PREDICTING AGE AND GENDER OF PEOPLE BY USING IMAGE PROCESSING TECHNIQUES

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TARIQ ALHADI MOHAMAD KHALIFA

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PREDICTING AGE AND GENDER OF PEOPLE BY USING IMAGE PROCESSING TECHNIQUES

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Approval of the Graduate School of Natural and Applied Sciences, Atılım University.

Prof. Dr. İbrahim Akman

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I certify that this thesis satisfies all the requirements as a thesis for the degree of Master of Science.

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ABSTRACT

PREDICTING AGE AND GENDER OF PEOPLE BY USING IMAGE PROCESSING TECHNIQUES

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Predicting the gender and age of people from their facial images is still on-going and active research issue. Many methods have been proposed by researchers to solve this problem but still there is a deficiency between the requirements and veritable performances. In this thesis, a statistical pattern recognition approach is proposed to solve this problem. In the proposed solution, two feature extraction algorithms, Histogram of Oriented Gradient (HOG), and Local Binary Pattern (LBP) are used as the feature extractors. In order to attain efficient approaches of gender and age prediction, we combined both HOG and LBP features. In extensive and intensified experiments, Support Vector Machine (SVM) and K-Nearest Neighbour (KNN) are used for the classification process in addition to using Leave-One-Out (LOO) and Confusion Matrix (CM) techniques to evaluate the performance of these classifiers. In the pre-processing stage, dimensions alignment, which unifies all images' size; and Histogram Equalization (HE) technique, which normalizes the effects of illumination; have been applied on the images. The proposed method has been evaluated on three separate gender and age facial image databases, FERET, UTD, and FG-NET. The proposed method system shows that combining HOG and LBP features improved the gender predicting rate up to 100% and age predicting to 99.87%.

Keywords: Facial Images; Gender Prediction; Age Prediction; Local Binary Pattern; Histogram of Oriented Gradient.

ÖZ

GÖRÜNTÜ İŞLEME TEKNİKLERİ İLE İNSANLARIN YAŞ VE CINSIYETLERİNİN TAHMİNİ

Khalifa, Tariq Alhadi Mohamad

Yüksek Lisans, Bilgisayar Mühendisliği Bölümü

Tez Yöneticisi: Yrd. Doç. Dr. Gökhan Şengül

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Yüz görüntülerinden görüntüdeki kişinin cinsiyetini ve yaşını tahmin etme, henüz tam olarak çözülememiş aktif bir araştırma problemidir. Bu problemin çözümü için birçok araştırmacı tarafından farklı yöntemler önerilmiş olmakla birlikte beklenen gereksinimlerle elde edilen performans arasında farklılıklar bulunmaktadır. Bahsedilen bu probleme yönelik olarak bu tez çalışmasında istatistiksel örüntü tanıma tabanlı bir yöntem önerilmiştir. Önerilen yöntemde özellik çıkarıcı olarak HOG (Histogram of Oriented Gradient) ve LBP (Local Binary Pattern) yaklaşımları kullanılmıştır. Ayrıca daha iyi sonuçlar elde etmek üzere bu iki özellik çıkarıcının sonuçları birleştirilerek de kullanılmıştır. Sınıflandırıcı olarak ise SVM (Support Vector Machines) ve KNN (K-Nearest Neighbour) yaklaşımları izlenmiştir. Performans ölçümleri için ise Birini Dışarıda Bırakma ve Hata Matrisleri kullanılmıştır. Ön işleme olarak; tüm görüntü boyutlarını aynı yapmak ve hesaplama zamanını azaltmak üzere boyut indirgeme ve görüntülerdeki aydınlık farklılıklarını ortadan kaldırmak üzere histogram eşitleme işlemleri gerçekleştirilmiştir. Önerilen yöntem FERET, UTD ve FG-NET veritabanlarından elde edilen görüntüler üzerinde test edilmiştir. Sonuç olarak HOG ve LBP özellikleri birarada kullanıldığından cinsiyet tahmininde 100%, yaş aralığı tahmininde ise 99.87% başarı elde edilmiştir.

Anahtar Kelimeler: Yüz Görüntüleri; Cinsiyetini Tahmini; Yaş Tahmini; Local Binary Pattern; Histogram of Oriented Gradient.

To My Parents

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I express sincere appreciation to my supervisor Asst. Prof. Dr. Gokhan Sengul for his guidance and insight throughout the research. To my wife, Samar, I offer sincere thanks for her continuous support and patience during this period.

Last but not the least; I would like to thank my family, friends, and colleagues who have helped me directly or indirectly. They were always supporting and encouraging me with their best wishes.

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LIST OF ABBREVIATIONS

AAM	Active Appearance Model
AM	Anthropometric Models
APM	Appearance Model
ANN	Artificial Neural Networks
CH	Color Histogram
CM	Confusion Matrix
CDF	Cumulative Distribution Frequency
CS	Cumulative Score
DCT	Discrete Cosine Transformation
FFH	Feature Fusion Hierarchies
GWT	Gabor Wavelet Transformation
GMM	Gaussian Mixture Model
GA	Genetic Algorithm
HE	Histogram Equalization
HOG	Histograms of Oriented Gradients
ICA	Independent Component Analysis
KFDA	Kernel Fisher Discriminant Analysis
KNN	K-Nearest Neighbour
LFW	Labelled Faces in the Wild
LOO	Leave-One-Out Cross-validation
LDA	Linear Discriminant Analysis
LBP	Local Binary Pattern
LCP	Local Circular Patterns
LEA	Locally Embedded Analysis
MFA	Marginal Fisher Analysis
MAE	Mean Absolute Error
PCA	Principal Component Analysis

RBF	Radial Basis Function
ROI	Region of Interest
SIFT	Scale-Invariant Feature Transform
SOM	Self-Organizing Map
SFP	Spatially Flexible Patch
SVM	Support Vector Machine
FERET	The Facial Recognition Technology Database
UTD	The University of Texas at Dallas Database
WLD	Weber's Local Descriptor
YGA	YAMAHA Gender and Aging Database

CHAPTER 1

1. INTRODUCTION

The human face holds very important quantity of attributes and information about the person, such as expression, ethnic, gender, and age. Human beings can detect and analyse these information easily, for instance, the majority of people are able to recognize human traits like gender, where they can tell if the person is male of female by only seeing his/her face. Likewise, they can determine the age of the person and say whether this person is a child or an adult. On the other hand, constructing applications to identify the people from their face and extract their age and gender information is a challenging task for computer vision, which modern world going to depend on it in many important sides of our daily life, because of the necessity of creating a general model that works for all human subjects.

Indeed, the majority of automatic facial trait classification systems are based on computer vision and pattern recognition. Computer vision includes methods and techniques for understanding, analysing, and extracting information from images. In other words, it's a science that tries to build a system that is able to make the computer see and describe our world. Whereas, pattern recognition is a technology providing identification, description, and interpretation of how machines can recognize and detect the pattern, which could be a shape, speech signal, fingerprint image, a handwritten word, environment, or a human face. The design of a pattern recognition system involves three main parts, which are pre-processing, features extraction, and classification (*see Figure 1.1*). Pre-processing and data collecting part is related to choose an appropriate database, normalizing samples, isolating unnecessary ones, and dividing it into training and test sets. In this part also some image modifications can be done like image resizing, segmentation, modification of the illuminations, or any other corrections may enhance the appearance of images. As for features extraction part, it is related to find good features, define pattern classes and representation, and reduce the data by measuring these features. About classification part, it is very critical section, where a classifier divides the features space into regions and assign a pattern to a category. Moreover, there is a fourth optional part in the design of a pattern recognition system called evaluation, which is concerned with evaluating the system's performance based on speed, accuracy, and cost [1].

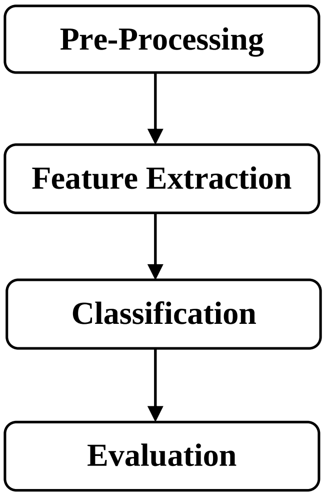


Figure 1.1. The Main Parts of a Pattern Recognition System

Although computer vision and pattern recognition have been an active field of research since 1970s, predicting the age and gender from facial images are more recently studied. In this thesis, two computer vision problems are studied: Gender classification and age estimation.

Predicting gender from facial images is an attractive research topic and important task for computer but still there is a deficiency between the requirements and current performances. This deficiency extends due to the variation in illumination, resolution, expression, pose etc. Gender prediction from facial images in turn can boost the performance of a large number of applications including human-computer interaction, customer information measurement, and access control. Furthermore, it can substantially effect on many fields, such as security systems, biometric authentication, medical imaging systems, surveillance systems and interfaces, content based searching, and demographic studies. To find a solution for the problem of gender prediction, most of the existing methods depend only on face classification methods. These methods are generally applied on standard databases having high-resolution aligned frontal faces.

On the other hand, the ability to predict a person's age from his/her facial image is more difficult than predicting his/her gender because of the large variation of face appearances like variety of human race, poses, and facial expressions. However, age prediction is particularly useful for many applications such as demographic profiling, forensic art, age-specific human-computer interfaces, security control, age-oriented advertisement systems, and Electronic Customer Relationship Management (ECRM).

1.1 Motivation

Age and gender prediction systems have been growing rapidly in recent days due its important modules and beneficial uses for many computer vision applications such as human-computer interaction, security systems, and visual surveillance. There are many examples that demonstrate the importance of a gender and age prediction. For instance, there are a specific age for getting alcohol, driving vehicles, traveling alone abroad, smoking cigarettes, etc. But the problem is that human skills of age prediction are limited and not accurate. Therefore, computer vision systems would be helpful to deny under-aged people. Another example is that following the increase of terrorist threats, airports are considering security measures at the security checkpoints to collect the gender information of the passengers automatically, which may help in observing a certain segment of people.

Automatic age and gender prediction systems are currently being used by hotels, airports, bus stations, casinos, government buildings, universities, hospitals, cinemas, etc. to increase the level of security and facing any possible threats or deficiencies. Besides the security applications, age and gender prediction techniques are used also in health care systems, information retrieval, academic studies and researches, and Electronic Customer Relationship Management (ECRM) systems, where customers are distributed to different gender and age groups like children, teenagers, adults and senior adults in addition to determine whether they male or female. Furthermore, gathering some customer's daily life information like activities, habits, traditions, priorities etc. may help the corporations to classify products and services depending on their gender or age groups, which lead to increase their incomes and earn more money. For example, clothes stores may offer appropriate fashions for males or females according to their age groups; restaurants want to know the most popular meals for each age or gender group; many companies want to make specific advertising to specific audiences depending on their gender or age groups.

1.2. Problem Description

In this thesis, two separate problems will be studied: gender classification, and age estimation from facial images. Thus, our main challenge is to propose a methodology, design, and implementation of accurate gender classification and age estimation systems, which can perform and obtain high accuracy by using and combining several feature extractors.

There are many applications and studies focusing on predict the age and gender of individuals from facial images. However, many obstacles may lead to incorrect results. For instance, the facial images have a wide degree of variations in illumination, unconstrained environments, head pose, facial expression, image background, image dimensions, shadows, quality, skin color, etc. which often can result in incorrect classification. Hence, the system shall standardize and normalize the photometric characteristics of the facial images, and then it shall extract the most descriptive features that allow more facial discrimination. As a result, these data are used to predict the face's gender and age category.

This thesis aims to increase the performance and accuracy of predicting gender and age of people from their facial images. The gender classifier should be able to classify two separate types of facial images that are grey scale images and colour images. Whereas, the age classifier should be able to classify eleven age groups that are: 0-15, 15-20, 20-25, 25-30, 30-35, 35-40, 40-45, 45-50, 50-55, 55-60, and +60 years old.

1.3. Thesis Outline

We begin this thesis by giving background information and general idea about age and gender prediction systems in computer vision framework, and also, reviewing the importance of them and discussing the potential problems that we may meet while developing an age and gender prediction system. In Chapter 2, we review some literature reviews and related works in the field of age and gender classification. In Chapter 3, we explain the core and methodology of this thesis; we first review a general description of the two basic used techniques to perform the face feature extraction. These techniques are HOG and LBP. Second, SVM and KNN classifiers are explained. Moreover, a brief insight into the evaluation techniques, which are used to train and evaluate the performance of classifiers, have been given. Then, we finish chapter 3 by providing a general overview of the databases that used in this thesis. In Chapter 4, many extensive experimentation were carried out to make the classifier obtain high accuracy performance. Our improvements for the dimensions alignment and illumination normalization of the facial images, and combining the feature extractors, have been applied in order to increase the accuracy and performance of the gender and age prediction systems. Moreover, the performance of our systems have been evaluated by using Leave-One-Out, K-fold and Confusion Matrix techniques. Then, we end this chapter by presenting the most accurate results of the proposed experiments.

Finally, Chapter 5 concludes and summarizes the most important points of this thesis, and indicate the future work and probable strategies to improve the performance of age and gender classification systems.

CHAPTER 2

2. LITERATURE REVIEW

The age and gender prediction of people is interesting field of research and has been given increased attention in recent years. Moreover, it is recognized as an important module for many computer vision applications. Although age and gender prediction have many common components, they may be different in the core approaches of classification.

In this chapter, Section 2.1 presents an overview of the papers that studied the gender prediction from facial images. Then, in Section 2.2, we review the papers about age prediction. In Section 2.3, we provide a brief review of some existing methods and robust approaches for both gender and age classification. Finally, we discuss the summary of these papers in part of differences and important approaches.

2.1. Gender Prediction Approach

In here, we review an overview of several gender prediction approaches, which are generally grouped into two categories that are face-based and gait-based. The face-based approaches use a face detection phase, or use facial images to extract the face features, whereas gait-based methods require human-detection algorithms to extract features of all body (silhouette) to predict the gender [2, 3]. However, in this thesis we focus only on the face-based methods, which can be divided into appearance-based and feature-based methods [4].

