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MASTER'S THESIS

# Fusion of trainable features for gender recognition from face images

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June 2018

Frans Juanda Simanjuntak: *Fusion of trainable features for gender recognition from face images*,, Master's in Computing Science, © June 2018

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Groningen

Dedicated to my beloved family and LPDP

# ABSTRACT

Gender recognition from face images has been a well-studied topic in computer vision for years and its popularity arises due to the fact that nowadays it has been applied on different fields such as biometric authentication, surveillance and security system, demographic information collection, marketing research, real time electronic marketing, criminology, and augmented reality. In order to address the challenge, researchers have proposed several approaches however a fixed solution has not been found yet. Recently, VGGFace has become the golden standard for face recognition and turns out its performance is quite impressive in inferring gender by achieving 96% classification rate. Another approach is using trainable filters for key detection called Combination of Shifted Filter Responses (COSFIRE). It is automatically configured to be selective for a local contour pattern specified by a prototype and it is able to achieve an accuracy of 94.7 % in recognizing gender.

In this thesis, we propose two novel approaches namely traditional and stacking techniques that fuse the trainable features from VGGNet and COSFIRE. The traditional technique appends the extracted features from VGGNet to the features from COSFIRE while the stacking technique makes use of the score vectors generated from VGGNet and COSFIRE. Both of the proposed techniques turn out to be outstanding by achieving their remarkable performances with an accuracy of 99.4% validated on the GENDER-FERET (GF) and 98.4% on Labeled Faces in the Wild (LFW) data sets.

# ACKNOWLEDGMENTS

First and foremost, I would like to thank God for giving me the strength, knowledge, and ability to undertake and complete this research study as my final journey of being a master student at the University of Groningen.

I would like to give my gratitude to both of my supervisors, dr. George Azzopardi and prof.dr. Dimka Karastoyanova for investing the time and also for sharing the knowledge and research skills for my thesis. I value all the hard work and patience you gave to me during the supervision which surely will be beneficial for my future.

Also, many thanks to my dad and my family in Indonesia who always support and gave me countless love and prayers. My beloved friends (Ika, Reni, Deka, Yovita, Citra, Azka, Alfian, Novita, Era, etc.), my Indonesian fellas in Groningen, and my class mates as well as my board games fellas (Stefan, Timon, Ankita, Robert, Win, Carlos, Luz), thank you for our love hate relationship, support, laugh, tears, and experience we shared for the last two years. My life would not be that meaningful and colorful in Groningen without all of you by my side.

Lastly and the second foremost, thanks to LPDP (Lembaga Pengelola Dana Pendidikan) who gave me opportunity to pursue my dream to study abroad in the Netherlands by awarding me a scholarship and lighting my financial burden which allows me to focus more on the most important aspect of school, learning. Thank you so much Indonesia.

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# ACRONYMS

| | |
|---|---|
| CNNs | Convolutional Neural Networks |
| COSFIRE | Combination of Shifted Filter Responses |
| LFW | Labeled Faces in the Wild |
| SVM | Support Vector Machines |
| SURF | Speeded Up Robust Features |
| PCA | Principle Component Analysis |
| ICA | Independent Component Analysis |
| LBP | Local Binary Pattern |
| GF | GENDER-FERET |

Part I

# MASTER THESIS

# 1 INTRODUCTION

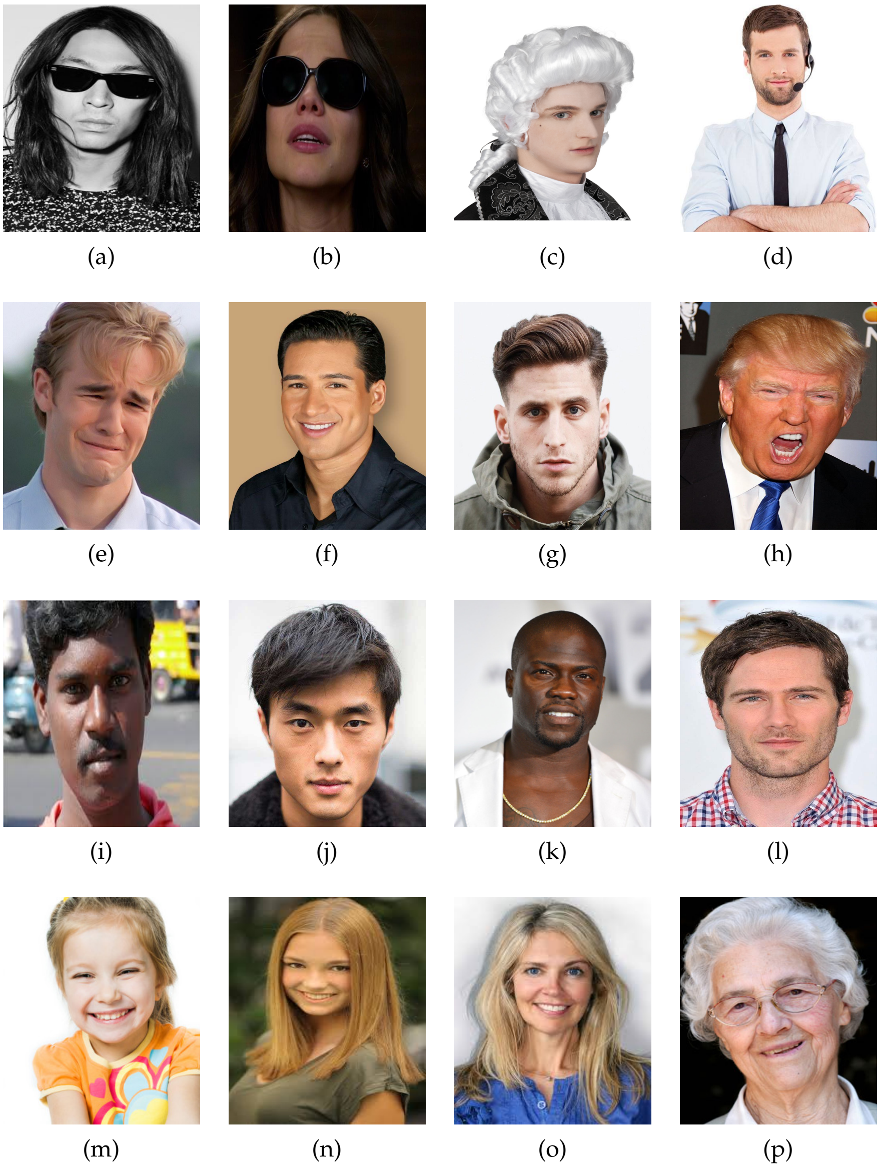
The face is a remarkable part of the human body and considered as one of the most important one since it has some distinctive physical and expressive features which allow the identification of certain properties [13]. The miraculous variety of facial features helps humans recognize each other that leads to the formation of complex societies. Since human face provides important biometric features regarding gender, age, ethnicity, and identity, therefore it has been extensively studied in computer vision.

Gender classification is one of the studies that makes use of human faces to distinguish whether a person is a man or a woman. This task is the basis for all advanced applications such as biometric authentication, surveillance and security system, demographic information collection, marketing research, real time electronic marketing, criminology, and augmented reality.

For instance, surveillance system implements gender recognition in order to investigate allegations of illegal behavior. This system process input image from recorded videos in real time. The main challenge of this system is the computational time needed for searching a match between the input face image and the thousand of samples stored in a reference database [13]. One way to reduce the computation time of matching the identity is to first detect the gender. After that, the system can easily match these parameter (input image and gender) with the samples in database. This approach reduces the computation time resulting in faster identification.

Another application of gender recognition is real time electronic marketing. This system aims at showing advertisements on a billboard to the majority of people approaching towards the billboard screen. If the majority are male, the screen shows an advertisement for male. Conversely, if the majority are female the advertisement are adjusted accordingly.

