in the wild". In *Workshop on faces in'real-life'images: Detection, alignment, and recognition*.
36. Yan, S., Wang, H., Tang, X., & Huang, T. (2007, April). "Exploring feature descriptors for face recognition". In *Acoustics, Speech and Signal Processing, 2007. ICASSP 2007. IEEE International Conference on* (Vol. 1, pp. I-629). IEEE.
37. Yang, H., & Wang, Y. (2007, August). "A LBP-based face recognition method with Hamming distance constraint". In *Image and Graphics, 2007. ICIG 2007. Fourth International Conference on* (pp. 645-649). IEEE.
38. Zhang, W., Shan, S., Gao, W., Chen, X., & Zhang, H. (2005, October). "Local Gabor binary pattern histogram sequence (LGBPHS)": a novel non-statistical model for face representation and recognition. In *Computer Vision, 2005. ICCV 2005. Tenth IEEE International Conference on* (Vol. 1, pp. 786-791). IEEE.

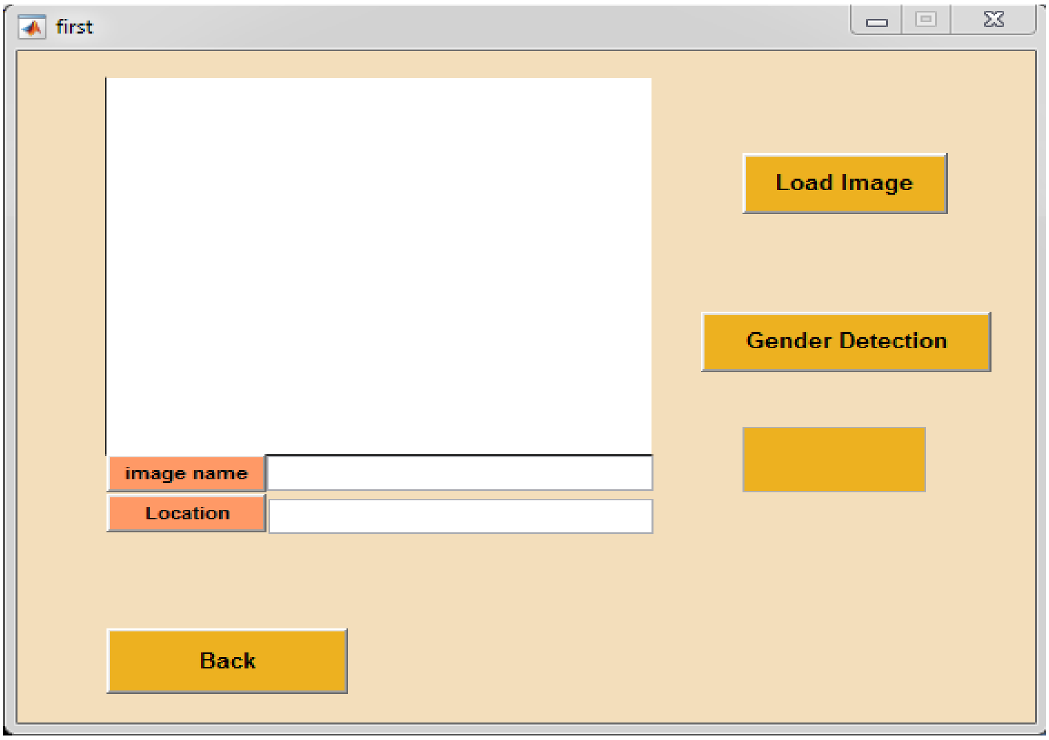
Appendix

Appendix A: Main Screen

It has two buttons, the close button and the start button when pressed, the second screen is entered.