Identifying gender information from the face images has attracted the interest of many researchers specialized in the field of computer vision. Sun *et al* [5] investigated the challenge of gender recognition from frontal facial images using Genetic Algorithm (GA). They used Principal Component Analysis (PCA) to extract features, and then appointed GA to select a subset of these features. Moreover, they used four different classifiers that are Bayesian, Neural Network, SVM, and Linear Discriminant Analysis (LDA). The comparison results show the superiority of PCA + SVM with 95.3% gender recognition accuracy. Moghaddam and Yang [6] performed SVM classifier with Radial Basis Function (RBF) kernel to increase the gender classification accuracy. However, by applying the methods on 1,755 facial images from FERET database, they got an accuracy of 96.62% in SVM + Gaussian RBF kernel, and 95.12% in SVM + Cubic Polynomial kernel. Jian and Huang [7] tried to classify the gender by employing Independent Component Analysis (ICA) as a feature extraction method, and LDA as a classifier. They evaluated these classifiers on 500 frontal facial images taken from FERET database [8, 9]. Using ICA with LDA leads to obtain an accuracy of 99.3%. Costen *et al* [10] developed a sparse classifiers for gender recognition. They used PCA to extract the facial features of 300 images taken from Japanese Face Images Database. Moreover, they classified these data by using three classifiers: LDA, Exploratory Basis Pursuit Classification (EBPC), and SVM. 10-folds cross-validation basis has been executed on the classification process, and then accuracy of 79.75%, 94.25%, 94.42% in PCA+LDA, PCA+EBPC, PCA+SVM, has been achieved, respectively. Sun *et al* [11] used LBP [12] to extract the features of images from FERET database for gender recognition. In addition, they employed both Self Organizing Map (SOM) and threshold Adaboost classifiers in their experiments and they claimed 95.75% recognition rate. Similarly, Lian and Lu [13] applied LBP features with SVM classifier and reported 96.75% gender recognition rate. Makinen and Raisamo [3] had done several experiments by combining gender prediction methods with automatic face detection. In details, they compared the results of two classifiers that are Multi-layer Neural Network and SVM on FERET and WWW databases. In addition, they used four feature extractors that are Look-Up Tables (LUT) Adaboost, Threshold Adaboost, Mean Adaboost, and LBP. As a result, the best classification accuracy they achieved on FERET database was 91.11% by applying LUT Adaboost and Neural Network, and 78.25% by applying LBP with SVM on WWW database. Fang and Wang [14] have employed PCA to decrease the high density of LBP feature to classify gender from facial images. They worked on FERET database and got success ratio of 92.16%. Scalzo *et al* [15] made experiments to recognize the gender by comparing the results of using three feature extraction methods that are PCA, Gabor, and Feature Fusion Hierarchies (FFH), and three classifiers that are LDA, Nearest Neighbours (NN), and SVM. By evaluating these classifiers on 400 images from FERET database, they got best accuracy of 96.2% at FFH + SVM. Zafeiriou *et al* [16] applied SVM and Kernel Fisher Discriminant Analysis (KFDA) with an RBF kernel on 2,360 images (1,256 male and 1,104 female) taken from XM2VTS database [17]. They claimed 97.20% gender classification rate. Lu and Shi [18] divided the face into three regions before extracting their features. Two-dimensional PCA (2DPCA) has been used as a feature extractor, and SVM as a classifier. By applying this method on 800 grey scale facial images taken from FERET database, 2DPCA+SVM gave 95.33% gender recognition rate.

Singh *et al* [19] were able to reach 95.56% success gender prediction by using "HOG + SVM", and accuracy of 89.43% by using "LBP + SVM" by applying given methods on 300 images selected from Indian face Database. Similarly, Liu *et al* [20] have reached to accuracy of 94.38% with "HOG + SVM" and 91.43% with "LBP + SVM" by applying these methods on LFW face database, and then they combined "HOG & LBP" and used it with SVM to reach to gender prediction accuracy of 94.88%. Luis Alexander [21] has used LBP with SVM for gender recognition on FERET and UND databases. The best result achieved was 93.46%. Lin and Zhao [22] studied a gender recognition scheme based on colour information. They developed an eye detection algorithm by combining SVM with some color features. By combining SVM classifier with these features, they achieved an accuracy of gender prediction scheme with 80.7%. Shan [23] investigated gender recognition using LBP feature extractor with both Adaboost and SVM classifiers. The result of this method was 94.81% success recognition rate on Labelled Faces in the Wild (LFW) database [24]. Ihsan Ullah *et al* [25] investigated Weber's Local Descriptor (WLD) for gender recognition. Their technique depends on dividing an image into a number of blocks, compute WLD histogram for each block and concatenate them to form a Spatial WLD descriptor (SWLD). They got overall accuracy of (99.08%) with (Chi-Square) technique. Chen Wang *et al* [26] proposed a method called Local Circular Patterns (LCP) for gender classification, which is an improvement of traditional LBP [12]. Their experiments have been carried out on the FERET database [8, 9]. Then both LBP and LCP features were extracted for different scales. SVM with a linear kernel is used for the classification. As a result, the gender classification accuracy was up to 95.36%, clearly highlighting the effectiveness of LCP method. Min Li *et al* [27] have combined three methods that are HOG, LBP, and Gabor descriptors together to represent the head-shoulder part of human body for gender recognition. Consequently, an accuracy of 88.55% has been achieved. Emon Dey *et al* [28] have described the gender detection from facial images in a novel approach. The system can detect facial area of image by Region of Interest (ROI), and then detect gender by using Discrete Cosine Transformation (DCT). Moreover, they used LBP to improve ROI matching accuracy. At the beginning, they got success ratio of 70%, but after applying Histogram Equalization, the ratio has increased to 78.91%. A summary of all above gender prediction methods is presented in Table 2.1.

2.2. Age Prediction Approach

In this part, we review an overview of several age prediction approaches, which are divided into two different groups that are age group classification and actual age estimation (cumulative years lived). In age group classification, the age range is divided into classes, each class has a range of years (e.g., from 15 to 20 years). Indeed, it is very similar to gender classification, except the problem of multi-class (because we need more than 2 classes in case of age prediction. In contrast, gender prediction need only two classes: male & female). On the other hand, in the actual age estimation, we need to determine the specific and correct age of the image, which is usually based on regression methods or a hybrid of classifications and regressions to give an exact number of the age. However, this part is very difficult, and to the best of our knowledge, there are no or very few studies for the actual age estimation on embedded platforms.

The first paper in age estimation area was published by Kwon and Lobo in 1994 [29], and studied the classification of age by using Anthropometric Models (AM) [6 , 30] to find the primary features of the face such as eyes, mouth, nose, and chin. In addition, an Appearance Model (APM) [31, 32] is also used to determine the density of wrinkles in each face using the snakelets [33]. They create a facial database for their study, which contains 47 faces, and then divided the images into three age groups: babies, young adults, and senior adults. To classify these images, they used six ratios computed from the distances of different facial features like eye to nose, mouth to chin, etc. and combined these ratios with wrinkles information to get overall result of 77% success age estimation. Lanitis *et al* [34] have used the Active Appearance Model (AAM) [35] for age prediction. They extracted facial features of 500 images from 0 to 35 years old by using PCA. To estimate the actual age, they adopted the Neural Network for classification of data, and reported 94.42% age estimation. Guo *et al* [36] also used the AAM to estimate the gender of 500 facial images from FG-NET [37] database between 0 to 69 years old. Images features have been extracted by using A Locally Adjusted Robust Regresses (LARR). Then, SVM and Support Vector Regression (SVR) methods are investigated to classify the age. The results of their experiments reported 94.93% success estimation rate. Yan *et al* [38] have used Gaussian Mixture Model (GMM) to model the allocation of coordinate spots from each image, which depicts the connection existing between the local appearance information and coordinate information. In addition, they implemented PCA, Locally Embedded Analysis (LEA) [39], and Sub-manifold Synchronized Embedding (SSE) to extract the important facial images features. The Regression framework from the Patch Kernel (RPK) has been used to classify the information that is extracted from YAMAHA gender and aging database and FG-NET aging database. Modelled by a GMM, their system obtained an accuracy of 95.05% age estimation. In another paper, Yan *et al* [40] presented a new feature extractor called Spatially Flexible Patch (SFP), which encodes the local appearance and position information at the same time. SFP also modelled by a GMM to handle the issues of geometric misalignment and noisy pixels. They used YGA database in their experimental results to achieve an accuracy of 92.18%. Guo *et al* [41] used the Biologically Inspired Features (BIF) [42] to estimate ages from the facial images of YGA. By employing SVM to classify the data, and applying leave-one-out technique, they achieved to accuracy of 97.42% age prediction. Kanno *et al* [43] used an APM [31, 32] to determine the density of wrinkles and extract the information of the faces. Consequently, accuracy of 80% has been achieved when Artificial Neural Networks (ANN) has been employed to classify four age groups of 110 facial images that were selected from FG-NET aging database.

Bauckhage *et al* [44] offered an accurate and efficient approach for age prediction from facial images. They combined HOG, Compute histograms of range filter, and LBP. They trained their system on UTD database and the FG-Net database. As a result, in a first experiment, they verified whether the algorithm correctly ordered the two images so they measured an accuracy of 77%. In a second experiment, they fixed the candidate images to strictly frontal pose of faces. As a result, the classification accuracy has been improved up to 85%. Shan [45] investigated age estimation by using illumination-invariant appearance feature like LBP [12] and Gabor to extract the information of faces. To get high accuracy, they divided Gallagher database [46] into seven categories: 0-2, 3-7, 8-12, 13-19, 20-36, 37-65, and 66+ years old. Then, Adaboost and SVM were used to classify and learn the discriminative local features. Their experiments show many results but the best one was LBP + SVM with 87.7% success rate. Similarly, Ylioinas *et al* [47] applied the same methods used in [45] but on *Image of Groups* database. In addition, they created regional histograms from the LBP features as a try to improve the age estimation accuracy. However, they got 87.7% success rate, which is the same accuracy of [45]. A summary of all above age prediction methods is presented in Table 2.2.

2.3. Both Gender and Age Prediction Approaches

In this part, we present an overview of several researches that studied both gender and age prediction approaches simultaneously. Iga *et al* [48] have used graph matching with Gabor Wavelet Transformation (GWT) [49] to extract images information such as, skin color, moustache, hair, etc. All these information were classified by applying SVM on 300 facial images (150 male and 150 female, divided into 6 age groups from 15 to 64 years old) taken from Softopia Japan HOIP database. Consequently, they achieved to 97.3% gender classification rate and 67.4% age estimation rate. Yang and Ai [50] employed LBP feature extractor to know the Chi square distance between the extracted LBPH and a reference histogram. Moreover, real Adaboost algorithm was used as a strong classifier, which learns a sequence of best local features. By using 3,540 facial images from FERET [8, 9] database and 696 images from PIE [51] database, accuracy of 93.30% gender prediction and 92.12% age prediction has been achieved. Guo *et al* [52] studied age prediction using YGA database. First, they investigated the influence of gender on age prediction based on face representations that combine biologically inspired features with variegated learning techniques. Then, they studied age prediction using smaller gender and age groups rather than on all ages.

Based on the results of using a large database and five different face representations, they were able to reduce The Mean Absolute Error (MAE) to 40% comparing to previous studies. Guo *et al* [53] investigated the effect of the person’s age on recognizing his/her gender. Therefore, they used HOG and LBP to 8,000 facial images selected from YGA database. Furthermore, the SVM has been used for learning classifiers. As a result, HOG + SVM gave accuracy of 96.03%, while LBP + SVM gave 94.56% gender classification. In addition, HOG + SVM gave 88.65%, while LBP + SVM gave 90.53% age estimation. Guo *et al* [54] presented some problems related with large-scale human age estimation. In addition, they studied the differences between "no crossings" and "crossing" of age estimation performance, when they found that crossing race and gender could increase the estimation error rate. Notably, they implement their system on large database called MORPH-II [55], which includes more than 55,000 facial images. For experiments, they used the Biologically-Inspired Features (BIF) classifier with four feature extraction techniques that are PCA, Marginal Fisher Analysis (MFA) [56], Orthogonal Locality Preserving Projections (OLPP) [57], and Locality Sensitive Discriminant Analysis (LSDA) [58]. Consequently, the accuracies of 95.56% age estimation and 100% gender classification have been reported.

Shirkey and Gupta [59] developed a gender and age recognition algorithm based on rectangle features method that are used to describe sub-regions of a human face, and hence component wise data can be transformed from pixel-wise data. They achieved a ratio of 90% for gender classification, and 85% for age classification. Mahalingam and Ricanek [60] investigated the effects of gender and age based on identical twins. They used and compared two well-known feature extraction techniques that are HOG and LBP [12]. Moreover, their study used also two databases that are ND/WVU [61] database and CASTA Twins Face [62] database. However, by comparing HOG and LBP results, we can see that HOG gave better accuracy than LBP in both gender and age classification, where 91.42% obtained in gender classification and 52.17% in age estimation, whereas, LBP gave accuracy of 82.84% gender classification and 33.15% age estimation. Fazl-Ersi *et al* [63] have compared between three methods that are LBP, Color Histogram (CH) and Scale-Invariant Feature Transform (SIFT) [64] to recognize the age and gender. Moreover, they used SVM classifier to classify the features that extracted from Gallagher facial images database [46]. As a result, the best accuracy they obtained was by combining LBP, CH, and SIFT features, which is reported 91.59% gender recognition and 63.01% age estimation. Eidinger *et al* [65] used LBP and the related Four Patch LBP codes (FPLBP) [66] to learn and extract the most important properties of images features. These images have been selected from Gallagher database. By combining LBP and FPLBP features and SVM, they achieved an accuracy of 88.4% of gender recognition and 80.7% of age estimation. Azarmehr *et al* [67] offered a complete system for age and gender classification, which performs a good accuracy even under unconstrained conditions. LBP has been used for face representation. In addition, LDA and PCA are also used to extract facial features. Their experiments used wide number of images selected from three databases that are 1,010 images from FERET database [8, 9], 13,000 images from MORPH-II database [55], and 5,080 images from Gallagher database [46]. By applying SVM classifier on all these data, accuracy of 99.5% gender classification and 98.8% age estimation were achieved. A summary of all above age and gender prediction methods is presented in Tables 2.1 and 2.2.

2.4. Summary

This chapter presented an overview of several attempts that have been done in order to predict the gender and age of people from facial images. Many approaches, feature extraction algorithms, databases, classifiers, techniques, and methods have been used by researchers to increase their systems performance and reach to high accuracies. Here, we will summarize and review the most important methods and databases that presented in this chapter, and compare the accuracies that have been obtained:

- **Gender prediction:**

Study	Method	Database	Number of Images	Accuracy
Azarmehr *et al* [67]	LBP + SVM	FERET	1,010	99.50%
Jian & Huang [7]	ICA + LDA	FERET	500	99.30%
Iga *et al* [48]	GWT + SVM	HOIP	300	97.30%
Zafeiriou *et al* [16]	RBF + SVM	XM2VTS	2,360	97.20%

Lian & Lu [13]	LBP + SVM	FERET	1,040	96.75%
Moghaddam & Yang [6]	RBF + SVM	FERET	1,755	96.62%
Scalzo *et al* [15]	FFH + SVM	FERET	400	96.20%
Guo *et al* [53]	HOG + SVM	YGA	8,000	96.03%
Sun *et al* [11]	SOM + Adaboost	FERET	600	95.75%
Singh *et al* [19]	HOG + SVM	Indian Faces	300	95.56%
Wang *et al* [26]	LCP + SVM	FERET	1,202	95.36%
Lu & Shi [18]	PCA + SVM	FERET	800	95.33%
Sun *et al* [5]	PCA + SVM	WWW	400	95.30%
Shan [23]	LBP + Adaboost	LFW	7,443	94.81%
Guo *et al* [53]	LBP + SVM	YGA	8,000	94.56%
Costen *et al* [10]	PCA + SVM	Japanese Faces	300	94.42%
Liu *et al* [20]	HOG + SVM	LFW	5,660	94.38%
Alexander [21]	LBP + SVM	UND	487	93.46%
Yang & Ai [50]	LBP + Adaboost	FERET	3,540	93.30%
Yuchun & Zhan [14]	LBP + ANN	FERET	1,199	92.20%
Yuchun & Zhan [14]	PCA + ANN	FERET	1,199	91.91%
Fazl-Ersi *et al* [63]	LBP & SIFT + SVM	Gallagher	200	91.59%
Liu *et al* [20]	LBP + SVM	LFW	5,660	91.43%
Makinen & Raisamo [3]	LUT + ANN	FERET	900	91.11%
Singh *et al* [19]	LBP + SVM	Indian Faces	300	89.43%
Eidinger *et al* [65]	LBP + SVM	Gallagher	1,270	88.40%
Costen *et al* [10]	PCA + LDA	Japanese Faces	300	79.75%
Makinen & Raisamo [3]	LBP + SVM	WWW	4,720	78.25%

Table 2.1. Common gender prediction methods

- **Age prediction:**

Study	**Methods**	**Databases**	**Number of Images**	**Accuracy**
Azarmehr *et al* [67]	LBP + SVM	Gallagher	5,080	98.80%
Guo *et al* [41]	BIF + SVM	YGA	1,600	97.42%
Guo *et al* [54]	PCA + BIF	MORPH-II	55,000	95.56%
Yan *et al* [38]	PCA + RPK	FG-NET	1,002	95.05%
Guo *et al* [36]	LARR + SVM	FG-NET	500	94.93%
Lanitis *et al* [34]	PCA + ANN	WWW	500	94.42%
Yan *et al* [40]	SFP + GMM	YGA	1,600	92.18%
Yang and Ai [50]	LBP + Adaboost	PIE	696	92.12%
Guo *et al* [53]	LBP + SVM	YGA	8,000	90.53%
Guo *et al* [53]	HOG + SVM	YGA	8,000	88.65%
Shan [45]	LBP + SVM	Gallagher	3,500	87.70%
Eidinger *et al* [65]	LBP + SVM	Gallagher	1,270	80.70%
Kanno *et al* [43]	APM + ANN	FG-NET	110	80.00%
Iga *et al* [48]	GWT + SVM	HOIP	300	67.40%
Fazl-Ersi *et al* [63]	LBP&SIFT + SVM	Gallagher	200	63.01%
Mahalingam and Ricanek [60]	HOG + SVM	CASTA	714	52.17%
Mahalingam and Ricanek [60]	LBP + SVM	CASTA	714	33.15%

Table 2.2. Common age prediction methods

From the tables, we can notify and understand that there are several important factors effecting the system's performance. These factors are:

- Increasing the number of images that is used in training set may help to achieve high accuracies. Nevertheless, the disadvantage of this is long processing time.
- Using robust methods (like LBP + SVM) and using it in correct way may help to increase the performance.