The systems mentioned above are only a few of the implementations of gender recognition. However, recognizing gender from facial images is not an easy task either for the computer or even for the human itself. For instance, a quick study of human behavior in gender recognition was performed by Mahmoud Afifi and Abdelrahman Abdekhamed. From the experiment, they notice that, beside the high importance of isolated facial features, the visual information from the general look of persons also possesses an important role in the classification process regardless of the visibility of facial features [1]. This results was also noticed in prior work by Liand Lu [39].



(a) (b) (c) (d)

(e) (f) (g) (h)

(i) (j) (k) (l)

(m) (n) (o) (p)

Figure 1.1: Typical problems of gender recognition due to the occlusion with spectacles: (a) (b), wig (c), microphone (d), different expressions: sad (e) happy (f) neutral (g) angry (h), different races: austroloid (i) mongoloid (j) negroid (k) caucasoid (l), and age variation: children (m) adolescent (n) adult (o) eldery (p).

Figure 1.1 shows typical problems of gender classification due to the occlusion with spectacles, wig, and microphone (a,b,c,d), different facial expressions (e,f,g,h), different races (i,j,k,l), and age variation (m,n,o,p). The examples in figure 1.1 (a) and (b) illustrate two images that are somehow difficult to distinguish their gender because the presence of spectacles and hairdo. For some people, the gender of the first model is not easy to infer because both of them are equipped with sun glasses and they also have a long hair. Their eyes are covered as well as some parts of the eye brows which prevent us to discriminate the differences using eyes and eyebrows. At a glance, we might guess that both of them are female which in fact it is wrong. However, the gender might be obvious and distinguishable to others because it can be differentiated by looking at the facial shape, cheekbones, and jawline. Generally speaking, the shape of the male face is longer and larger than female, the cheek bone is sharp, and the jawline is a bit rougher and prominent which lead to a conclusion that figure 1.1 (a) is definitely male and (b) is female.

Moreover, we also might encounter another problem such as dealing with blurred face images. This is a situation when we can barely see the shape or the area in the frame because it has no distinct outline. As an example of this particular situation, figure 1.2 shows the blurred version of male face and female face of the GF data set. In this case, it is difficult to infer the gender from these images because the intensity distribution of the hair as well as the eyes regions are almost similar. One might decide they are male because of the short hair.

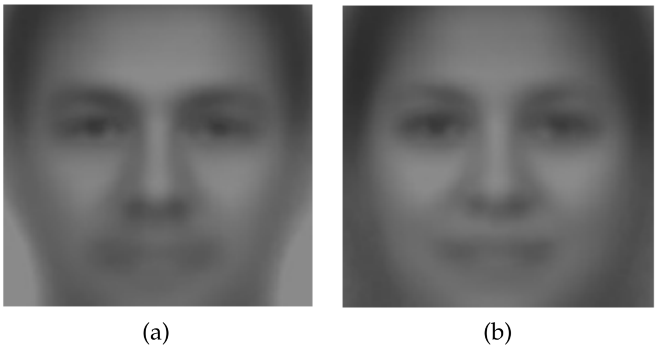


Figure 1.2: The blurred face images of (a) male and (b) female from a subset of the GF dataset [46].

We have mentioned several applications and some challenges we might encounter in gender classification, and at the time of writing this field has been a well-studied topic in computer vision for many years which motivated researches to create a better algorithm for extracting features from facial images. Recently, CNNs [14] have become the golden standard for object recognition [35] [50]. CNNs are often used to recognize objects and scenes, and perform object detection and segmentation. They learn directly from image data, eliminating the need for manual feature extraction in which the features are learned directly by the CNNs. In general, the performance of CNNs when dealing with gender classification problems is around 95 - 97% [3] [42].

Another method to extract features from facial image by using trainable filters for key detection is called COSFIRE. This method is automatically configured to be selective for a local contour pattern specified by a prototype [6]. The configuration comprises selecting given channels of a bank of Gabor Filters and determining certain blurs an shift selected Gabor filters. The performances of this trainable filter are quite promising by achieving approximately 95% accuracy tested on three different cases: the detection of vascular bifurcations in retinal fundus images [9] [11], the recognition of handwritten digits, and the detection of traffic signs in complex scenes [6].

Since both CNNs and COSFIRE are demonstrated to be effective in extracting the most important features of such object, further study is required to investigate whether combining both features would improve the performance of model in gender classification.

## 1.1 RESEARCH QUESTIONS

The existing studies investigate the performance of extracted features either from CNNs or COSFIRE and subsequently use SVM as classifier. These approaches are demonstrated to be effective in dealing with classification related problems such as the detection of vascular bifurcations in retinal fundus images, handwritten digits, detection of traffic signs, gender classification, and many other cases. Also, their performances are quite promising and comparable to the state-of-the-art. These facts lead to the main research questions:

1. What would happen with the performance if the extracted features from both CNNs and COSFIRE are combined and trained with the same classifier (SVM) to infer gender? Will the performance increase or decrease?

2. How will the performance be affected when this approach is applied on constrained and unconstrained data sets which deal with the pose variations, partial occlusion of the face, age, race, and expression?

3. How will the performance be affected using other classifier, for instance, decision tree?

## 1.2 METHODOLOGY

To answer the questions in section 1.1, we first start with a literature study to discover the state of the art of existing methods which focused on gender recognition. We also review the state of the art of both CNNs and COSFIRE. Moreover, we also take into consideration the data sets that we are going to use in order to be able to compare the results with existing studies. Since we expect that our system should be able to validate both constrained and unconstrained data sets, therefore pre-processing task need to be performed on both data sets to make sure they are valid as input for CNNs and COSFIRE. After that, features will be extracted from both methods and subsequently merged as a large feature vector. The term *"merged"* refers to appending CNNs features to COSFIRE.

In this study we proposed two techniques in classifying gender:

1. Traditional technique
   This approach uses the fusion of features from both methods as input by appending the extracted features from CNNs to the features from COSFIRE and subsequently train and validate them using SVM classifier.

2. Stacking technique
   This approach is an extension of traditional method by using the score vectors generated by SVM. First, we extract the features from CNNs and COSFIRE and train them separately. Then, the score vectors generated from each classifier are merged and used as input for a new SVM classifier.

After our models ready, then we validate the performance by comparing the accuracy of CNNs, COSFIRE, and the fusion of CNNs and COSFIRE. We also conduct an experiment to investigate the performance of the traditional approach using another classifier such as XGBoost decision tree [18].

## 1.3 THESIS ORGANIZATION

The rest of the thesis is structured as follows. Section 2 presents the related works that correlates with the present study. The experimental setup and its implementation regarding fusion of CNNs and COSFIRE features is described in section 3. Then, the experimental results and the discussion are explained in section 4 and 5 respectively. Finally, the conclusion is drawn in section 6.

# 2 RELATED WORK

Several studies in relation to gender recognition have been found. These studies are usually based on extracting features from the given images and subsequently use the features to train classifier.

In general, vision-based gender recognition methods can be grouped into three categories: geometric-based, appearance-based, and combination of geometric-based and appearance-based [1]. The geometric-based measures the distance between different key points in the facial image, the appearance-based is based on the pixel-values of facial images[44], while the latter uses the combination of the methods mentioned above.

An overview of existing studies with regard to gender recognition is elaborated in below sections.

## 2.1 GEOMETRIC-BASED

As mentioned earlier, the geometric-based methods extract and utilize geometric features from the given image to predict gender [1]. This method was firstly introduced by Burton et al. 15 year ago in a paper named *"What's the difference between men and women? Evidence from facial measurement"*. The total of 179 monochrome photographs (91 male and 88 females faces) were used in which all faces were of young adults in a neutral expression. In order to avoid the hair that might conceal the most important parts of the face, all volunteers were asked to wear swimming caps. Also, all males were clean shaved and females asked to not wear any makeup.