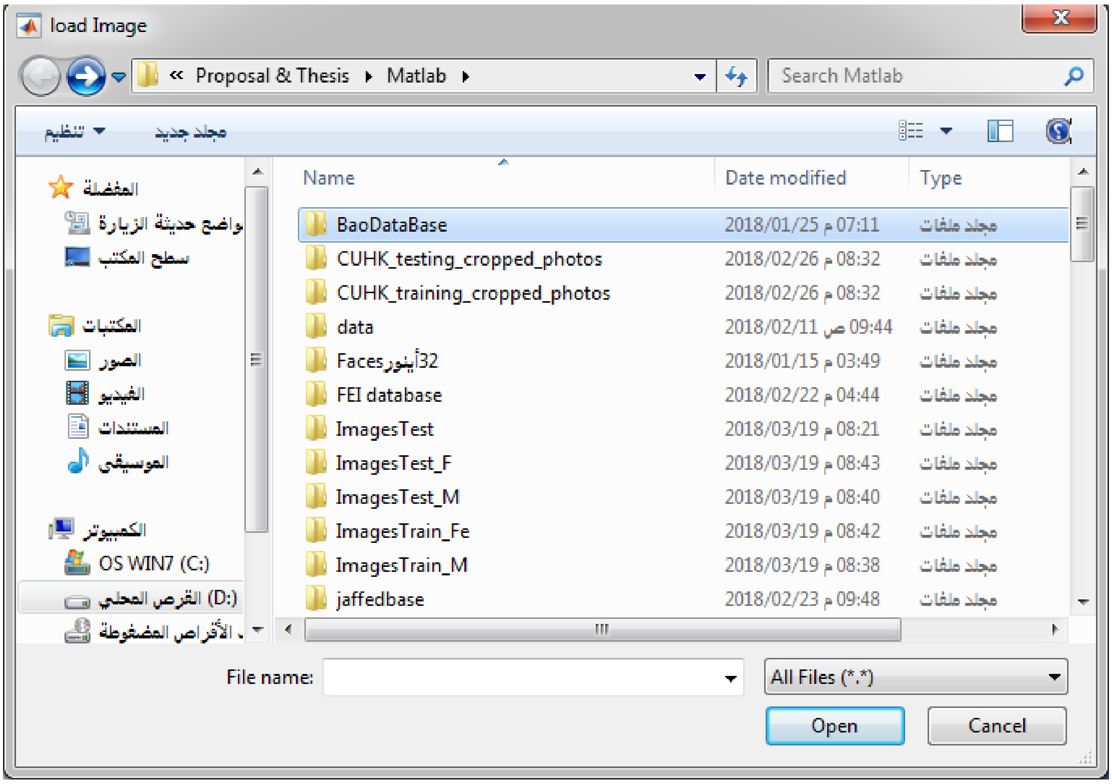
Appendix B: Load Image Screen

Contains the load image button, test button, image name button, location button, and back button for the home screen.