- Choosing an appropriate database for each specialty (e.g. FERET database for gender prediction, and FG-NET database for age prediction) may help to save time and get good results.

The remainder of this thesis is organized as follows: In Chapter 3, we explain the core and methodology of this thesis; we first review a general description of the techniques used to perform the face feature extraction. These techniques are HOG and LBP. Second, details about the classification algorithms using SVM and KNN are provided. Moreover, a brief insight into the evaluation techniques, which are used to train and evaluate the performance of classifiers, have been given. Then, we finish Chapter 3 by providing a general overview of the databases that used in this thesis.

In Chapter 4, many extensive experimentation were carried out to make the classifier obtain high accuracy performance. Our improvements for the dimensions alignment and illumination normalization of the facial images, and combining the feature extractors, have been applied in order to increase the accuracy and performance of the gender and age prediction systems. Moreover, the system’s performance have been evaluated by using Leave-One-Out and Confusion Matrix techniques. Then, we end this chapter by presenting and explaining the most accurate results of the proposed experiments. Finally, Chapter 5 concludes and summarizes the most important points of this thesis, and indicate the future work and probable strategies to improve the performance of age and gender classification systems.

CHAPTER 3

3. METHODOLOGY

In this chapter, we explain the core and methodology of this thesis (*see Figure 3.1*); we first review a general description of the used techniques and pre-processing stages of the proposed system (that are illumination normalization and dimensions alignment). Second, we present HOG and LBP algorithms to perform the face feature extraction. Third, details about the classification algorithms using SVM and KNN are provided. Then, we finish Chapter 3 by providing a brief insight into the databases that algorithms used in this thesis evaluated and applied on.

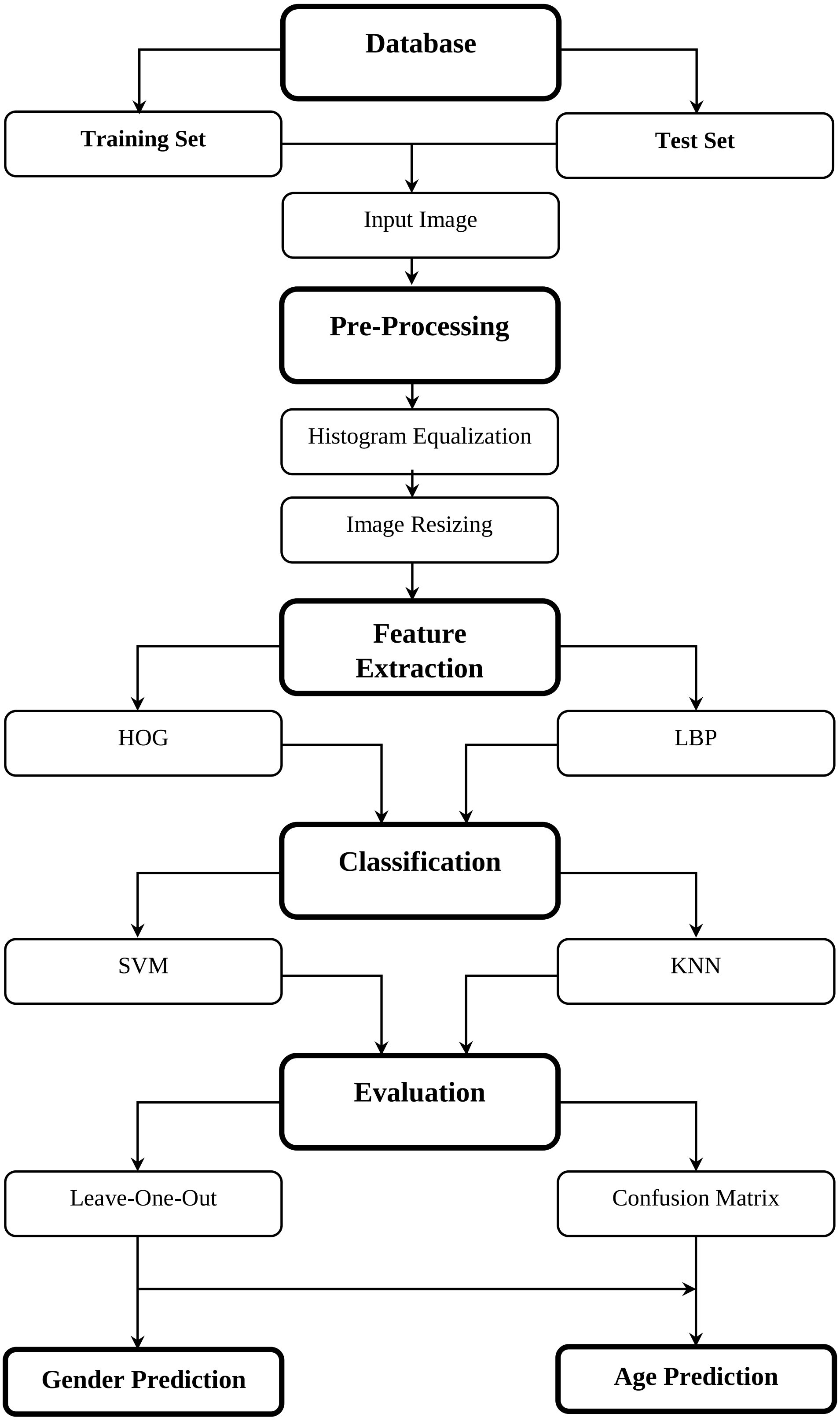


Figure 3.1. General Methodology of Gender and Age Prediction System

3.1. Pre-Processing

Solving gender and age prediction problems require overcoming some main difficulties, such as differing image dimensions and qualities, varying levels of luminosity, choosing appropriate database for each problem, and employing sufficient number of images in each experiment. Therefore, we should apply some important pre-processing techniques before processing the system to provide accurate and robust ways of solving these problems. In this part, we will summarize these techniques and propose a gender and age prediction approaches that are robust, simple, and efficient to use.

3.1.1. Illumination Normalization:

To normalize the illumination we applied Histogram Equalization (HE) technique, which helps to reduce the effect of light and unify luminosity of all images in the databases, and this positively affects the accuracy and performance of the system.

Histogram Equalization (HE) [28, 31] is a fast, simple and effective image illumination enhancing technique, which can effectively confirm the details of the density in any region (*see Figure 3.2*). In general, HE works like this:

- For each pixel in an image, put grey value in variable i, $\text{hist}[i] = \text{hist}[i] + 1$ when $i = 0 : 255$.
- Find the Cumulative Distribution Frequency (CDF) from hist [ ] matrix.

  $$\text{hist}_{(\text{cdf})}[i] = \text{hist}_{(\text{cdf})}(i-1) + \text{hist}[i]$$

- For each new i, calculate Histogram Equalization by following this formula:

  $$\text{EH}[i] = \left[\frac{(255 * \text{hist}_{(\text{cdf})}[i]) - M \times N}{M \times N}\right]$$

  $(M \times N)$ is the dimensions of an input image.

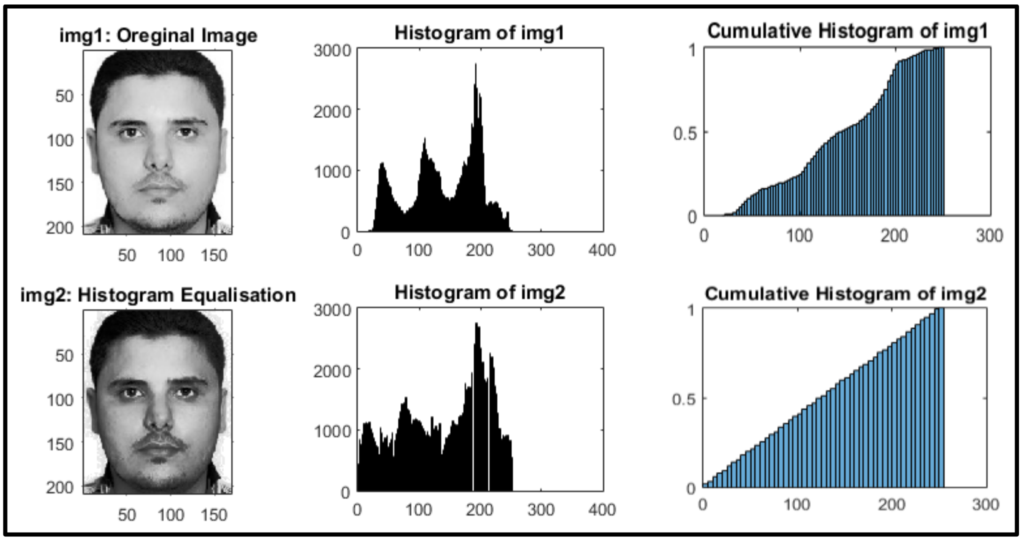


Figure 3.2. Histogram Equalization (HE).

Figure 3.2 shows the histogram for an image before and after Histogram Equalization. It describes the distribution of an image's intensity values and the range of illumination. We can see that histogram equalization improves the image's contrast, where the intensity values can be affected by faraway pixels, so it tries to redistribute these values equally across the image. However, the Cumulative Histogram line indicates the distribution of intensity values, which the exact linear ramp means the number of intensity values are equalized. Noticeable in the Figure 3.2, after applying Histogram Equalization on the image, the Cumulative Histogram is almost linear, which means that the intensity values have been distributed equally.

3.1.2. Dimensions Alignment (Image Resizing):

Dimensions alignment (image resizing) means making an input image size smaller from a bigger image, or making an input image size bigger from a smaller image (*see Figure 3.3*). However, in this thesis, we used three databases with wide number of images, each image has a large resolution dimensions (more than 400×400). Therefore, we applied the image resizing to decrease the resolution and size of images, and make all images' size equal (all images = 192×128 size). This has advantages of helping the feature extractor (e.g., HOG) to extract same number of features from all images. Moreover, it helps to decrease the processing time, and hence increases the system performance. For instance, image resolution of 600×400 may take 30 seconds to extract its features and another 30 seconds to classify these features with overall processing time of 60 seconds. Nevertheless, by downsizing the resolution of this image to 192×128, the overall processing time will decrease to only 10 seconds with same results, and this will help us to increase system's performance.

Figure 3.3. Image Resizing

3.1.3. Gender Classification Dataset:

In this step, we created two main image databases that are grey scale images database and color images database. Grey scale images database includes 531 female images and 731 male images. Whereas color images database contains 400 female images and 543 male images as shown in Table 3.1. All these images have been selected from FERET database [8, 9], which is a database of facial images sponsored by the DOD Counterdrug Technology Development Program Office. This database contains several grey scaled and coloured images with a guidebook providing several information such as gender, age, ethnicity, facial points, light conditions and more.

Data Sets	Number of Male Images	Number of Female Images	Total Number of Images
Grey Scale database	731	531	1,262
Color database	543	400	943
Total Number of Images	1,274	931	2,205

Table 3.1. Databases that Selected from FERET Database.

3.1.4. Age Classification Dataset:

In this step, we used two aging databases, which are FG-NET database, which includes 1,002 facial images, and UT Dallas Database, which includes 580 facial images. Then, we combined both databases in one big database including 1,582 total number of facial images. We distributed all images on 11 main classes; each class has a period of ages between 0 and 99 (*see Table 3.2*). These classes created in this way:

- Class 1 includes 575 images under 15 years old (from 0 to 15).
- Class 2 includes 208 images between 16 – 20 years old.
- Class 3 includes 213 images between 21 – 25 years old.
- Class 4 includes 103 images between 26 – 30 years old.
- Class 5 includes 62 images between 31 – 35 years old.
- Class 6 includes 50 images between 36 – 40 years old.
- Class 7 includes 45 images between 41 – 45 years old.
- Class 8 includes 29 images between 46 – 50 years old.
- Class 9 includes 28 images between 51 – 55 years old.
- Class 10 includes 9 images between 56 – 60 years old.
- Class 11 includes 260 images upper 60 years old (from 61 to 99).

Databases	Database Classes											Total
	0 to 15	16 to 20	21 to 25	26 to 30	31 to 35	36 to 40	41 to 45	46 to 50	51 to 55	56 to 60	+60	
FG-NET	575	155	81	61	39	31	26	13	12	1	8	1,002
UTD	0	53	132	42	23	19	19	16	16	8	252	580
Total	575	208	213	103	62	50	45	29	28	9	260	1,582

Table 3.2. The Number of Images in Aging Database (FG-NET & UTD)

3.2. Feature Extraction

Extracting the image features is the most important part of the age and gender prediction approach. In this study, two different feature extraction approaches (the first one is the HOG approach and the second one is the LBP approach) are used. The details of these approaches are given below.

3.2.1. Histograms of Oriented Gradients (HOG)

The HOG was introduced by Dalal and Triggs in 2005 [68] which became later one of the excellent local feature descriptors that has largely been used in computer vision and image processing for grabbing and capturing the distribution of local intensity gradients or the edge direction of objects. It has given promising performance in variety of computer vision problems related to object detection and recognition as an appearance based feature extraction method (*see Figure 3.4*). In addition, HOG has many advantages such as the easy to use with discriminate classifiers (e.g. support vector machine), and due to its ability to capture shape of an object from edges (gradients), HOG gives good results to identify object from cluttered background without using any segmentation algorithm [69, 70].