The analysis of this study relies on 73 facial points which restricted to simply computes the Euclidean distance between points. Subsequently, the discriminant analysis was used to infer the gender. The results of this experiment shows that with 12 variables, the study was able to demonstrate the level of performance at around 85 %. However, this technique might be unreliable since it attempts to use of a linear combination of variables. Such approach by analyzing the distance between key points is not sufficient to infer the gender. More information from multiple source needs to gather in order to develop a reliable technique which is able to discriminate between males and females.

Likewise, Brunelli et al. [48] also conducted a study based on geometrical features. They extracted 16 geometric features from faces such as eyebrow thickness and pupil to eyebrow separation, as input to HyperBF network to learn the differences between the genders [39].

The result of this experiment using face images of twenty males and twenty females as training set shows an average performance of 79% correct gender classification on images of new faces.

Another algorithm based on geometric technique is called COSFIRE filters. This method was inspired by the mechanism of neurons in the human visual cortex that can be used for key points detection and pattern recognition. The filters are contour based detectors in which the responses calculated as the weighted geometric mean of the shifted responses of simple orientation selective filters [6]. Since the performance of COSFIRE was really impressive in recognition of handwritten digits by achieving 99.48 percent accuracy, the authors of that study attempted to apply the filters to infer gender from the given facial images. First, they extract the features from the images and then train the features with SVM classifier [5].This study demonstrated the effectiveness of COSFIRE filters on GF dataset achieving an accuracy rate of 93.7 %.

In the following year, they extended the study by combining COSFIRE filters with domain-specific so-called Speeded Up Robust Features (SURF). SURF is scale- and rotation-invariant interest point detector and descriptor. It consists of fixing a reproducible orientation based on information from a circular region around the interest point and constructs a square region aligned to the selected orientation, and extract the SURF descriptor from it [15]. In particular, they used SURF to extract the most important features related to eyes, nose, and mouth. It turns out, the fusion of these methods achieves 94.74 % on GF and 99.4% on LFW which outperforms the state-of-the-art.

## 2.2 APPEARANCE-BASED

The appearance-method extracts features from either the whole face images (holistic features), regions of the face images (local features), or the combination of holistic and local features [1]. This approach is based on the pixel values of the face images. Neural networks is one of the techniques that follows this approach. It trains single or multiple neural networks with image pixels as input.

In 1990, Golomb et al. conducted a research regarding gender recognition using Neural Networks in which the networks was called *"SexNet"*. In this study, they trained a network with 90 training samples of size 30x30. The result of this study shows that the network's average error rate of 8.1% compared favorably to humans, who averaged 11.6% [30]. This study was then followed by Cottrell et al. who performed gender classification task based on face and motions using holons[21], Burton et al. who measured the facial images in three ways: (i) simple distances between key points in the pictures; (ii) ratios and angles formed between key points in the pictures; (iii) three-dimensional (3-D) distances derived by combination of full-face and profile photographs[16], and Tamura et al. who identified gender with more than 90% accuracy from low frequency components of mosaic 8 × 8 images of the cental part of the human face, which cannot be recognized any more as human faces.[54].

In addition to neural networks, Sun et al. [53] also performed another experiment with Principle Component Analysis (PCA). PCA is a statistical procedure that transforms a number of possibly correlated variables into a smaller number of uncorrelated variables. This study considered the problem of gender classification from frontal facial images using genetic feature subset selection. They used PCA to represent each image as a feature vector in a low-dimensional space and subsequently employed Genetic algorithm to select a subset of features from the low-dimensional representation by disregarding certain eigenvectors that do not seem to encode important gender information. Then, four different classifiers were used to train and classify the features. Turns out, the best performance was obtained using the SVM classifier with an error rate of 4.7%.

Not only did PCA get the attention of researches to be applied on gender classification problem, Independent Component Analysis (ICA) was also taken into account as another approach. Jain and Huang [34] used ICA to represent each image as a feature vector in a low dimensional subspace. In this study, they used frontal facial images so-called GF which consists of 500 images (250 females and 250 males) randomly withdrawn from the facial database.Using a classifier based on linear discriminant analysis (LDA) in a lower dimensional subspace, it achieved an accuracy of 99.3%.

Another approach of appearance-based method is Local Binary Pattern (LBP). It is a type of visual descriptor used for classification in computer vision particularly the case of texture spectrum model. Hadid et al. [32] applied this approach by firstly reviewing 13 recent and popular local binary patterns variants on two different problems (gender and texture classification) using benchmark databases. From the experiments, they found out that basic LBP provides good results and generalizes well to different problems.The best results were obtained with binarized statistical image features (BSIF) however it has a downside regarding the cost of higher computational time.

Subsequently, this approach was also followed by Moeini and Mozafarri [43]. They proposed to learn separated dictionaries for male and female genders for representing the gender in facial images by using LBP to extract 64 features of the face.During the training process, they define two dictionaries to learn the defined dictionaries and then the Sparse Representation Classification (SRC) was employed for classification in the testing process. After validated using three public databases, GF, LFW and Groups databases, they obtained convincing results which were comparable to several state-of-the-arts.

Recently, the presence of deep neural networks has caught so much attention of researches to apply this method on gender classification problems because of its performance in achieving remarkable improvements on accuracy. A simple CNNs was applied by Levi and Hassner [38] to the Adiance benchmark [23] for age and gender classification in a holistic manner [1]. The results of this experiments outperforms the current state-of-the-art method by achieving around 86% accuracy. Another experiment using minimalistic CNN-based ensemble model was also conducted by Antipov et al [3]. They trained 3 instances of CNNs in which each instance was trained from scratch with a random initialization of weights. Then, those instances were combined into a single ensemble model by averaging the outputs of softmax layers. The performance of CNNs applied on LFW dataset was 97.31%.

Moreover, Mansanet et al. [42] used a local deep neural networks (Local-DNN) which is based on local features and deep architecture. By using a standard DNN, this model was trained to classify small patches extracted from images. A simple voting was carried out to the final classification by taking into account the contributions from all patches of the image. The best model of this approach was DCNN by achieving 96.25% accuracy applied on LFW dataset.

## 2.3 GEOMETRIC AND APPEARANCE-BASED

The Geometric and Appearance-based approach is the combination of both Geometric and Appearance method mentioned earlier.This approach was introduced by Mozaffari et al. [44] in a paper named *"Gender Classification Using Single Frontal Image Per Person: Combination of Appearance and Geometric Based Features"*. They proposed a new method which is based on single frontal image per person bu utilizing Discrete Cosine Transform (DCT) and Local Binary Pattern (LBP) from appearance-based approach and geometrical distance feature (GDF) based on physiological differences between male and female faces. The fusion of these three methods achieved around 95% accuracy which is 12% higher than the performance of when DCT and LBP were combined.

Tapia et al. also proposed a new method based on fusion of different spatial scale features selected by mutual information from histogram of LBP, intensity, and shape [55]. In order to select features, they employed four different features: minimum and maximal relevance (mRMR), normalized mutual information feature selection (NMIFS), conditional mutual information feature selection (CMIFS), and conditional mutual information maximization (CMIM).

In the first experiment, they applied the model on GF and UND dataset. The best result was obtained from GF with 99.13% accuracy using the fusion of 18,900 selected features. In the second experiment, they tested the model on LFW dataset with the fusion of 10,400 features from 3 different spatial scales. They obtained a classification rate of 98.01%.

## 2.4 STATE-OF-THE-ART SUMMARY

Three methods of vision-based gender recognition were explained already in the previous sections. Thus, the existing studies can be summarized as shown in Table 2.1.