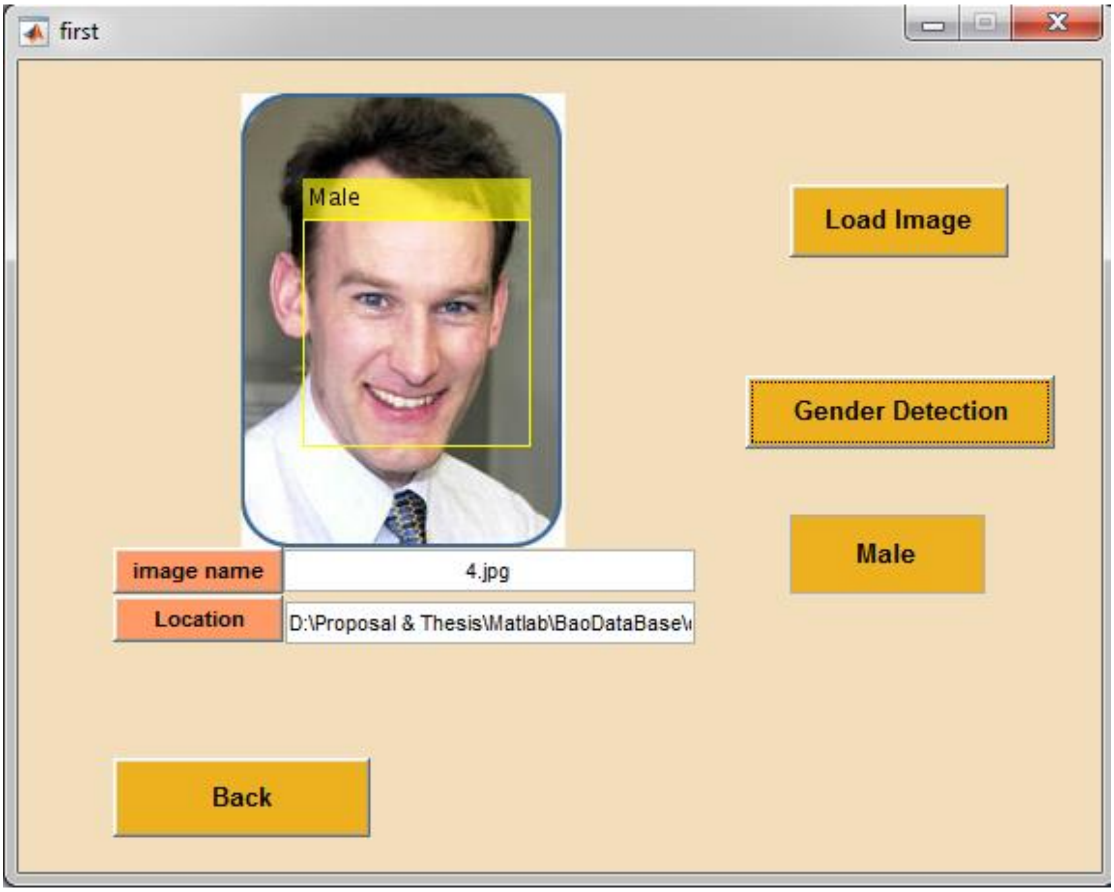
Appendix C: The image selection screen from the database

When the load image button is pressed, a set of files appears, including a file database you want to select an image to test, then select an image. This image is shown on the screen.