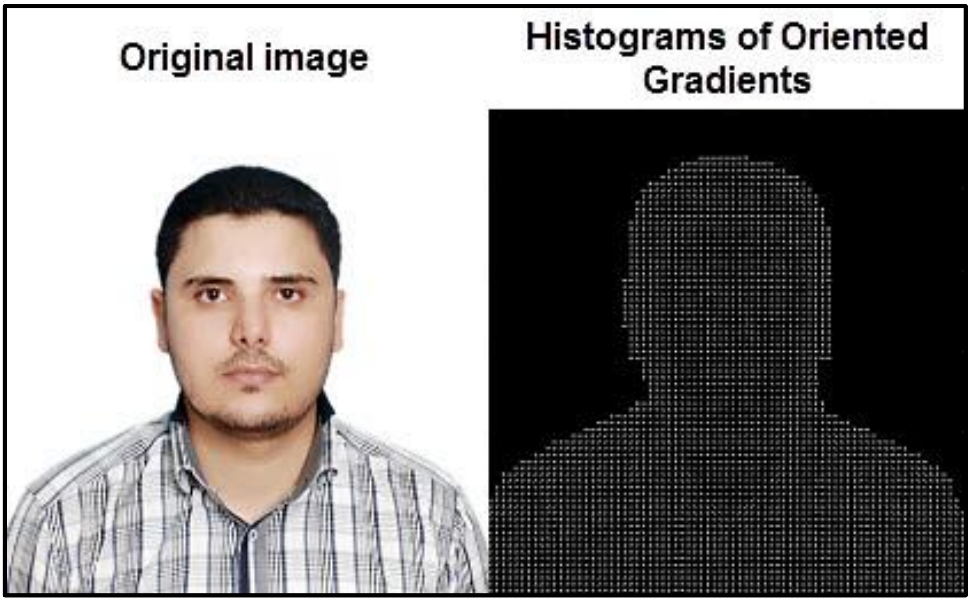


Figure 3.4. Example of Histogram of Oriented Gradients

Figure 3.4 shows the ability of HOG algorithm to capture the shape of body in the image according to its edges (gradients). However, all pixels within the detected body will be computed, where the HOG will extract all the features of this body and present a one-dimensional array of histograms that can be classified later by using any classification algorithm.

The main idea of HOG technique is that objects in images are described by the distribution of the gradients intensity or edge directions. The image is divided into small square cells, as many cells as possible, and then compiled the histogram of oriented gradient directions in each cell. A histogram is generated from these gradient values, and the combination of all histograms then represent the descriptor. For better accuracy, the local histograms can be calculated a value of the intensity across large spatially connected cells (blocks) (*see Figure 3.5*). Then this value is used to normalize all cells within the block from the upper-left corner down to the right one, where the final HOG features are created by concatenating all the normalized cell histograms from each block into a single vector. This normalization gives better invariability to changes in illumination and shadowing [71, 72]. Notably, Dalal [68], who presented HOG algorithm with Triggs in 2005, has recommended some values for the HOG parameters to get good performance. The recommendations are for setting window size equal to 64×128, block size equal to 16×16, and cell size equal to 8×8. However, now this algorithm is a ready function, which is simple and very easy to use, in many image processing tools (e.g., Matlab), so no need to change any parameters.

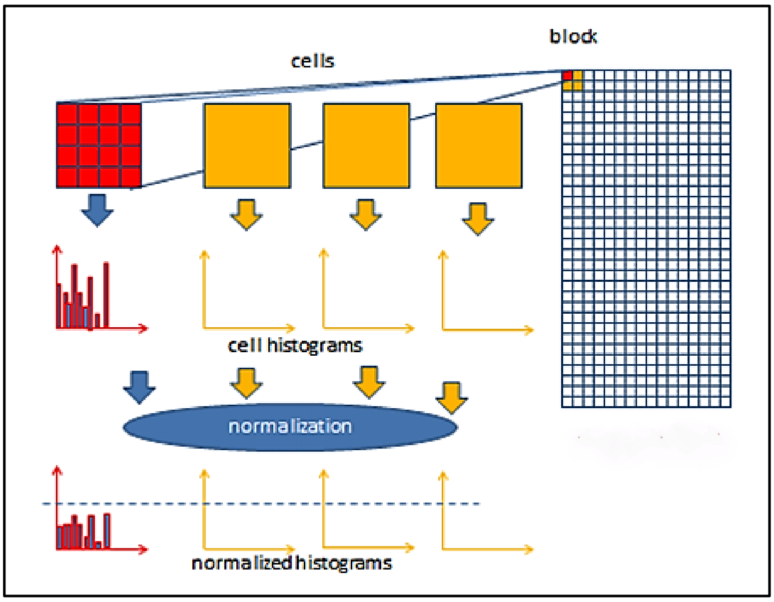


Figure 3.5. HOG Implementation Scheme

Figure 3.5 explains the implementation scheme of HOG algorithm, which follows some substantial steps. First, it divides the input image into blocks, and divides each block into smaller connected cells. Then computes a histogram of gradient directions for all the pixels within the cell [73].

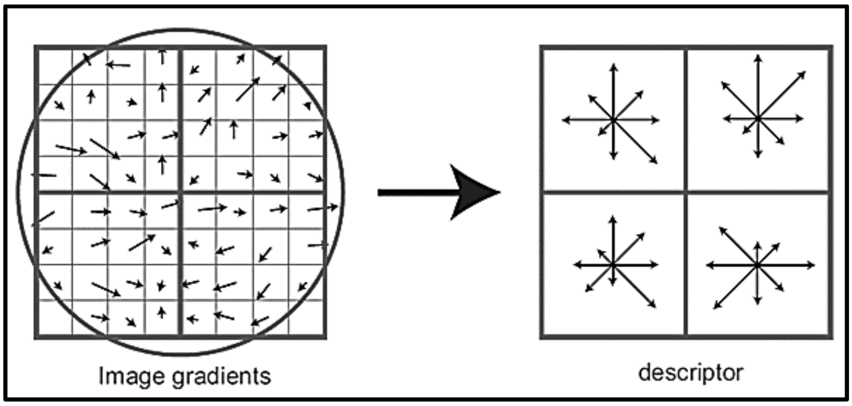


Figure 3.6. Image Gradients

According to these gradient orientations, each cell's pixel will reshape into angular bins and then participate gradient to its parallel bin as shown in Figure 3.6. Then it normalizes the group of cells (block) histograms, which represent a one-dimensional array of histograms called the descriptor.

3.2.2. Local Binary Pattern (LBP)

The LBP, which was presented by Ojala *et al* in 2002 [74], is an efficient and powerful texture descriptor that is widely used in image processing and computer vision areas as a feature and histogram representation (*see Figure 3.7*).

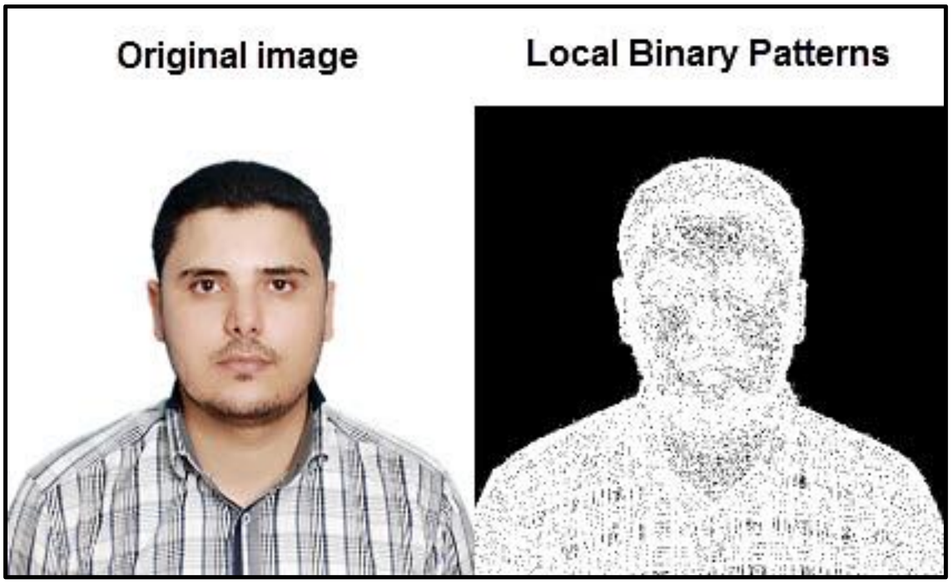


Figure 3.7. Example of Local Binary Patterns

This figure shows the ability of LBP algorithm to capture the shape of body in the image by looking to each pixel's neighbours. However, all pixels within the detected body will be computed, where the LBP will extract all the features of this body and present a one-dimensional array of patterns that can be classified later by using any classification algorithm.

The main LBP mechanism is that the input image is divided into 'N×N' local regions, each local region is composed of a '3×3' neighbourhood of each pixel by the central pixel's value. Then, type of binary pattern will be assigned a label to each pixel according to its intensity value, where the distribution of these binary patterns in each block represents the results with an 8-bits integer, where the calculation of these patterns are used as a feature representation (*see Figure 3.8*) [12]. In general, by assuming a pixel at (X_c; Y_c), the LBP results can be calculated as the following formula:

$$LBP(X_c, Y_c) = \sum_{n=0}^{N-1} s(i_n - i_c)2^n$$

Where $\mathbf{i_n}$ is a neighbour pixel of the **N** pixels around the central pixel $\mathbf{i_c}$.

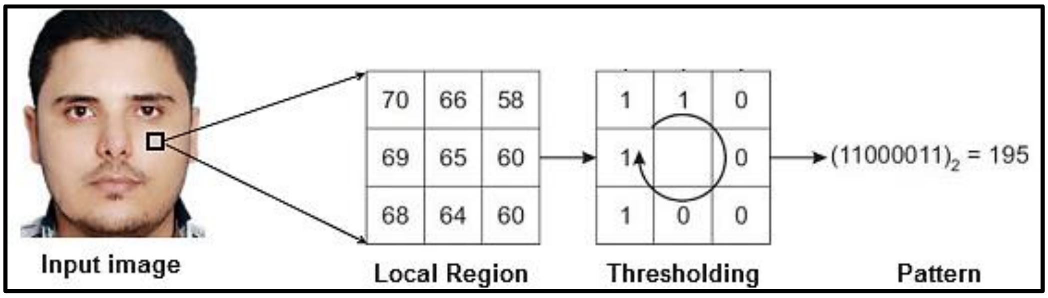


Figure 3.8. LBP Mechanism

To explain the LBP mechanism in Figure 3.8, we assume that the input image has been divided by LBP algorithm into 100 blocks, and it is now processing the block number 29. This block is divided into '3×3' neighbourhood pixels (9 cells), and then encoded each pixel by using its intensity value. By threshold from the value of the central pixel (which is 65 in above example), LBP ordering all surrounding pixels within the block from the upper-left corner down to the right one depending on whether have bigger or smaller intensity value than the central pixel (bigger value = 1; smaller = 0). Finally, we will get a 8-bit binary number (it is "11000011" in above example), which can be converted to a decimal number later, e.g. $(11000011)_2 = (195)_{10}$, where the calculation of these numbers represent a one-dimensional array of patterns.

3.3. Classification

In this step, different classifiers are trained and tested by facial features that are already extracted. The classification follows standard steps that a classifier takes one image randomly from a Training set as a test image and use the rest as the training set, then it compares these images with all other images, this is called Leave-One-Out (LOO) technique. In our study, we will use two different classifiers that are Support Vector Machine (SVM) and K-Nearest Neighbour (KNN).

3.3.1. Support Vector Machine (SVM)

SVM was developed by Cortes and Vapnik in 1995 [75] and has extensively been used as a popular and powerful supervised learning tool for general pattern recognition applications. In addition, it gives promising and excellent performance on the range of machine learning and many other fields by applying it to different classification problems, data separation, regression, and density estimation [76].

SVM classifier has many advantages, which make it one of the most accurate and robust algorithm, such as:

- Gives high performance even with small number of images in training set.
- Not sensitive to the number of dimensions, which gives it promising performance with any images size.
- Ability to minimize both empirical and structural risk, which leads to better generalization for data classification even when the number of test set is high.

The main task of SVM is based on searching for the OSH "Optimal Separating Hyper-plane", which is the closest point between two classes (positive and negative samples) of data in the training set. By increasing the margin between these classes, SVM can modify the input data into a high-dimensional feature space where a hyper-plane may be found. Furthermore, it can reduce the structural risk; hence reducing the number of predictable errors [77, 78]. However, the nearest OSH data to the border of each class are called the "Support Vectors" (*see Figure 3.9*).

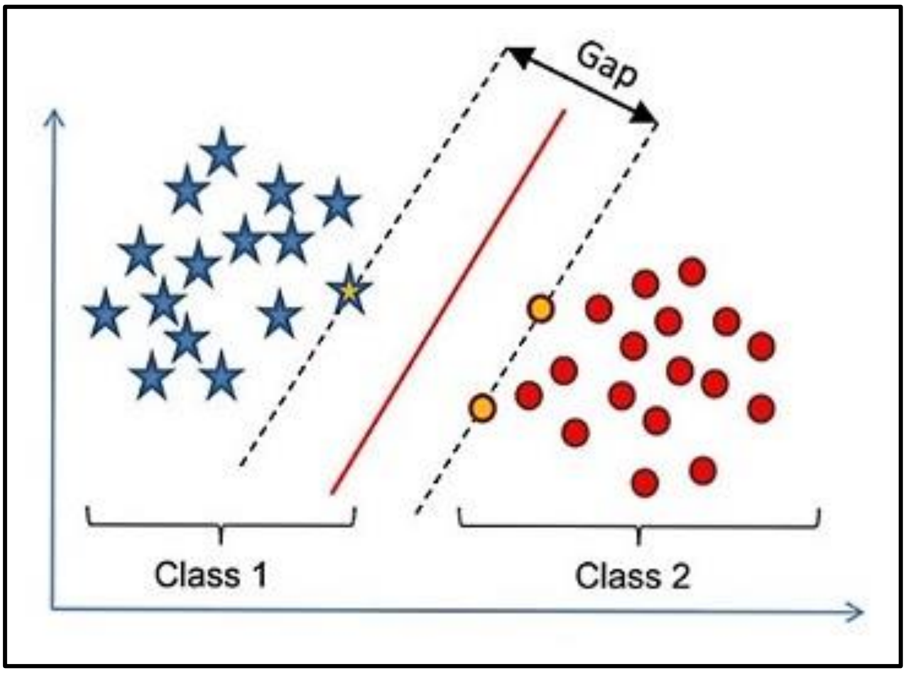


Figure 3.9. Basic Concept of SVM

Figure 3.9 shows how SVM classifier can distinguish between two classes, where the Class 1 (star shapes) contains the positive features; and Class 2 (circular shapes) contains the negative features. SVM starts increasing the margin between the two classes bit by bit to find the OSH, which is the closest points between these classes. The OSH features in each class (the orange color) are known as "Support Vectors" and used by SVM in classification process.