The summary in table 2.1 shows that the performance of appearance-based approach is higher than the geometric one with an accuracy of above 90%. However, when both geometric- and appearance-based were combined, the performance of the model improves as explained in [42].

The existing studies also indicate that LFW and GF are the most popular dataset ever used on gender classification. The LFW dataset is used to validate the model on unconstrained environment while the GF is used to test facial images without the presence of noise in the frame. By far, the best approach is able to reach almost an accuracy of 100% which tested on GF and 98.01% on LFW dataset.

In order to validate the proposed approach, we are going to apply LFW and GF on our model so the results can be comparable to the existing studies. The details of the implementation will be elaborated in the following chapters.

Table 2.1: Literature review summary.

| Group | Method | Dataset | Performance |
|---|---|---|---|
| Geometric-based | Burton et al. [16] | 179 monochrome photographs | 85% |
| | Brunelli et al. [48] | Face images of 20 males and 20 females | 79% |
| | COSFIRE (Azzopardi et al.) [5] | GF | 93.7% |
| | Fusion of COSFIRE and SURF (Azzopardi et al.) [13] | GF | 94.74% |
| | Fusion of COSFIRE and SURF (Azzopardi et al.) [13] | LFW | 99.4% |
| Appearance-based | Neural Networks (Golomb et al.) | 90 images | 93.90% |
| | Neural Networks (Tamura et al.) [54] | Low frequency of mosaic images | 90% |
| | PCA (Sun et al.) [53] | 400 frontal images from 400 distinct people | 95.3% |
| | ICA (Jain and Huang) [34] | GF [34] | 99.3% |
| | LBP (Moeini and Mozzafari) [34] | GF | 91.9% |
| | [34] | LFW | 94.9 |
| | CNN (Antipov et al.) [3] | LFW | 97.31% |
| | CNN (Mansanet et al.) [42] | LFW | 96.25% |
| Geometric and Appearance-based | DCT+LBP+GDF (Mozaffari et al.) [44] | Ethnic and AR databases | 96.5% |
| | Fusion of different spatial scale features (Tapia et al.) [55] | GF | 99.13% |
| | [55] | LFW | 98.01% |

# 3 METHODOLOGY

In this chapter, we present our proposed approach to addressing the gender classification problem. First, we start giving an overview of pre-processing steps using popular techniques namely Viola-Jones [58] and facial landmark tracking [56]. These methods are used to detect and align a face in a given image so the most relevant parts can be obtained, adjusted, and resized accordingly. Then, we describe CNNs followed by an elaboration of one of the most widely used CNNs architecures for face recognition so-called VGGFace [45].

Moreover, we also give an overview of COSFIRE filters including a detailed explanation in dealing with gender classification problems. Finally, we present the architectures of our proposed system which are grouped into traditional and stacked architecture. The corresponding architectures show the pre-processing steps until leading to the final classification decision.

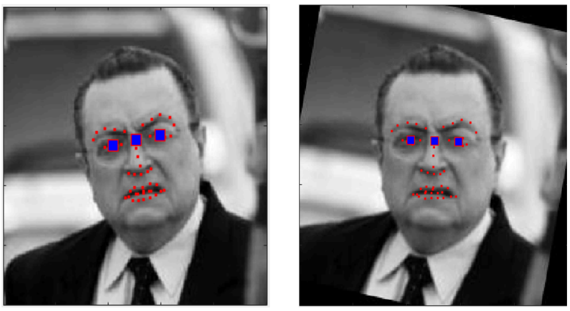
## 3.1 FACE DETECTION AND ALIGNMENT

Face detection is a technique to identify human faces in digital images. It is commonly used in many computer systems as a pre-processing task in order to obtain the most relevant parts of an image. One of the most popular techniques that is used widely in image classification problems is Viola-Jones algorithm. It is a detection framework that is capable of processing images extremely rapidly while achieving high detection rates [58]. This framework was constructed with three important keys:

- Introducing a face detector which is able to compute very fast (Integral Image)
- A very simple and efficient classifier should be used in selecting critical visual features from a large set of potential features. This framework uses Adaboost [25] learning algorithm as classifier.
- This framework combines classifiers which allows to discard the background of the image and focus on face regions resulting in fast computation.

After performing a set of experiments and validating the algorithm on data set under a very wide range of condition including: illumination, scale, pose, and camera variation, this framework achieved its best performances comparable to the best methods from the previous studies. In this study, we use Viola-Jones algorithm in order to detect face from the given images before further processing.

Another preprocessing task that we perform is face alignment which was proposed by Uricar et al. [56]. This framework works by using Viola-Jones algorithm to detect faces in an image and subsequently applying facial landmark tracking. The purpose of this method is to detect a set of 51 facial landmarks from a given facial image. Originally this algorithm is able to find 68 fiducial points but since Viola-Jones algorithm sometimes excludes 17 points which belongs to face contour, therefore they are not taken into account as important features [13]. After obtaining the fiducial points, the average location of the two sets of eye-related landmarks is computed which gives us the opportunity to define the orientation of the line and connect the corresponding lines(the angle of the face). We can use the angle to align the face image horizontally and subsequently rotate the image around the center of the line as shown in figure 3.1.

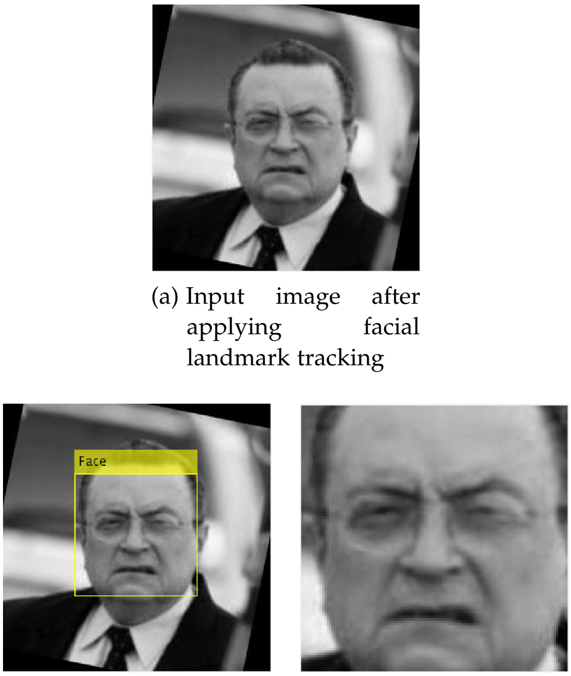


(a) Original image

(b) After applying facial landmark tracking

Figure 3.1: Representation of the face alignment algorithm. The positions of the facial landmarks are indicated by the 51 red dots and the tree blue markers indicate the left eye center, the center of the line that connects the two eye, and the right eye centers.

The output of the pre-processing after applying facial landmark tracking and Viola-Jones algorithm on the LFW data set is shown in Figure 3.2.



(a) Input image after applying facial landmark tracking

(b) After applying Viola-Jones face detector

(c) Cropped face

Figure 3.2: Pre-processing using Viola-Jones face detector on LFW data set.

## 3.2 neural networks-based classifier

Neural networks have been a field of research for more than six decades now. Throughout their history, neural networks have had a typical architecture; multiple layers of interconnected nodes, representing biological neurons.They generally have input layer, hidden layer, and output layer. By using weights and inter-node connections, the values of output nodes are calculated from layer to layer. The idea behind Neural Networks is to find optimal weights on each layer of the networks which normally adjusted using forward and backward propagation [40]. The forward propagation provides initial information to the hidden units at each layer and finally produce the output [19] while the back-propagation algorithm relies on the chain rule of differentiation for making a connection between the loss computed at the output layer and any hidden nodes. The connection of networks helps to relay the final loss of the network back to any earlier layers so that the weights of those layers may be proportionally adjusted [57].