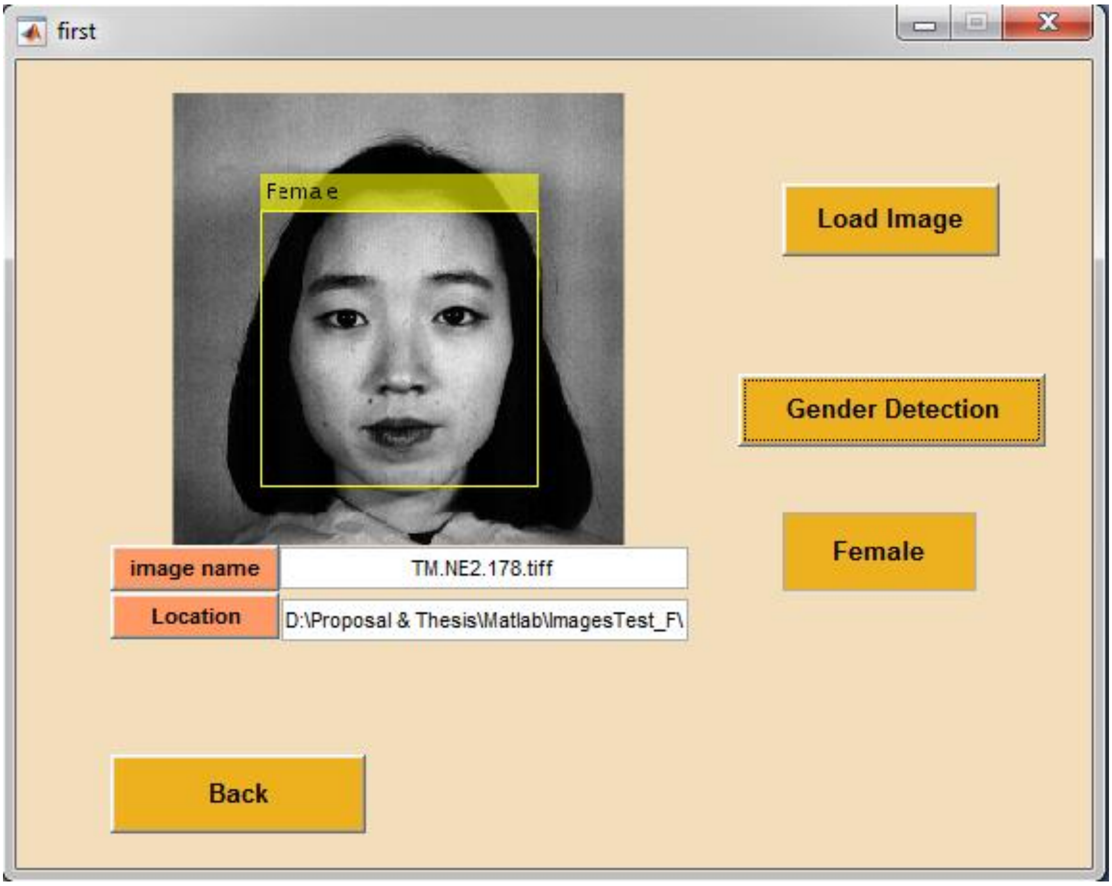
Appendix D: Screen Test Image Face Man

After the selection of the image, it is tested by pressing the button Gender Detection, it shows us the result of the test in the bottom button either male or female. It also shows us in two buttons the name and the location of the image.



Appendix E: Screen Test Image Face Female

After the selection of the image, it is tested by pressing the button Gender Detection, it shows us the result of the test in the bottom button either male or female. It also shows us in two buttons the name and the location of the image.



كشف الجنس من صور الوجه

اعداد

عز عمر السليماني

المشرف

د. أشرف سعد هويدي

الملخص

يستخدم التعلم الآلي اليوم على نطاق واسع في مختلف المجالات. على سبيل المثال، الأنظمة الاحتيالية، أنظمة الموصي بها، التنبؤات المستغلة والعديد من التطبيقات الأخرى. يتم استغلال أحد هذه التطبيقات في هذا البحث. يقدم هذا البحث مقاربة لاكتشاف جنس الشخص من خلال صورة الوجه الأمامية، باستخدام ميزات الاستخراج وتقنيات التصنيف. يمكن أن يكون التنبؤ بنوع الجنس طريقة مفيدة جدًا في أنظمة تفاعل الإنسان (HCI). كطريقة قوية للغاية لاستخراج البيانات، يتم استخدام التصنيف هنا لجمع بيانات الصف وتصنيف الجنس على أنه ذكر أو أنثى. لاستخراج ميزات البيانات، يتم استخدام النمط الثنائي المحلي (LBP)، في حين يتم استخدام خوارزمية الغابات العشوائية (RF) للتصنيف لقياس أقصى درجة من الدقة. تم استخدام نماذج قواعد بيانات مختلفة في هذا البحث: قاعدة بيانات ORL ، قاعدة بيانات FEI ، قاعدة بيانات LFW ، قاعدة بيانات Jaffe ، وقاعدة بيانات CUHK حيث أعطت قاعدة بيانات Jaffe مستوى عاليًا جدًا من الدقة وهو 99.89٪ في المقابل ، قاعدة بيانات CUHK التي أعطت مستوى أدنى من الدقة 76.25 ٪ مع الاستقرار النسبي. تفاصيل نموذج التنبؤ ونموذج النتائج يتم الإبلاغ عنها هنا.

كشف الجنس من صور الوجه

قدمت من قبل:

عز عمر السليماني

تحت إشراف:

د. أشرف هويدي

قدمت هذه الرسالة استكمالا لمتطلبات الحصول على درجة الماجستير في علوم الحاسوب

جامعة بنغازي

كلية تقنية المعلومات

يناير 2019