3.3.1.1. Multi-Class SVM problem

SVM, as a default, designed for a binary classification, so it can classify data only into two classes; therefore, we used it in gender prediction without any problems because we have only two classes, male and female. However, in age prediction approach, we needed to divide the data into 11 classes. Therefore, we meet the problem that is known as Multi-Class SVM problem. To solve this problem, researchers have been developing many approaches and methods such as One-vs.-One approach [79], One-vs.-All approach [80], Weston and Watkins' method [81], Crammer and Singer's method [82], and Simplified Multi-Class SVM (SimMSVM) method [83].

In this thesis, we have used One-vs.-All approach in order to overcome this problem and implement an age prediction system. However, One-vs.-All approach is a mechanism that depends on using each class against all other classes, for instance, suppose that our classes are Class_1; Class_2; Class_3; … to Class_11. Thus, the SVM trains up a binary classification as: Class_1 vs. not Class_1, Class_2 vs. not Class_2; Class_3 vs. not Class_3; … until Class_11 vs. not Class_11, where the Class_1 contains the positive samples, and the classes from 2 to 11 combined together to form one class containing the negative samples. Then, it trains up a Class_2 vs. not Class_2, where the Class_2 contains the positive samples, and the other classes combined together to form one class containing the negative samples, and the algorithm goes like this up to the last class. Finally, it picks and decides the appropriate class related to each tested sample.

3.3.2. K-Nearest Neighbour (KNN)

KNN is one of the simplest classifiers for predicting the class of a test sample used in machine learning, which is based on training samples that are very close to each other in the features scope [84]. The main idea of the KNN classifier mechanism is calculating and computing the distances between all training objects to test object, then finding and gathering a collection of *k* objects in the training set that are nearest to the test object, and finally calculating the average of them (*see Figure 3.10*). Although the KNN classifier performance is highly sensitive to the number of *k* value and the results are affected by any changes in it, KNN classifier is widely used and very easy to implement with high performance in many classification problems [77, 78].

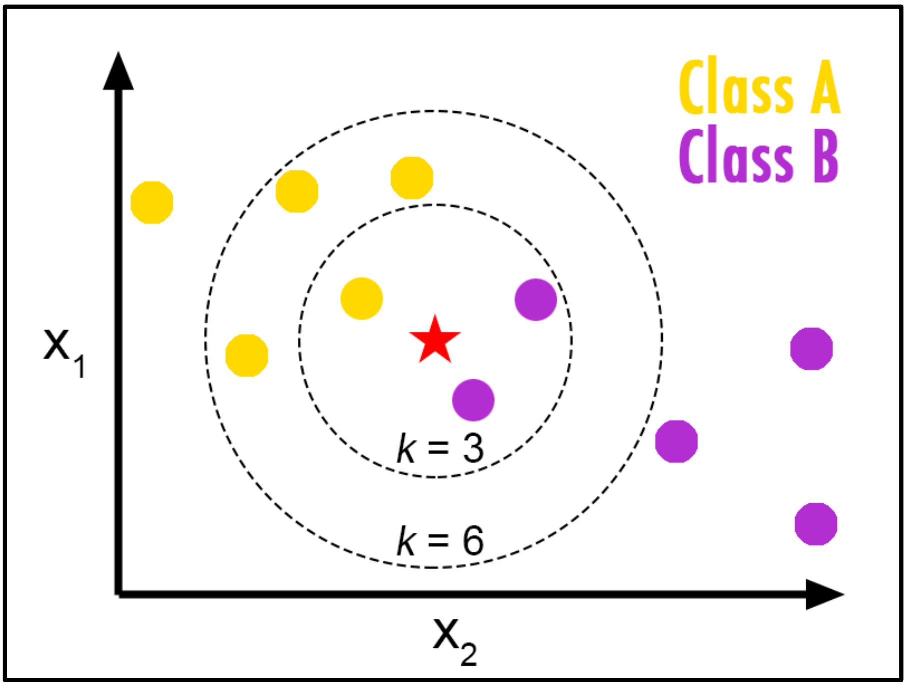


Figure 3.10. Basic Concept of KNN

Figure 3.10 shows the mechanism of KNN classifier. It is based on the value of '*k*', which is used to compute the distances between training objects (circular shapes) and test object (star shape). For instance, if we take the *k* value = 3, KNN will classify the closest 3 training objects to the test object, and then calculates the average of them. Similarly, if we take *k* value = 6, KNN will classify the closest 6 training objects to the test object, and then calculates the average of them.

However, determining *k* value is not easy, because it is effected by the parameters like number of samples that we have in Training set, and the type of feature extractor algorithm we used. Therefore, many extensive experimentations were carried out in order to determine the best optimal *k* value that can give high performance.

3.4. Evaluation Techniques

This section is optional part in the design of pattern recognition systems, which is concerned with evaluating the system's performance in terms of accuracy. Notably, there are many techniques used to evaluate performance of pattern recognition systems such as Leave-One-Out Cross-validation, *k*-folds Cross-validation, Mean Absolute Error (MAE), Cumulative Score (CS), and Confusion Matrix. However, in this thesis, we will use two techniques to evaluate the gender and age prediction systems that are: Leave-One-Out Cross-validation and Confusion Matrix techniques, which will be briefly discussed in following sub-sections.

3.4.1. Leave-One-Out and K-fold Cross-validation

Cross-validation is a technique used to evaluate system classification. The basic idea of this technique depends on exception some data from the dataset before training begins (to use it for test), and using all other data for training. In general, there are two types of Cross-Validation technique, Exhaustive Cross-Validation, that is known as Leave-One-Out (LOO), and Non-Exhaustive Cross-Validation that known as K-fold.

Leave-One-Out Cross-Validation (LOO) mechanism is simple; the dataset is split into *N* subsets, where *N* is the number of samples in the dataset. Then, the classification process is repeated *N* times, in each time, *N*-1 of subsets are used to train the classifier, and only one subset is used for evaluation. For example, we assume that the dataset includes 100 samples, so it is divided into 100 subsets (each subset has one sample). Then, the classification process will be repeated 100 times, in each time, it will use one sample (1 subset) for evaluation, and 99 samples (all remained subsets) for training the classifier.

K-fold Cross-Validation mechanism is a slightly different from LOO, the dataset is distributed on *k* folds (e.g., 5-folds), and then the classification process is repeated *k* times, in each time, only one fold is used for the evaluation (test set), and the other folds are combined together to form the Training Set. For example, assume that the dataset includes 100 samples, and it is divided into 5 folds (each fold has 20 samples). Then, the classification process will repeat 5 times, in each time, it will use 20 samples (1-fold) for evaluation, and 80 samples (the total number of 4-folds) for training the classifier.

In this thesis, Leave-One-Out Cross-Validation (LOO) technique have been applied on FERET, FG-NET, and UTD databases in order to evaluate the performance of SVM and KNN classifiers. Grey Scale FERET database has 1,262 samples, and hence 1,262 subsets will be used. In each loop, the classifier uses one subset for evaluation and the remaining subsets for training, and continues like this until finishing all subsets one by one. Finally, all 1,262 predictions are summarized and confirmed the evaluation of stable performance without any object dependencies between test and training set.

3.4.2. Confusion Matrix

The confusion matrix, which is also called an error matrix or a contingency table, provides a simple detail and visualization about predicted and actual classes that are accomplished by a classifier. The systems performance is generally evaluated by using the details mentioned in this matrix. Figure 3.11 shows the confusion matrix layout of a two classification classes.

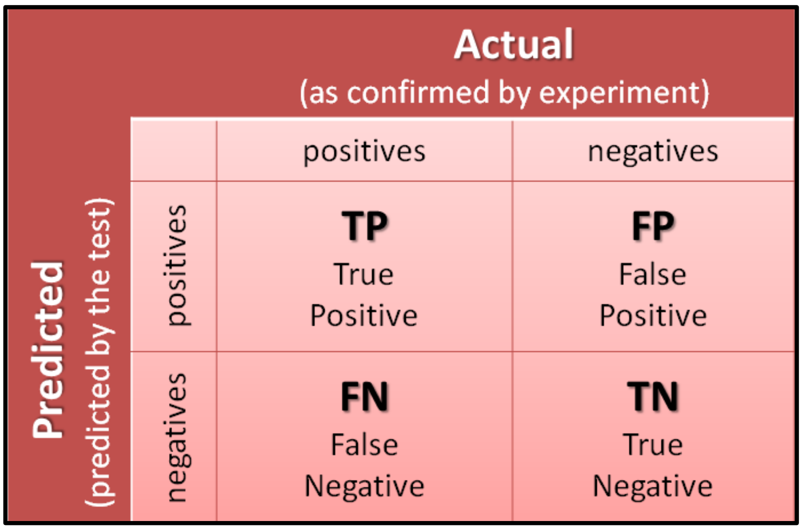


Figure 3.11. Confusion Matrix

Each column in the above table shows the number of actual and correct class samples, whereas each row shows the number of predicted class samples. In more details:

- "True Positive" is the number of true or correct predictions that an example is positive.
- "False Negative" is the number of false or incorrect predictions that an example is negative.
- "False Positive" is the number of false or incorrect predictions that an example is positive.
- "True Negative" is the number of true or correct predictions that an example is negative.

3.5. Databases

3.5.1. FERET Database

The Facial Recognition Technology (FERET) database [85] is a standard and non-commercial large database of facial images, used mainly for facial recognition system evaluation. The DoD Counterdrug Technology Development Program Office progressed the Face Recognition (FERET) program between 1993 and 1998 with total funding of 6.5 million dollars. Then, the Defence Advanced Research Projects Agency (DARPA) and the National Institute of Standards and Technology (NIST) have managed this program. The database contains 14,126 grey scale facial images distributed on 1,564 sets of images (1,199 individuals and 365 duplicate sets) (*see Figure 3.12*). In 2003, DARPA released a high-resolution color version of these images, which includes 2,413 facial images representing 856 individuals (*see Figure 3.13*). Moreover, both FERET databases (grey scaled and coloured databases) contains a guidebook, which provides several information about each image in the database such as gender, age, ethnicity and more [8, 9].

Figure 3.12. Examples from Grey Scale FERET Database

Figure 3.13. Examples from Color FERET Database

3.5.2. UTD Database

The University of Texas at Dallas (UTD) Database is a non-commercial facial image database used mainly for age and gender prediction. It contains 580 facial images of people from 18 to 99 years old, where 352 of these images are Female and 228 images are Male. UTD can be used also for emotional recognition because all images in the database are detailed with happy, angry, annoyed, disgusted, grumpy, sad, or surprised expressions as shown in Figure 3.14.

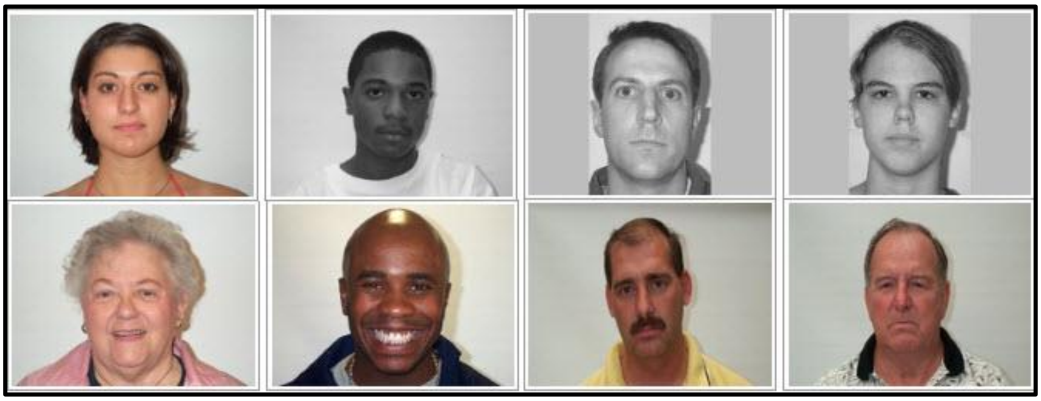


Figure 3.14. Examples from UTD Database

3.5.3. FG-NET Aging Database

The FG-NET aging database [37] was released in 2004 to help understanding the changes in facial appearance caused by the age. It is provided for free (non-commercial) to support researchers in various disciplines such as age progression, age estimation, age-invariant face recognition, or any other academic research-related activities. The FG-NET database contains 1,002 facial images from 82 different individuals that age-ranging from 0 to 69 years old, with large variability in illumination, resolution, expression, and pose (*see Figure 3.15*).

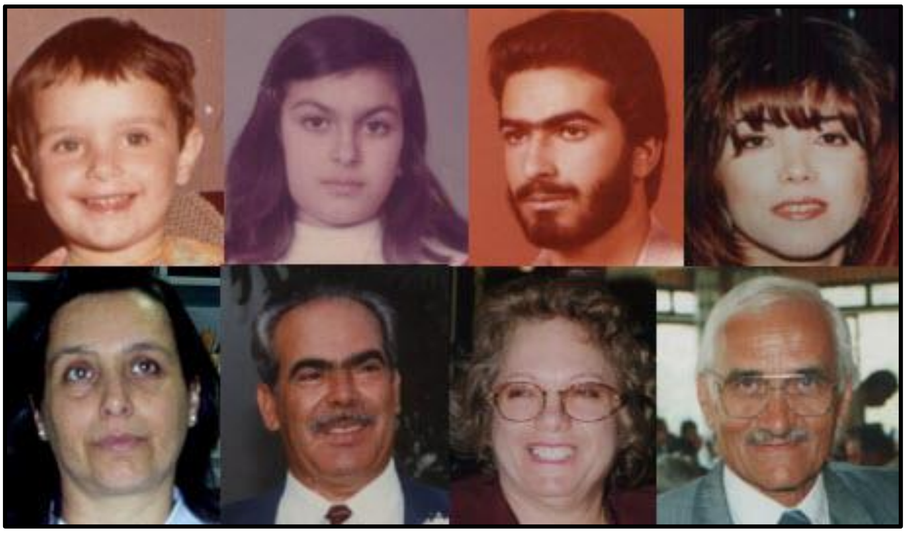


Figure 3.15. Examples from FG-NET Database

3.6. Summary:

In this chapter, we described the pre-processing techniques applied to the proposed system. In this context, dimensions alignment (image resizing) has advantages of helping the feature extractor (e.g., HOG) to extract same number of features from all images. Moreover, it helps to decrease the processing time, and hence increases the system performance. Whereas, normalizing the illumination by applying Histogram Equalization technique helps to unify luminosity of images, which reflects positively on the accuracy and system's performance.

In Chapter 4, many extensive experimentation carried out to make the classifier obtain high accuracy performance are given.

CHAPTER 4

4. IMPLEMENTATION AND RESULTS

4.1. Experiments

In here, we will elucidate the intensified experiments that we made in order to predict gender and age of people from their facial images. Remember that we have employed four image datasets that are:

- FERET grey scale images database, which contains 1,262 facial images of people, where 531 of these images are female images and 731 male images. This dataset has been used only in gender prediction experiments.
- FERET color images database, which contains 943 facial images of people, where 400 of these images are female images and 543 male images. This dataset has been used also only in gender prediction experiments.
- UTD database, which contains 580 facial images of people ranged from 18 to 99 years old, where 352 of these images are female images and 228 male images. This dataset has been used in both gender and age prediction experiments.
- FG-NET aging dataset, which contains 1,002 facial images ranging from 0 to 69 years old. This dataset has been used only in age prediction experiments.