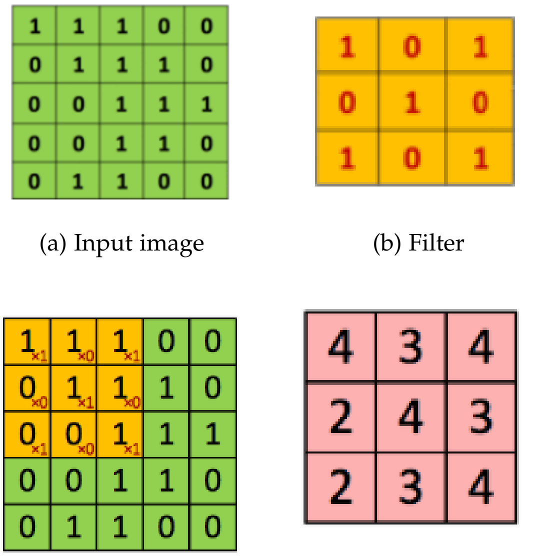
There are several types of Neural Networks: Conventional Neural Networks, Recurrent Neural Networks [41], and the most recent one is Convolutional Neural Networks or commonly called as CNNs. We will elaborate more about CNNs in the following subsection since this method is part of our study.

### 3.2.1 *Convolutional Neural Networks (CNN)*

One type of Neural Networks which so popular for object detection is CNNs. It was firstly introduced by K.Fukushima in 1983 as neocognitron [26] inspired by the feline visual processing system. In the following years it was enhanced by several researches and the most impressive work was done by Yann LeCun et al. who helped establish how we use CNNs today—as multiple layers of neurons for processing more complex features at deeper layers of the network [36]. Thus, CNNs have been applied on so many fields such as image recognition, video analysis, natural language processing, and drug discoveries.

By definition CNNs is a neural network where a signal feeds into a set of stacked convolutional pooling layer pairs, and the output of the last layer feeds into a set of stacked fully connected layers that feed into a softmax layer [57]. CNNs consist of four main operations: convolutional, non linearity (ReLU), pooling or sub sampling, and classification or fully connected layer. In order to form an architecture, these operations are divided into three forms of layer namely convolutional layer, sub-sampling layer, and fully connected layer.

Convolutional layer This layer derives its name from the convolution operator. The primary purpose of this layer is to extract features from the given input images. Then, the spatial relationship between pixels is preserved on this layer by learning image features using small squares of input data. The weights on these connections are similar for each node in the convolutional layer. This causes the weights to have the same effect as a convolution kernel. The weight behaves like a filter in an image extracting particular information from the original image matrix [4]. Figure 3.3 shows the process of convolution on images.



| | | | | |
|---|---|---|---|---|
| 1 | 1 | 1 | 0 | 0 |
| 0 | 1 | 1 | 1 | 0 |
| 0 | 0 | 1 | 1 | 1 |
| 0 | 0 | 1 | 1 | 0 |
| 0 | 1 | 1 | 0 | 0 |

(a) Input image

| | | |
|---|---|---|
| 1 | 0 | 1 |
| 0 | 1 | 0 |
| 1 | 0 | 1 |

(b) Filter

| | | | | |
|---|---|---|---|---|
| 1 ×1 | 1 ×0 | 1 ×1 | 0 | 0 |
| 0 ×0 | 1 ×1 | 1 ×0 | 1 | 0 |
| 0 ×1 | 0 ×0 | 1 ×1 | 1 | 1 |
| 0 | 0 | 1 | 1 | 0 |
| 0 | 1 | 1 | 0 | 0 |

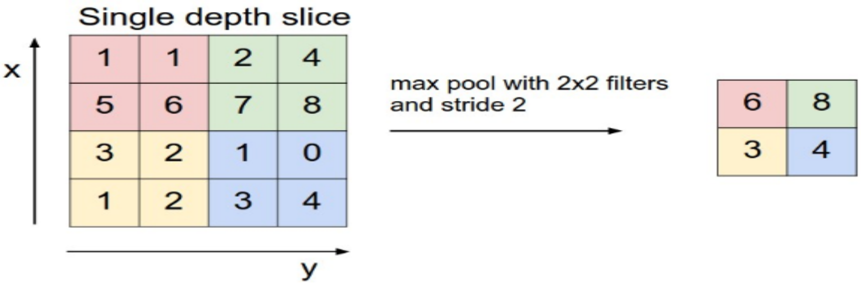
(c) Convolving using given filter

| | | |
|---|---|---|
| 4 | 3 | 4 |
| 2 | 4 | 3 |
| 2 | 3 | 4 |

(d) Convolved feature

Figure 3.3: The process of convolution on images. The filter(kernel) (b) is applied to a patch of the input image which highlighted in yellow (c). The result is the value of the pixel in the output image that correspond the center of the patch from the input image (d) [2].

Sub-sampling layer The purpose of this layer is to reduce dimensionality of each feature map without discarding the most important features. Sub-sampling or pooling is usually placed in between convolutional layers and it is done independently on each depth dimension, therefore the depth of the image remains unchanged [4]. CNNs has three types of pooling: average, max, and stochastic pooling [37], however the most commonly used is max-pooling which takes the maximum of input values as can be seen in figure 3.4.



| | | | |
|---|---|---|---|
| 1 | 1 | 2 | 4 |
| 5 | 6 | 7 | 8 |
| 3 | 2 | 1 | 0 |
| 1 | 2 | 3 | 4 |

| | |
|---|---|
| 6 | 8 |
| 3 | 4 |

Figure 3.4: An example of max pooling. Here shown pooling with a stride of 2. That is, each max is taken over 4 numbers (little $2 \times 2$ square) [20].

**Fully connected layer** The fully connected layer implies every neuron in the previous layers is connected to every neuron in the next layer. This layer uses an activation function called "softmax" [51]. The aim of fully connected layer is to classify the input into various classes based on the training data set. An example of this layer is shown in figure 3.5.

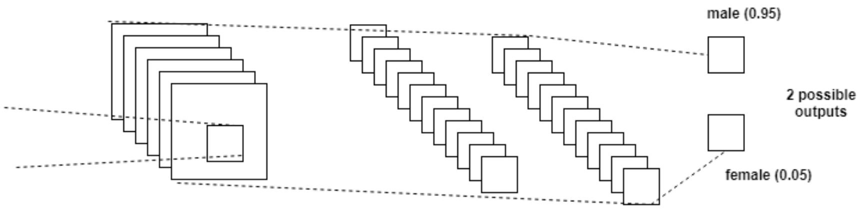


Figure 3.5: An example of fully connected layer with 2 possible outputs either male or female.

Putting all layers together, Figure 3.6 shows an example of a complete CNNs architecture. It starts with an input image followed by subsampling, then another convolution and sub sampling layer, and finally a fully connected layer which acts as a classifier.

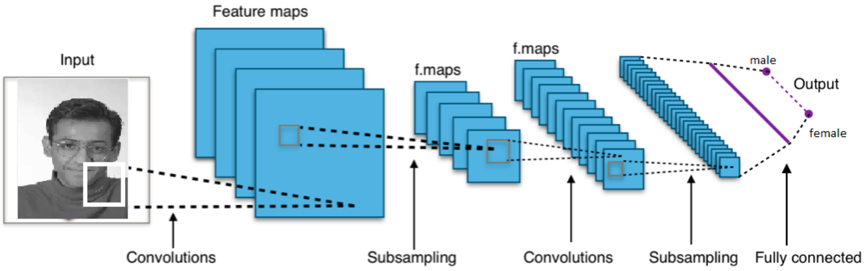
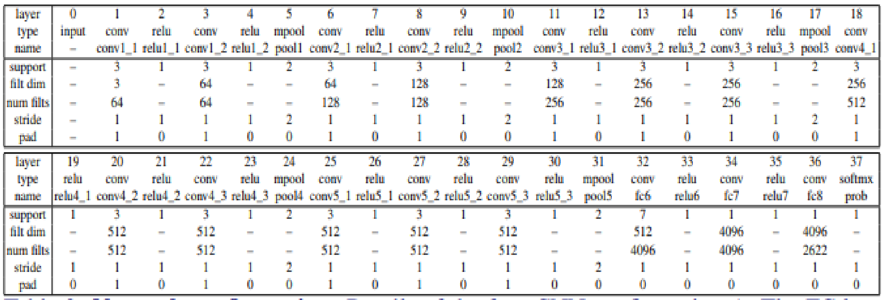


Figure 3.6: The architecture of a convolutional neural networks.

Nowadays there are many existing CNNs architectures available, starting from the very simplest one until the most complex design. The most common architectures are Lenet, Alexnet, GoogLeNet, VGGNet, and ResNet. Since the main focus of this study is to infer gender from facial images, therefore we will not explain the details of the architectures mentioned above. In particular, we just elaborate an extension of VGGNet [50] CNNs architecture which was designed for face recognition so-called VGGFace [45]. The details of VGGFace [45] as one approach of this study is given in below section.

### 3.2.2 *VGGFace*

VGGFace is an extension of VGGNet which developed by Karen Simonyan and Andrew Zisserman [50] in 2014 which contributes in showing that the depth of the network is a critical component for good performance. The goal of VGGFace architecture is to deal with face recognition either from a single photograph or a set of faces tracked in a video [45]. Since this work was inspired by VGGNet, therefore VGGFace architecture is almost similar to its ancestor as shown in figure 3.7.



| layer | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| type | input | conv | relu | conv | relu | mpool | conv | relu | conv | relu | mpool | conv | relu | conv | relu | conv | relu | mpool | conv |
| name | – | conv1_1 | relu1_1 | conv1_2 | relu1_2 | pool1 | conv2_1 | relu2_1 | conv2_2 | relu2_2 | pool2 | conv3_1 | relu3_1 | conv3_2 | relu3_2 | conv3_3 | relu3_3 | pool3 | conv4_1 |
| support | – | 3 | 1 | 3 | 1 | 2 | 3 | 1 | 3 | 1 | 2 | 3 | 1 | 3 | 1 | 3 | 1 | 2 | 3 |
| filt dim | – | 3 | – | 64 | – | – | 64 | – | 128 | – | – | 128 | – | 256 | – | 256 | – | – | 256 |
| num filts | – | 64 | – | 64 | – | – | 128 | – | 128 | – | – | 256 | – | 256 | – | 256 | – | – | 512 |
| stride | – | 1 | 1 | 1 | 1 | 2 | 1 | 1 | 1 | 1 | 2 | 1 | 1 | 1 | 1 | 1 | 1 | 2 | 1 |
| pad | – | 1 | 0 | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 0 | 1 |

| layer | 19 | 20 | 21 | 22 | 23 | 24 | 25 | 26 | 27 | 28 | 29 | 30 | 31 | 32 | 33 | 34 | 35 | 36 | 37 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| type | relu | conv | relu | conv | relu | mpool | conv | relu | conv | relu | conv | relu | mpool | conv | relu | conv | relu | conv | softmx |
| name | relu4_1 | conv4_2 | relu4_2 | conv4_3 | relu4_3 | pool4 | conv5_1 | relu5_1 | conv5_2 | relu5_2 | conv5_3 | relu5_3 | pool5 | fc6 | relu6 | fc7 | relu7 | fc8 | prob |
| support | 1 | 3 | 1 | 3 | 1 | 2 | 3 | 1 | 3 | 1 | 3 | 1 | 2 | 7 | 1 | 1 | 1 | 1 | 1 |
| filt dim | – | 512 | – | 512 | – | – | 512 | – | 512 | – | 512 | – | – | 512 | – | 4096 | – | 4096 | – |
| num filts | – | 512 | – | 512 | – | – | 512 | – | 512 | – | 512 | – | – | 4096 | – | 4096 | – | 2622 | – |
| stride | 1 | 1 | 1 | 1 | 1 | 2 | 1 | 1 | 1 | 1 | 1 | 1 | 2 | 1 | 1 | 1 | 1 | 1 | 1 |
| pad | 0 | 1 | 0 | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

Figure 3.7: The architecture of VGGFace [45].

From the above image it can be seen that VGGFace consists of 13 convolutional layers, 15 Rectified Linear Units (ReLu), 5 sub sampling (max pooling), 3 fully connected layers, and 1 softmax probability. The input to all network is a face image of size 224 × 224 pixels.

The convolutional layers are divided into 5 groups. The first group contains 64 filters and this number increases by similar size (64) in the second group. In the following group, the filters increases by 128, then two times this number in the fourth group, and finally it stays at 512 in the last group. Between each convolution layer and fully connected layer, a ReLu is placed.

Moreover, a max pooling layer with the stride of 2 is placed after the convolution layer on each group which makes it in total 5 max pooling layers. Three fully connected layers are also placed after the last pooling layer in which a ReLu is present in between. The first and the second fully connected layers contain 4096 features while the latter 2622 features only. The last layer of the architecture is a softmax probability which aims at classifying images into classes.

Not only does this architecture allow us to perform classification but also it supports feature extraction. Features can be extracted from each fully connected layers. Usually, the features are extracted the second fully connected layer (fc7) which contains 4096 features.

In this study, we use pre-trained VGGFace to extract features from a fully connected layer. First, we apply face detection and alignment algorithm as the pre-processing steps and then we resize the face images to the size of 224 × 224 pixels. After that, they are fed into networks as input and subsequently we extract the features from the second fully connected layer (fc7). The output of this layer is 4096 features from each input image which we normalize in the range between zero and one. The normalization is needed in order to avoid bias between the features of VGGFace and COSFIRE. Finally, we use the extracted features to train SVM classifier in order to infer gender. An overview of VGGFace as a feature extractor is shown in figure 3.8.

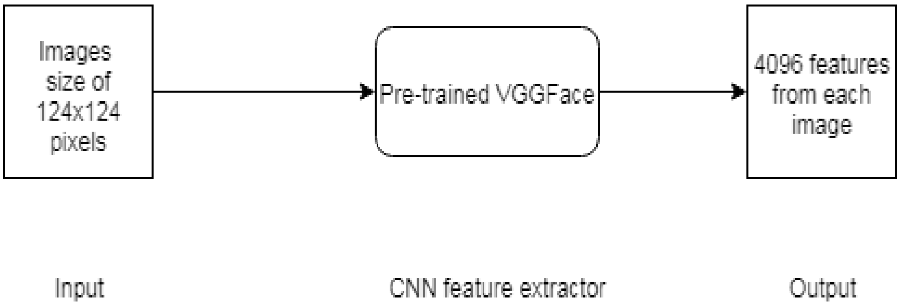


Figure 3.8: An overview of VGGFace as feature extractor in gender classification.

### 3.2.3 *VGGFace Classification Model*

We use the extracted features from the images in a given training set to learn an SVM classification model namely Compact Classification ECOC for support vector machines [1]. It is a compact, multiclass,and error-correcting output codes (ECOC) model which returns a compact ECOC model composed of linear classification models. This SVM model is very well known for its performance in fitting multiple class in classification tasks.

Another classifier so-called eXtreme Gradient Boosting (XGBoost) decision tree is also employed in this study. This classifier is an implementation of gradient boosted decision trees designed for speed and performance. We use XGBoost as additional classifier because it is generally fast and it dominates structured or tabular data sets on classification and regression predictive modeling problem [2].