In addition, dimensions alignment (image resizing) with dimensions of "128×192" pixels, and Histogram Equalization (HE) technique have been applied on all these facial images. Then, both HOG and LBP features have been extracted from each facial image, and used for gender and age recognition experiments, whereas SVM and KNN have been used to classify these features.

In this study, we used two separate paths (approaches) of experiments to determine the performance of the classifiers (SVM & KNN) that are:

- In first approach, Holdout approach, we put about 90% of images we have in the Training Set, and about 10% of these images in the Test Set. Thus, we will train the classifiers by using images in the Training Set, and then we use the Test Set images to evaluate the classifier's performance.
- In second approach, we used Leave-One-Out (LOO) technique to evaluate the performance of the classifiers. In this technique, only one images is used as a test sample in each turn, while all remaining images are used to train the classifier. However, this operation is repeated (N-1) times by taking new sample as a test in each time.

The main important difference between the first and second approaches is that first approach uses limited amount of data for training the classifier, which may influence its effectiveness. On the other hand, the second approach (LOO) is able to train a classifier with all images we have in the dataset, which can reflect positively on its performance and make it more robust, accurate and effective.

In general, we made experiments in order to predict gender and age of people from their facial images by using HOG with SVM, LBP with SVM, combined HOG & LBP with SVM, HOG with KNN, LBP with KNN, and combined HOG & LBP with KNN. Each method has been used twice; once by applying the first approach (Holdout) and the other by applying the second approach (LOO). Furthermore, in case of using KNN classifier, we made many extensive experimentations in order to determine the best optimal *k* value that can give high performance (*see Figures: 4.1, 4.4, 4.5, 4.6, and 4.7*). We will comprehensively study all these experiments in following sub-sections.

4.2. Results

4.2.1. Gender Prediction Experimental Results

In here, we review results of all experiments done in order to predict the gender.

4.2.1.1. Applying Holdout Approach on FERET Datasets

- **Experimental Results 1: SVM Based Classification:**

In these experiments, we employed 600 images in each of FERET grey scale and FERET color images as a Training Set and 100 images as Test Set. As a result, when SVM classifier is used with HOG features, gender prediction accuracies were **93**% and **87**% for grey scale and color images respectively. Likewise, when LBP features are used with SVM, gender prediction accuracies were **97**% and **85**% for grey scale and color images respectively. However, in order to improve the performance of the classifier, we combined both HOG and LBP features to see the effectiveness of SVM classifier with these combined features. As a result, we got **99**% and **97**% performance when using combined HOG and LBP features with SVM for grey scale and color images, respectively. Table 4.1 shows a summary of all SVM based classification results done in the experiment 1.

Method	Dataset	Accuracy
HOG + SVM	FERET Grey Scale	93 %
	FERET Color	87 %
LBP + SVM	FERET Grey Scale	97%
	FERET Color	85 %
Combined (HOG&LBP) + SVM	FERET Grey Scale	99 %
	FERET Color	97 %

Table 4.1. SVM Based Classification Results of FERET DB (Holdout Approach)

- **Experimental Results 2: KNN Based Classification:**

In these experiments, we employed same amount of data used in former experiment.

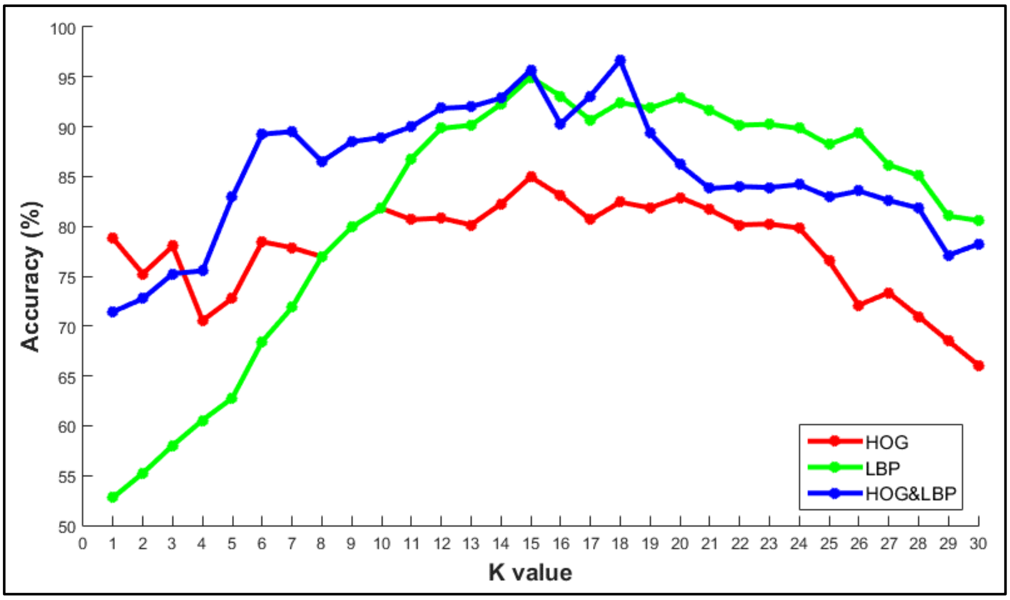


Figure 4.1. The Performance of Experiment 2 According to *k* Value

As can be seen from the Figure 4.1, changing *k* value from 1 to 30 leads to attain different performance. In addition, we notice that the best performance can be achieved when *k* value is equal to 15, 15, and 18 in case of using HOG, LBP, combined HOG & LBP features, respectively.

However, when KNN classifier is used with HOG features, gender prediction accuracies were **84**% and **66**% for grey scale and color images respectively. To get this result with KNN classifier we have determined that *k* value = 15. Likewise, when LBP features are used with KNN, the gender prediction accuracies were **93**% for grey scale images and **94**% for color images with *k* value = 15. Then, we combined both HOG and LBP features to see the effectiveness of KNN classifier with these combined features. As a result, we got **96**% and **95**% when using combined HOG and LBP features with KNN for grey scale and color images respectively (*see Table 4.2*). Note that in this case we determined *k* value = 18 as shown in Figure 4.1.

Method	Dataset	Accuracy
HOG + KNN *(k = 15)*	FERET Grey Scale	84 %
	FERET Color	66 %
LBP + KNN *(k = 15)*	FERET Grey Scale	93 %
	FERET Color	94%
Combined (HOG&LBP) + KNN *(k = 18)*	FERET Grey Scale	96 %
	FERET Color	95 %

Table 4.2. KNN Based Classification Results of FERET DB (Holdout Approach)

From above experimental results, we notice that the performance of the system has increased by combining HOG and LBP features even if the amount of data and classifiers used are same. However, Figures 4.2 and 4.3 review a general comparison between all results according to the type of images.

- <u>FERET Grey Scale images:</u>

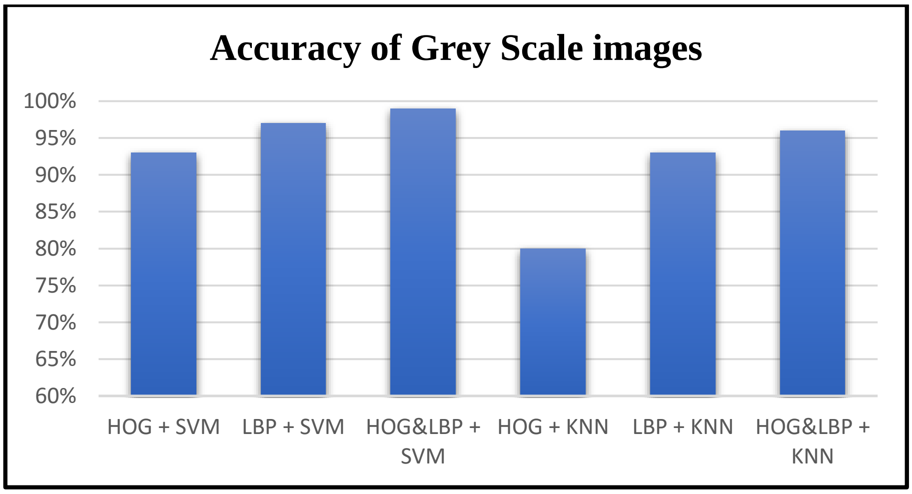


Figure 4.2. Accuracies of Applying Holdout Approach on Grey Scale Dataset

- <u>FERET Color images:</u>

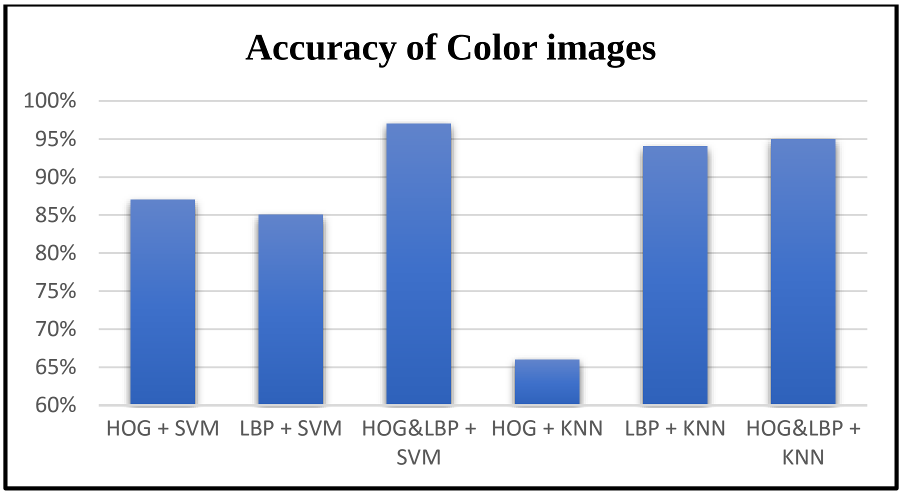


Figure 4.3. Accuracies of Applying Holdout Approach on Color Dataset

<u>4.2.1.2. Applying LOO Approach on FERET Datasets</u>

- **Experimental Results 3: SVM Based Classification:**

By applying LOO ("Leave-One-Out") approach, which uses one sample in each turn as a Test Set and all other data as a Train Set, on all images we have in FERET dataset, the HOG features with SVM gave us gender prediction accuracies of **99.68**% and **100**% for grey scale and color images, respectively. Whereas, the accuracies of using LBP features with SVM were **99.84**% for grey scale images and **100**% for color images. From previous experiments, we can notify that HOG features with SVM classifier gave us different results than LBP features with SVM in both grey scale and color images. Therefore, we combined both HOG and LBP features again to see the effectiveness of SVM classifier with these combined features. As a result, we got **100**% accuracies for both grey scale and color image types when we used these methods with LOO technique. Table 4.3 shows a summary of all SVM based classification results.

Method	Dataset	Accuracy
HOG + SVM	FERET Grey Scale	99.68 %
	FERET Color	100 %
LBP + SVM	FERET Grey Scale	99.84%
	FERET Color	100 %
Combined (HOG&LBP) + SVM	FERET Grey Scale	100 %
	FERET Color	100 %

Table 4.3. SVM Based Classification Results of FERET DB (LOO Approach)

- **Experimental Results 4: KNN Based Classification:**

In these experiments, we applied LOO ("Leave-One-Out") approach, which uses one sample in each turn as a Test Set and all other data as a Train Set, on all images we have in FERET dataset.

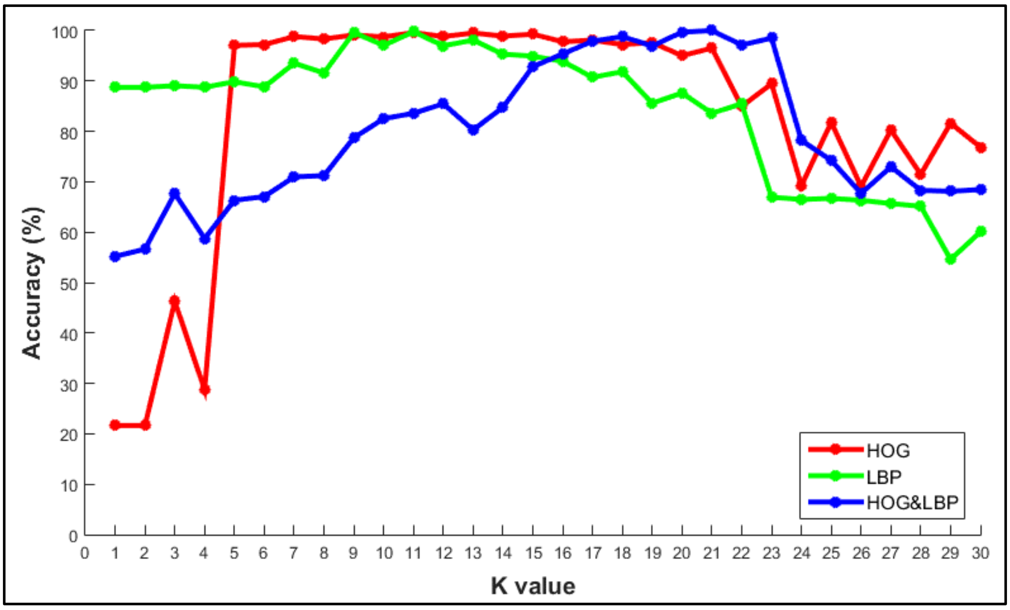


Figure 4.4. The Performance of Experiment 4 According to *k* Value

As can be seen from the Figure 4.4, changing *k* value from 1 to 30 leads to attain different performance. In addition, we notice that the best performance can be achieved when *k* value is equal to 11, 11, and 21 in case of using HOG, LBP, combined HOG & LBP features, respectively.

However, when HOG features are used with KNN, we achieved to accuracies of **99.60**% for grey scale images and **98.30**% for color images when *k*=11. Likewise, the accuracies of using LBP features with KNN were **99.76**% and **80.49**% for grey scale and color images respectively, with respect of *k* value = 11. Then, we combined both HOG and LBP features to see the effectiveness of KNN classifier with these combined features. As a result, we got **100**% when using combined HOG and LBP features with KNN for grey scale and color images respectively (*see Table 4.4*). Note that in this case we determined *k* value = 21 as shown in Figure 4.4.

Method	Dataset	Accuracy
HOG + KNN *(k = 11)*	FERET Grey Scale	99.60 %
	FERET Color	98.30 %
LBP + KNN *(k = 11)*	FERET Grey Scale	99.76 %
	FERET Color	80.49%
Combined (HOG&LBP) + KNN *(k = 21)*	FERET Grey Scale	100 %
	FERET Color	100 %

Table 4.4. KNN Based Classification Results of FERET DB (LOO Approach)

Experimental results 3 and 4 show the best performance that we had in order to predict the gender. We notice that the performance of the system has significantly increased by combining HOG and LBP features. In addition, although LOO approach consumes a lot of computing time, it trains and evaluates classifiers very well and give excellent performance.

4.2.1.3. Applying Holdout Approach on FERET and UTD Datasets

- **Experimental Results 5: SVM Based Classification:**

In here, we used FERET database, which includes "1,262" facial images, as a Training Set, and UTD database, which includes "580" facial images, as a Test Set. Consequently, when the HOG features are used with SVM, gender recognition accuracy was **87.76**%. Likewise, when LBP features are used with SVM, we got an accuracy of **94.74**%. Then, we combined both HOG and LBP features to see the effectiveness of SVM classifier with these combined features. As a result, **98.79**% gender prediction rate has been achieved by using combination of HOG and LBP features with SVM classifier. Table 4.5 shows the performance of experiment 5.

Method	Train Dataset	Test Dataset	Accuracy
HOG + SVM	FERET Grey Scale	UTD	87.76%
LBP + SVM	FERET Grey Scale	UTD	94.74%
Combined (HOG&LBP) + SVM	FERET Grey Scale	UTD	98.79%

Table 4.5. SVM Based Classification of FERET and UTD Databases (Holdout Approach)

- **Experimental Results 6: KNN Based Classification:**

In these experiments, we employed same FERET database, which includes "1,262" facial images, as a Training Set, and UTD database, which includes "580" facial images, as a Test Set.

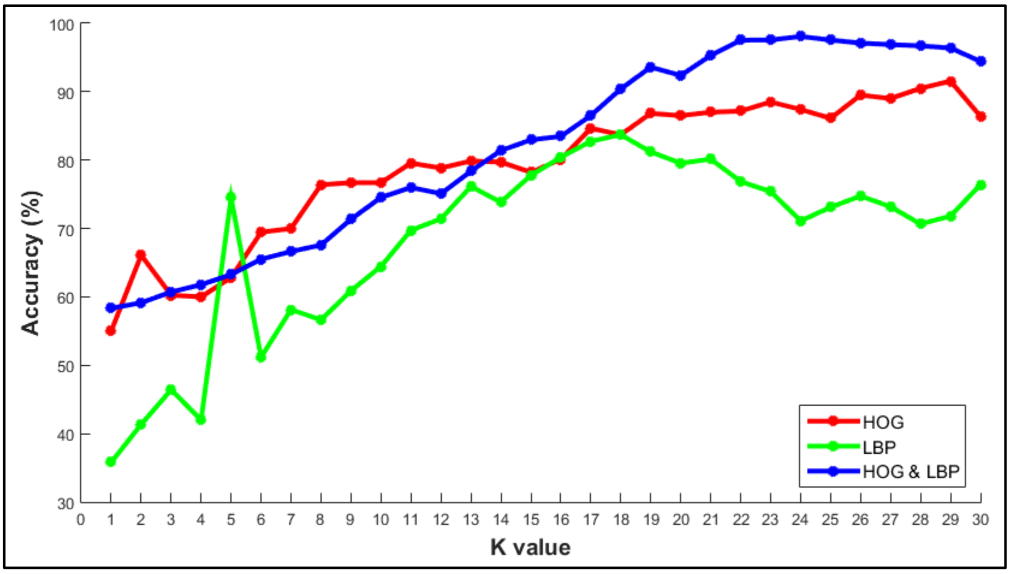


Figure 4.5. The performance of experiment 6 according to *k* value

As can be seen from the Figure 4.5, changing *k* value from 1 to 30 leads to attain different performance. In addition, we notice that the best performance can be achieved when *k* value is equal to 29, 18, and 24 in case of using HOG, LBP, combined HOG & LBP features, respectively.

As a result, when KNN classifier is used with HOG features, gender prediction accuracy was **91.55**%. To get this result with KNN classifier we have determined that *k* value = 29. Likewise, when LBP features are used with KNN, the gender prediction accuracy was **83.70**%. *k* = 18 is the best-determined value for this experiment. Then, we combined both HOG and LBP features to see the effectiveness of KNN classifier with these combined features. As a result, with respect to *k* value = 24 we got **98.08**% by using combined HOG and LBP features with KNN, which reflect the high performance of the system (*see Table 4.6*). Figure 4.5 shows the performance of the experiment 6 according to *k* value.

Method	Train Dataset	Test Dataset	Accuracy
HOG + KNN *(k = 29)*	FERET Grey Scale	UTD	91.55%
LBP + KNN *(k = 18)*	FERET Grey Scale	UTD	83.70%
Combined (HOG&LBP) + KNN *(k = 24)*	FERET Grey Scale	UTD	98.08%

Table 4.6. KNN Based Classification of FERET and UTD Databases (Holdout Approach)

The second type of experiments is applying HOG and LBP with SVM and KNN on UTD database only (LOO approach).

4.2.1.4. Applying LOO Approach on UTD Dataset

- **Experimental Results 7: SVM Based Classification:**

In here, we used only UTD database, which includes “580” facial images, with LOO (“Leave-One-Out”) approach. Consequently, when the HOG features are used with SVM, gender prediction accuracy were **99.82**%, whereas when LBP features are used with SVM, the accuracy was **99.65**%. However, **100**% gender prediction rate has been achieved by using combined HOG and LBP features with SVM classifier, as shown in Table 4.7.

Method	Dataset	Accuracy
HOG + SVM	UTD	99.82%
LBP + SVM	UTD	99.65%
Combined (HOG&LBP) + SVM	UTD	100%

Table 4.7. SVM Based Classification of UTD Database (LOO Approach)

- **Experimental Results 8: KNN Based Classification:**

By applying LOO approach on all images we have in UTD dataset (*see Table 4.8*), the HOG features with KNN gave us gender prediction accuracies of **98.95**% when k = 30. Likewise, when we used LBP features with KNN, we got an accuracy of **99.50**% when k = 30. Furthermore, in order to increase the system's performance, we combined HOG and LBP features. Thus, we got **100**% gender prediction ratio by applying KNN classifier and considering k value = 24 (*see Figure 4.6*).

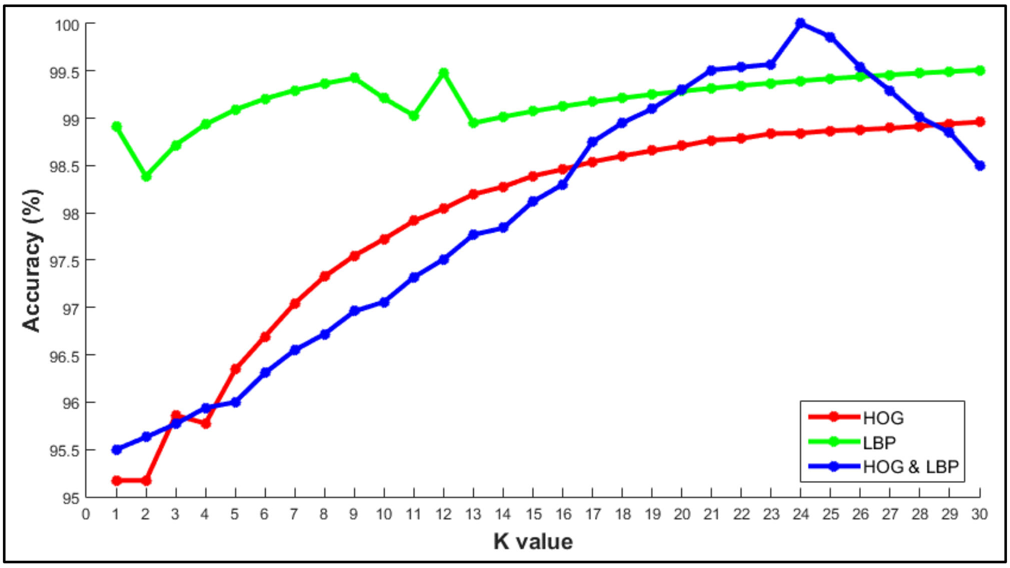


Figure 4.6. The Performance of Experiment 8 According to k Value

As can be seen from the Figure 4.6, changing k value from 1 to 30 leads to attain different performance. In addition, we notice that the best performance can be achieved according to *k* value is 30, 30, and 24 in case of using HOG, LBP, combined HOG & LBP features, respectively.

Method	Dataset	Accuracy
HOG + KNN *(k = 30)*	UTD	98.95%
LBP + KNN *(k = 30)*	UTD	99.50%
Combined (HOG&LBP) + KNN *(k = 24)*	UTD	100%

Table 4.8. KNN Based Classification of UTD Database (LOO Approach)

4.2.2. Age Prediction Experimental Results

According to the gender prediction experimental results, we understood that training the classifiers by using LOO technique is more accurate and efficient than dividing a database into train and test sets (Holdout approach). Therefore, in age prediction experiments, we used only the LOO technique to train and evaluate the classifiers. As we explained at section (3.1.4), FG-NET aging database contains 1,002 facial images, whereas UTD database contains 580 facial images. Therefore, we have combined both databases in one bigger database, containing 1,582 facial images, and then separated these images into 11 classes depending on their ages. We review all experiments done in order to predict the age of people in following sub-sections.

4.2.2.1. Applying LOO Approach on FG-NET and UTD Datasets

- **Experimental Results 9: SVM Based Classification:**

In here, we trained the SVM classifier on 1,582 images from FG-NET and UTD databases by using LOO technique. Consequently, when the HOG features are used with SVM, age prediction accuracy was **98.60**%, whereas when LBP features are used with SVM, the accuracy was **98.29**%. In case of combined HOG and LBP features, **99.87**% age prediction rate has been achieved by using the combined features with

SVM. Table 4.9 shows the performance of the proposed method. In addition, we have evaluated the classifiers by using Confusion Matrix (CM), which provides details and visualization about predicted and acual classes that accomplished by the SVM classifier with HOG, LBP and combined HOG&LBP features, as shown in tables 4.10, 4.11, and 4.12, respectively.

Method	Dataset	Accuracy
HOG + SVM	FG-NET + UTD	98.60%
LBP + SVM	FG-NET + UTD	98.29%
Combined (HOG&LBP) + SVM	FG-NET + UTD	99.87%

Table 4.9. SVM Based Age-Classification of FG-NET and UTD Databases (LOO Approach)

		Actual Classes										
		0-15	16-20	21-25	26-30	31-35	36-40	41-45	46-50	51-55	56-60	Up 60
Predicted Classes	0-15	574	1	0	0	0	0	0	0	0	0	0
	16-20	1	206	1	0	0	0	0	0	0	0	0
	21-25	0	1	211	0	0	0	0	0	0	0	0
	26-30	0	0	0	102	0	0	0	0	0	0	0
	31-35	0	0	0	0	60	0	0	0	0	0	0
	36-40	0	0	0	0	1	47	1	0	0	0	0
	41-45	0	0	0	0	0	1	43	0	0	0	0
	46-50	0	0	0	0	0	0	0	26	0	0	0
	51-55	0	0	0	0	0	0	0	0	24	0	0
	56-60	0	0	0	0	0	0	0	0	0	7	0
	Up 60	0	0	1	1	1	2	1	3	4	2	260
Total		**575**	**208**	**213**	**103**	**62**	**50**	**45**	**29**	**28**	**9**	**260**

Table 4.10. CM Evaluation of HOG + SVM

		Actual Classes										
		0-15	16-20	21-25	26-30	31-35	36-40	41-45	46-50	51-55	56-60	Up 60
Predicted Classes	0-15	575	1	0	0	0	0	0	0	0	0	0
	16-20	0	205	0	0	0	0	0	0	0	0	0
	21-25	0	0	211	0	0	0	0	0	0	0	0
	26-30	0	0	0	101	0	0	0	0	0	0	0
	31-35	0	0	0	0	60	0	0	0	0	0	0
	36-40	0	0	0	0	0	48	0	0	0	0	0
	41-45	0	0	0	0	0	0	43	0	0	0	0
	46-50	0	0	0	0	0	0	0	27	0	0	0
	51-55	0	0	0	0	0	0	0	0	25	0	0
	56-60	0	0	0	0	0	0	0	0	0	0	0
	Up 60	0	2	2	2	2	2	2	2	3	9	260
Total		**575**	**208**	**213**	**103**	**62**	**50**	**45**	**29**	**28**	**9**	**260**

Table 4.11. CM Evaluation of LBP + SVM

		Actual Classes										
		0-15	16-20	21-25	26-30	31-35	36-40	41-45	46-50	51-55	56-60	Up 60
Predicted Classes	0-15	575	0	0	0	0	0	0	0	0	0	0
	16-20	0	208	0	0	0	0	0	0	0	0	0
	21-25	0	0	213	0	0	0	0	0	0	0	0
	26-30	0	0	0	103	0	0	0	0	0	0	0
	31-35	0	0	0	0	62	0	0	0	0	0	0
	36-40	0	0	0	0	0	50	0	0	0	0	0
	41-45	0	0	0	0	0	0	45	0	0	0	0
	46-50	0	0	0	0	0	0	0	29	0	0	0
	51-55	0	0	0	0	0	0	0	0	28	0	0
	56-60	0	0	0	0	0	0	0	0	0	8	1
	Up 60	0	0	0	0	0	0	0	0	0	1	259
Total		**575**	**208**	**213**	**103**	**62**	**50**	**45**	**29**	**28**	**9**	**260**

Table 4.12. CM Evaluation of Combined HOG & LBP + SVM

- **Experimental Results 10: KNN Based Classification:**

In these experiments, we trained the KNN classifier on 1,582 images from FG-Net and UTD databases by using LOO technique. Consequently, when the HOG features are used with KNN, age prediction accuracy were **98.23**%, with respect of *k* value = 12. Similarly, when LBP features are used with KNN, the accuracy were **88.05**%, in case of considering *k* value = 19. In order to increase the system's performance, we combined HOG and LBP features. Thus, we got **99.43**% age prediction rate by applying KNN classifier and considering *k* value = 21 (*see Figure 4.7*). Table 4.13 shows the performance of the proposed method. In addition, we have evaluated the classifiers by using Confusion Matrix (CM), which provides simple details and visualization about predicted and acual classes that accomplished by the KNN classifier with HOG, LBP and combined HOG&LBP features, as shown in tables 4.14, 4.15, and 4.16, respectively.

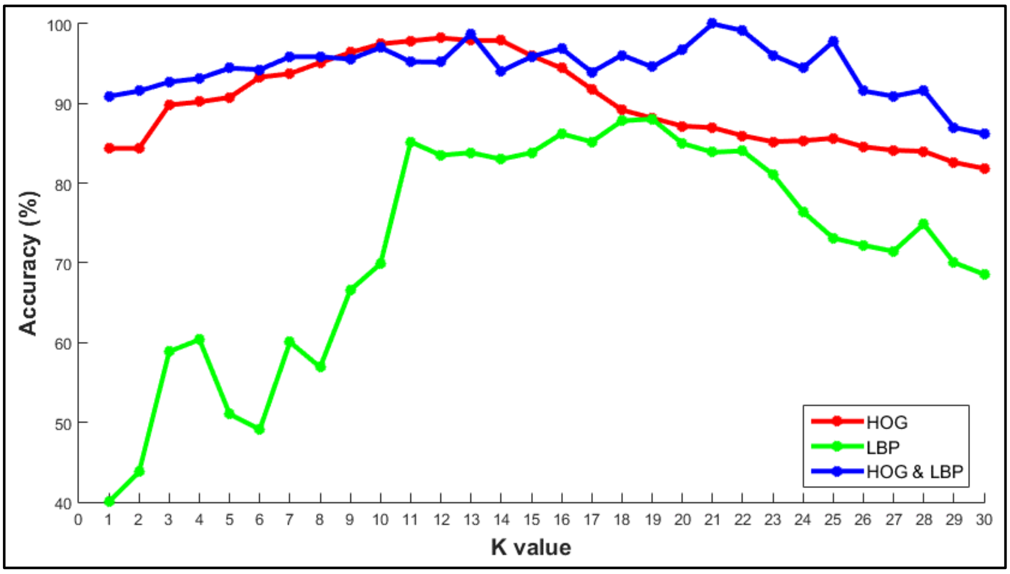


Figure 4.7. The Performance of Experiment 10 According to *k* Value

As can be seen from the Figure 4.7, changing *k* value from 1 to 30 leads to attain different performance. In addition, we notice that the best performance can be achieved when *k* value is equal to 12, 19, and 21 in case of using HOG, LBP, combined HOG & LBP features, respectively.