## 3.3 COSFIRE-BASED CLASSIFIER

Trainable COSFIRE filters have been taking into consideration as an effective approach for key point detection and pattern recognition. This approach was proposed by Azzopardi et al. in 2013 and it has been used and developed extensively ever since in dealing with several problems on different fields such as localization and detection of traffic signs, recognition of handwritten digits [6], contour detection of Vascular Bifurnications [10] [28] [12] [52], and vessel segmentation [9] [11]. Recently, they also used this approach in dealing with gender recognition problems as mentioned in [13] and [7]. The trainable COSFIRE filters are considered to be useful because it is automatically

[1] https://nl.mathworks.com/help/stats/compactclassificationecoc-class.html
[2] https://machinelearningmastery.com/gentle-introduction-xgboost-applied-machine-learning/

configured to be selective for a local contour pattern specified by a prototype.

The following sub sections explain the details of how the filters works, how to configure, train, and apply them on images.

### 3.3.1 *COSFIRE Method and 2D Gabor filters*

As previously mentioned that COSFIRE filters are contour based detectors. This method is a trainable filter in which the pattern of such prototype is automatically analyzed. The obtained pattern is subsequently applied to images in order to localize pattern which similar to the given prototype [13]. The response of these filters are calculated as the geometric mean of the shifted response of simples orientation selective filters. In order to be able to obtain the shifted responses, the support at different locations are combined to obtain sophisticated filters. Then, geometric mean is applied on this computation in order to obtain the response of COSFIRE filters. This approach did not employ arithmetic mean while computing the responses because the geometric mean is considered to be very resistant to contrast variation and the multiplications of responses from the sub-units are sensitive to different parts of the curves. It helps the filters to generate the responses only when all elements of the pattern of interest are present.

In brief, the trainable COSFIRE filters works in three main steps. First, it applies the selected Gabor filters on image with size of $128 \times 128$ pixels whose output goes through Gaussian blurring. Then, the responses of Gaussian blurring are shifted by distinct vector. And finally the shifted responses are multiplied in order to calculate the weighted geometric mean which determines the final response.

The initial step of COSFIRE filters which considered to be important is the detection of orientation using 2D Gabor filters. A Gabor filter is made by modulating sinusoid by a Gaussian and it is considered to be important in this work because its selectivity to texture representation and discrimination which happen to be the core of COSFIRE filters. Once the Gabor filter has been applied on the images, the responses of the filters are normalized in order to keep the sum of all positive responses to 1 and negative responses to -1. Then, all the responses are thresholded $t_1$ of the maximum response $g_{\lambda,\theta}(x,y)$ for the combination of values $(\lambda,\theta)$ at every point $(x,y)$ of the image.

In this study, the original Gabor-based type of COSFIRE filters are used because color is not considered to be a distinctive feature to recognize gender. The basic working principle of COSFIRE filters can be seen in [6].

### 3.3.2 *COSFIRE Filter Configuration*

After applying the selected Gabor filters on images, the responses are used as an input for COSFIRE filter. Each of these Gabor filters is defined by parameter values ($\lambda_i$,$\theta_i$) around each of the points ($\rho_i$,$\phi_i$) with respect to the center of COSFIRE filter. These four parameters ($\lambda_i$,$\theta_i$,$\rho_i$,$\phi_i$) represent the properties of the contour in the region of a given point of interest. The width is represented by $\lambda_i/2$, the orientation by $\theta_i$, while the latter $\rho_i$ and $\phi_i$ indicate the location of specified area. At each of the positions along the circle, the maximum of all responses for all the possible values of ($\lambda$,$\theta$) that are used in the bank of filters is considered. The positions of which the values are higher than the corresponding values in the nearby positions along an angle $\phi/8$ are chosen as the most dominant points in the region of interest. Then, the polar coordinates ($\rho_i$,$\phi_i$) are computed for all these values.

Finally, the parameters values of all points is grouped into a set of 4-tuples:

$$S_f = \{(\lambda_i, \theta_i, \rho_i, \phi_i) | i = 1...n\} \tag{3.1}$$

The subscript $f$ represents the local prototype pattern around the region of point of interest and $n$ denotes the number of local maximum points. Every tuple in the corresponding set determines the parameters of some contour part in $f$ [6].

Figure 3.9 shows the configuration of COSFIRE filters by using parts of the lips as prototype patterns selected from a male face images of GF.

### 3.3.3 *COSFIRE Filter Response*

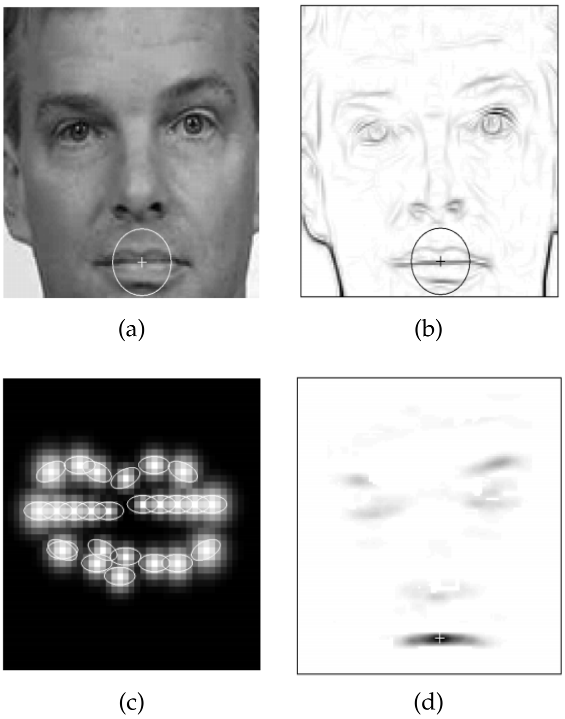
As mentioned earlier, the response of a COSFIRE filter is a geometric mean of all the responses of the thresholded Gabor filter responses. However, the responses from COSFIRE filters are first blurred in order to bring some tolerances in the position of corresponding contour parts using a Gaussian function G$_\sigma$($x$,$y$) as shown in equation (3.2).

$$\sigma = \sigma_0 + \alpha\rho \tag{3.2}$$

The values of $\sigma_0$ and $\alpha$ are constant with the default value of $\sigma_0$ = 0.67 and $\alpha$ = 0.1 as proposed in [6]. The orientation bandwidth can be increased by adjusting the value of $\alpha$. Morover, all the responses are shifted by the polar vector ($\rho_i$, -$\phi_i$) to bring all afferent responses towards the center of the filter.

Finally, all the blurred and shifted Gabor responses are combined using a geometric mean function described by s$_f$:

$$r_{sf}(x, y) = |(\prod_{i=1}^{|sf|}(s\lambda_i, \sigma_i, \rho_i, \phi_i^{(x,y)})^{w_i})^{1/\sum_{i=1}^{sf} w_i}|_{t_3} \tag{3.3}$$



(a) (b)

(c) (d)

Figure 3.9: Configuration of COSFIRE filters using a training male face GF. (a) An example of a training image of size 128 × 128[2].The encircle regions indicate the prototype of pattern of interest which are used to configure COSFIRE filters. (b) The inverted response maps og a bank of Gabor filters with 16 orientations ($\theta = \{0, \phi, ....15\phi/8\}$ and a single scale ($\lambda$=4)). (c) The structures of the COSFIRE filters that are configure to be selective for the prototype shown in (a). (d) The inverted response maps of the concerned COSFIRE filters to the input image in (a). The darker the pixel the higher the response [5].

where $|.|_{t_3}$ denotes the that the response is thresholded at a fraction $t_3$ of the maximum value of across all the coordinates($x$,$y$) of the image.