Method	Dataset	Accuracy
HOG + KNN *(k = 12)*	FG-NET + UTD	98.23%
LBP + KNN *(k = 19)*	FG-NET + UTD	88.05%
Combined (HOG&LBP) + KNN *(k = 21)*	FG-NET + UTD	99.43%

Table 4.13. KNN Based Age-Classification of FG-NET and UTD Databases (LOO Approach)

		Actual Classes										
		0-15	16-20	21-25	26-30	31-35	36-40	41-45	46-50	51-55	56-60	Up 60
Predicted Classes	0-15	575	5	0	0	0	0	0	0	0	0	0
	16-20	0	202	0	0	0	0	0	0	0	0	0
	21-25	0	1	212	1	0	0	0	0	0	0	0
	26-30	0	0	1	102	0	0	0	0	0	0	0
	31-35	0	0	0	0	62	0	0	0	0	0	0
	36-40	0	0	0	0	0	50	0	0	0	0	0
	41-45	0	0	0	0	0	0	45	8	0	0	0
	46-50	0	0	0	0	0	0	0	20	2	0	0
	51-55	0	0	0	0	0	0	0	1	26	1	0
	56-60	0	0	0	0	0	0	0	0	0	0	0
	Up 60	0	0	0	0	0	0	0	0	0	8	260
Total		**575**	**208**	**213**	**103**	**62**	**50**	**45**	**29**	**28**	**9**	**260**

Table 4.14. CM Evaluation of HOG + KNN

	Actual Classes										
Predicted Classes	0-15	16-20	21-25	26-30	31-35	36-40	41-45	46-50	51-55	56-60	Up 60
0-15	575	127	2	0	0	0	0	0	0	0	0
16-20	0	76	6	0	0	0	0	0	0	0	0
21-25	0	5	204	4	0	2	0	0	0	0	0
26-30	0	0	0	99	0	0	0	0	1	0	0
31-35	0	0	0	0	49	0	0	0	0	0	0
36-40	0	0	0	0	0	30	0	0	0	0	0
41-45	0	0	0	0	0	0	43	0	0	0	0
46-50	0	0	0	0	0	0	0	26	0	0	0
51-55	0	0	0	0	1	0	0	0	25	0	0
56-60	0	0	0	0	0	0	0	0	0	6	0
Up 60	0	0	1	0	12	18	2	3	2	3	260
Total	**575**	**208**	**213**	**103**	**62**	**50**	**45**	**29**	**28**	**9**	**260**

Table 4.15. CM Evaluation of LBP + KNN

	Actual Classes										
Predicted Classes	0-15	16-20	21-25	26-30	31-35	36-40	41-45	46-50	51-55	56-60	Up 60
0-15	575	0	0	0	0	0	0	0	0	0	0
16-20	0	208	0	0	0	0	0	0	0	0	0
21-25	0	0	213	0	0	0	0	0	0	0	0
26-30	0	0	0	103	0	0	0	0	0	0	0
31-35	0	0	0	0	62	0	0	0	0	0	0
36-40	0	0	0	0	0	50	0	0	0	0	0
41-45	0	0	0	0	0	0	45	0	0	0	0
46-50	0	0	0	0	0	0	0	29	0	0	0
51-55	0	0	0	0	0	0	0	0	28	0	0
56-60	0	0	0	0	0	0	0	0	0	0	0
Up 60	0	0	0	0	0	0	0	0	0	9	260
Total	**575**	**208**	**213**	**103**	**62**	**50**	**45**	**29**	**28**	**9**	**260**

Table 4.16. CM Evaluation of Combined HOG & LBP + KNN

4.3. Summary

In order to predict the gender or age of any person from his/her face image, many extensive experimentations were carried out to make the classifiers obtain high accuracy and performance. Moreover, our improvements for combining HOG and LBP features, dimensions alignment, and illumination normalization of the facial images, have been applied successfully on all images, and hence gave us very good and accurate results. Furthermore, we noticed that using LOO technique with combined HOG and LBP gave excellent performance. On the other hand, LOO technique has a disadvantage that it may consume a lot of processing time when applying it on large amount of data because it evaluates all images we have in the dataset one by one.

To sum up all gender prediction results, Figures 4.8 and 4.9 review a general comparison between all accuracies according to the applied approach (Holdout or LOO) and the type of FERET dataset images (Grey scale or Color).

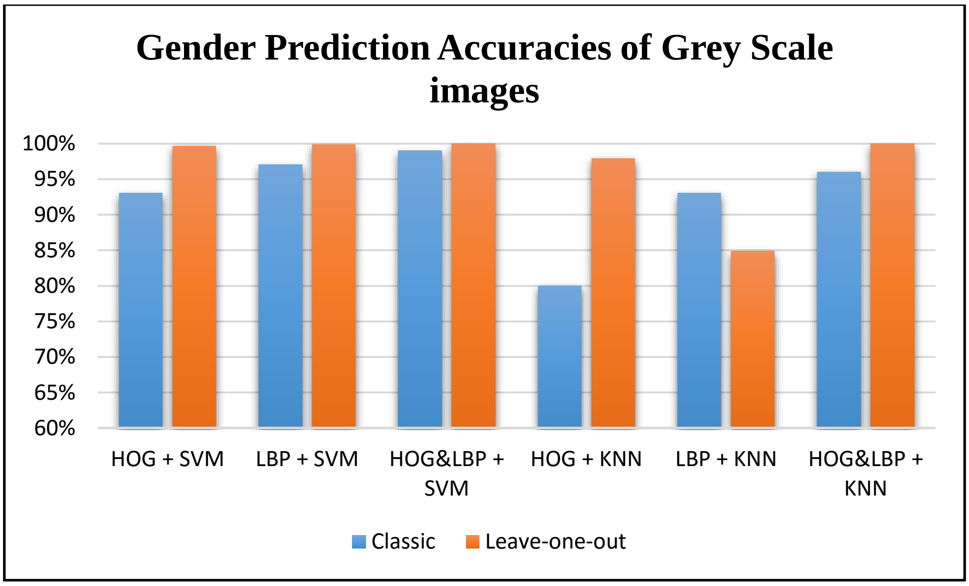


Figure 4.8. All Gender Prediction Accuracies by Applying Holdout and LOO Approaches on FERET Grey Scale Dataset

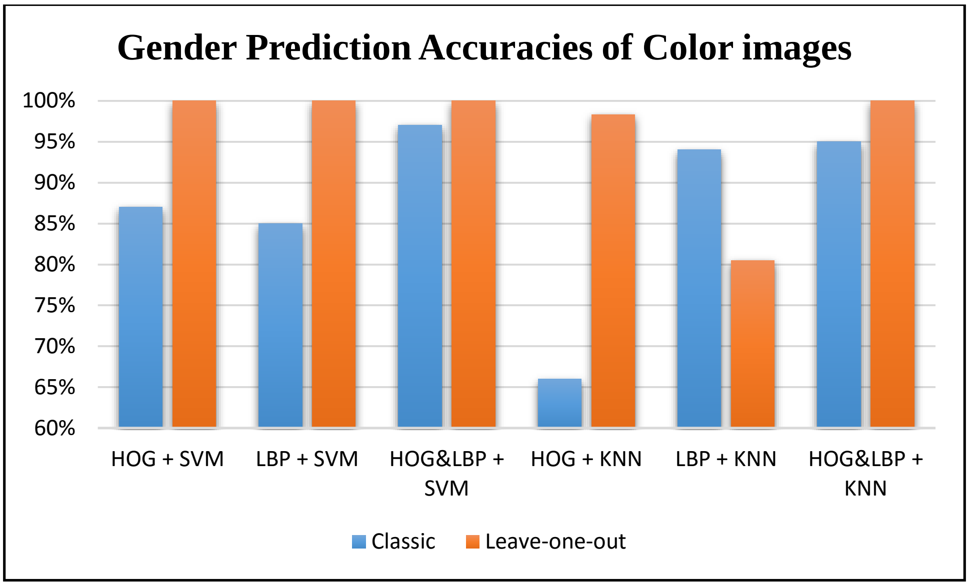
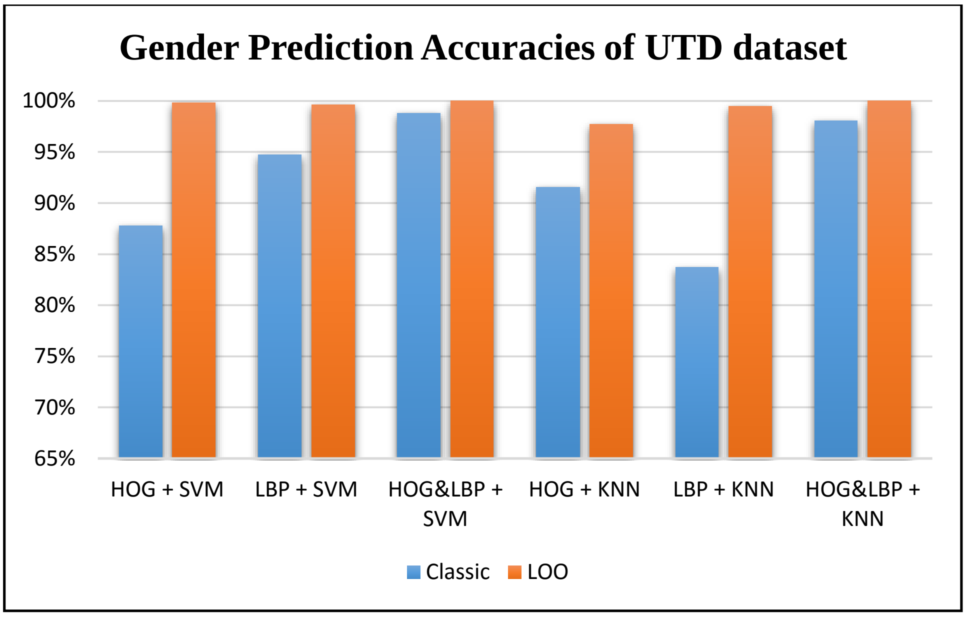


Figure 4.9. All Gender Prediction Accuracies by Applying Holdout and LOO Approaches on FERET Color Dataset

In addition we used first and second approaches on FERET database, we made also extra experiments in order to predict the gender by using first approach on FERET database (Training Set) and another database called UTD (Test Set), and second approach on only UTD database. However, Figure 4.10 reviews a general comparison between all results according to using FERET and UTD datasets with Holdout approach, and using only UTD with LOO approach.



Figures 4.10. All Gender Prediction Accuracies by Applying Holdout and LOO Approaches on FERET and UTD Dataset

Similarly, to sum up all age prediction results, experiments 9 and 10 show that training the classifiers by using LOO technique is more efficient than dividing a database into train and test sets (Holdout approach). In addition, combining HOG and LBP features is an accurate method that helps classifiers to achieve high performance, where we were able to increase the age prediction system's performance from 88.05% (lowest prediction result) up to 99.87% (best prediction result) as shown in Tables 4.9 and 4.13.

CHAPTER 5

5. CONCLUSION AND FUTURE WORK

In this chapter, we conclude and summarize the most important points presented in the previous chapters, and indicate the future work and probable strategies to extend the capabilities and improve the performance of age and gender classification systems.

5.1. Conclusion

In this thesis, we investigated two of image processing field problems, gender prediction, and age prediction, and an extensive study of these problems has been done. However, solving these problems is not easy because prediction methods suffer from some difficulties in analysing data, and making these data generalized, thus applying it to everyone is not an easy task. We began this thesis by introducing the challenges about the prediction of gender and age from facial images, and discussed the motivations that encouraged us to study this field. Moreover, we described the main problems related to these tasks in Chapter 1. Next, in Chapter 2 we presented an overview of several researches, potential applications, and robust approaches have been done in the gender and age prediction realm.

In Chapter 3, we explain the core and methodology of this thesis; we first review a general description of the basic techniques used to perform the face feature extraction. Then, details about the classification algorithms used in the work have been provided. Due the challenge and importance of choosing a good database since the majority of databases' images were taken in unconstrained conditions and having variation in face position and luminosity, we finished this chapter by providing a brief insight into the databases that our algorithm is evaluated and applied on. In general, using proper methods and databases, and convenient number of images are effecting positively on the system's performance and results. Next, comprehensive studies, which includes two experimental approaches, show that combining of HOG and LBP features can results in much improvement in the recognition accuracy of gender and age prediction problems. In addition, dimensions alignment and illumination normalization of the facial images are significant factors to improve the system's performance. Furthermore, our investigation confirms that using correct *k* value when using KNN classifier in addition to extracting and using the correct image features can strongly effects on the prediction accuracy even if we use changeable number of data. Comparing to other similar studies, this work attains honourable and significant results at the area of identifying the gender and age information from facial images. For instance, by combining HOG and LBP we have achieved a gender accuracy of 100% in the LOO experimental approach, whereas we achieved age prediction accuracies of 99.87% and 99.43% by using combining HOG and LBP with SVM and KNN respectively. To sum up, using high number of image features by combining HOG and LBP features, unifying the luminosity of images, and aligning the dimensions of these images give high gender and age prediction accuracies.

Generally, from the performance of proposed methods, we noticed that SVM classifier is more accurate when used with LBP features than HOG features. Whereas, KNN classifier is more accurate when used with HOG features. Therefore, in general SVM classifier is better than KNN because SVM can attain high performance even with few number of training data, on opposite of KNN classifier, which need to well training to achieve high performance. In addition, HOG feature extractor is a slightly better than LBP feature extractor because HOG can extract more features from an image than LBP, hence, this helps classifiers for better classification. For this reason, to increase the number of features extracted from each face image, we combined both HOG and LBP features, and then classified all these features image by image. As a result, we notice that the performance of classifiers has been significantly improved. To verify the efficiency of the proposed methods, we evaluated them on different databases. Consequently, we got nearly the same performance on two different databases. However, although HOG and LBP features combination may improve the performance of the classifiers, we notice that it consumes a lot of time and computational power.

5.2. Future Work

Within the context of the promising results that obtained by applying presented methods on gender and age prediction problems, similar efforts can be employed to improve ethnic prediction, which is also sensitive to pose changes. Thus, instead of using gender or age databases, a possible solution would be to employ ethnic databases, which could offer the most distinctive ethnic information, and applying the same gender and age approaches on it.

Another suggestion of the gender and age prediction problem is investigating the possibility of using other feature extraction algorithms instead of HOG and LBP. Hence, it can be possible to evaluate the effectiveness of these algorithms comparing to those used in this thesis. Similarly, using other classifiers instead of SVM and KNN is also another area of study and evaluation.

Another potential future tendency is employing the methods that is used in this study to improve face recognition problem, where the mechanism is to apply the features extracted from the face image to connect and find similar likelihoods. This will open new fields of study by using some existing methods and techniques.

Last but not the least; we suggest applying the gender and age approaches that used in this thesis to improve the performance of mood estimation problem. However, one of possible solutions for this problem would be to apply proposed approaches on emotional expression databases (e.g., UTD), which could offer the most distinguishing face emotional expression like happiness, sadness, anger, annoyance, disgust, surprising expressions … etc.

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