In the original paper [6], it also proposed the ability of COSFIRE to tolerate the rotation, scale, and reflection by adjusting the parameter properly. However, these invariances are not necessary for this study.

### 3.3.4 *Face Descriptor*

After applying the COSFIRE filters on a given test image, a spatial pyramid of three levels is subsequently used to obtain the face descriptors. A face descriptor is formed using the maximum responses of all COSFIRE filters across the entire image which are selective for different regions of a face.

In level zero, only one tile is considered but in the following levels each COSFIRE response map of COSFIRE filters is divided into (2 × 2

=)4 and (4 × 4 =)16 tiles respectively. From the total of 21 tiles of a spatial pyramid which are obtained from the summation of the three levels, we take the maximum value of each COSFIRE filters. That said, for *n* COSFIRE filters and 21 tiles, we describe a face image with a 21n-element feature vector.

Moreover, the set of *n* COSFIRE filter maximum responses per tile is normalized to unit length [13]. An example of the COSFIRE face descriptor using a single filter is shown in figure 3.10.

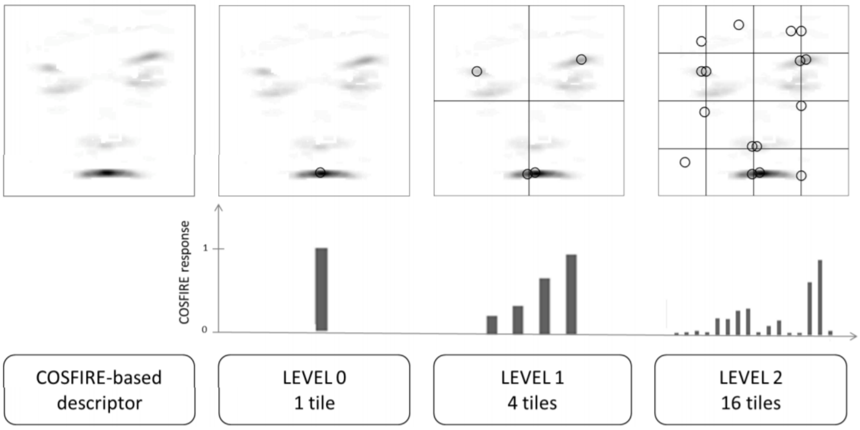


Figure 3.10: Application of the COSFIRE filters on a face image. In level zero only one tile is considered. In level one we consider four tiles in a 2 × 2 spatial arrangement and in level two we consider 16 tiles in a 4 × 4 grid [5].

### 3.3.5 *COSFIRE Classification Model*

In order to classify gender based on the extracted features from COSFIRE filters, SVM chi-squared kernel [17] is employed as classifier. The chi-squared kernel can be formulated as follows:

$$K(x_i, y_j) = \frac{(x_i - y_j)^2}{\frac{1}{2}(x_i + y_j) + \epsilon} \tag{3.4}$$

where $x_i$ and $y_j$ denote the feature vectors of training images *i* and *j* and $\epsilon$ [3] represents a very small value which is used to avoid numerical errors.

Moreover, we also employ XGBoost tree [18] to verify whether the performance of the COSFIRE filters would be affected or not.

## 3.4 THE PROPOSED METHODS

In this study, we propose two techniques to combine the decision made by the trainable COSFIRE filters and VGGFace CNNs using tradi-

[3] Function *eps* is used in practice

tional and stacked classification technique. The details of each technique are explained as follows:

### 3.4.1 *Traditional Technique*

The traditional technique is an approach that uses the fusion of features from both methods as input for new classifiers by appending the extracted features from VGGFace CNNs to the features of COSFIRE. The total of 4096 features extracted from VGGFace and 5040 features from COSFIRE are merged into a large feature vectors that makes the fusion of features from both methods as much as 9136. These features are subsequently fed as an input for both classifiers. We use SVM Compact Classification ECOC and XGBoost multi class as classifiers since they perform well in classifying multiple classes.

Furthermore, the output of each classifier is used to compare the performance of the proposed method with each individual approach (VGGFace and COSFIRE) as well as the performance of existing studies. An overview of the traditional method architecture is shown in figure4.1.

# 4 THE ARCHITECTURES

## 4.1 TRADITIONAL METHOD

4.1.

### 4.1.1 *Stacked Technique*

Another approach called stacked technique is also employed in this study as one of the proposed methods. This approach is slightly different compare to the previously explained technique because it considers the score vector generated from each SVM classifier as an input for a new model instead of the merged features. First, the features generated from both COSFIRE filters and VGGFace CNNs are trained separately using SVM classifier. Then, the score of each input feature belongs to either female is used as input for new classifier. The size of this vector is $n \times 2$ where $n$ shows the total number of inputs and 2 denotes the number of features (the score as male and female). Then, the score vectors from both methods are merged which create a new feature vector of size $n \times 4$. Moreover, the new feature vector is used as input for a new SVM classifier in order to classify gender (See figure 4.2).

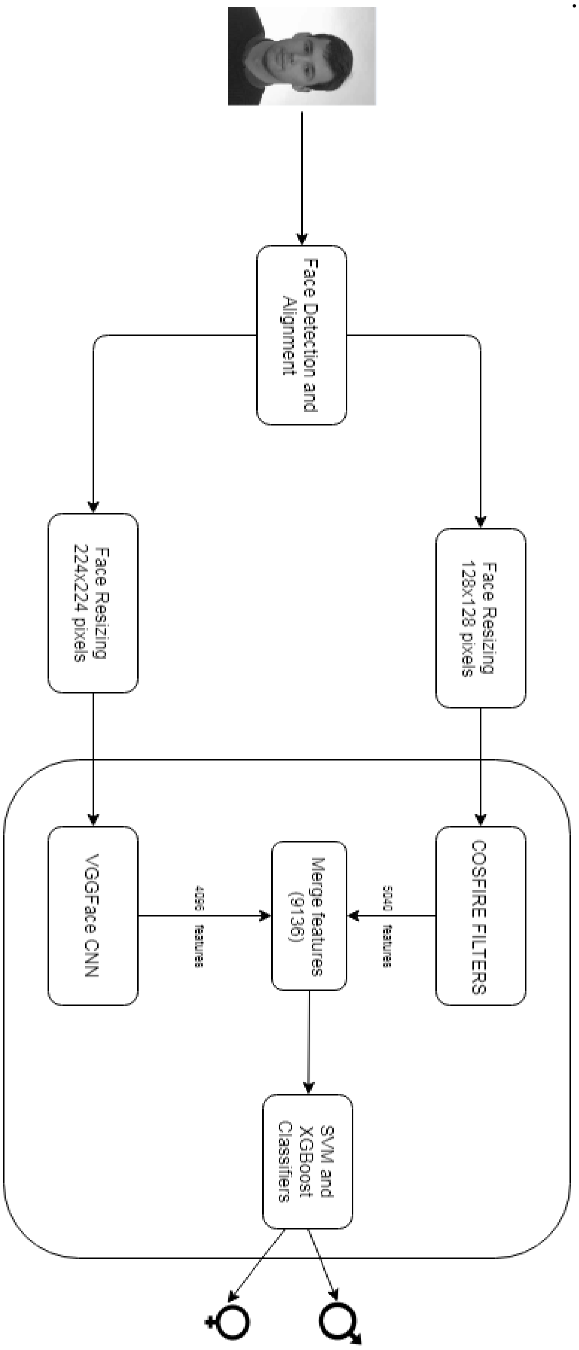

Face Detection and Alignment
Face Resizing 224x224 pixels
Face Resizing 128x128 pixels
VGGFace CNN
4096 features
Merge features (9136)
5040 features
COSFIRE FILTERS
SVM and XGBoost Classifiers

Figure 4.1: Traditional technique.

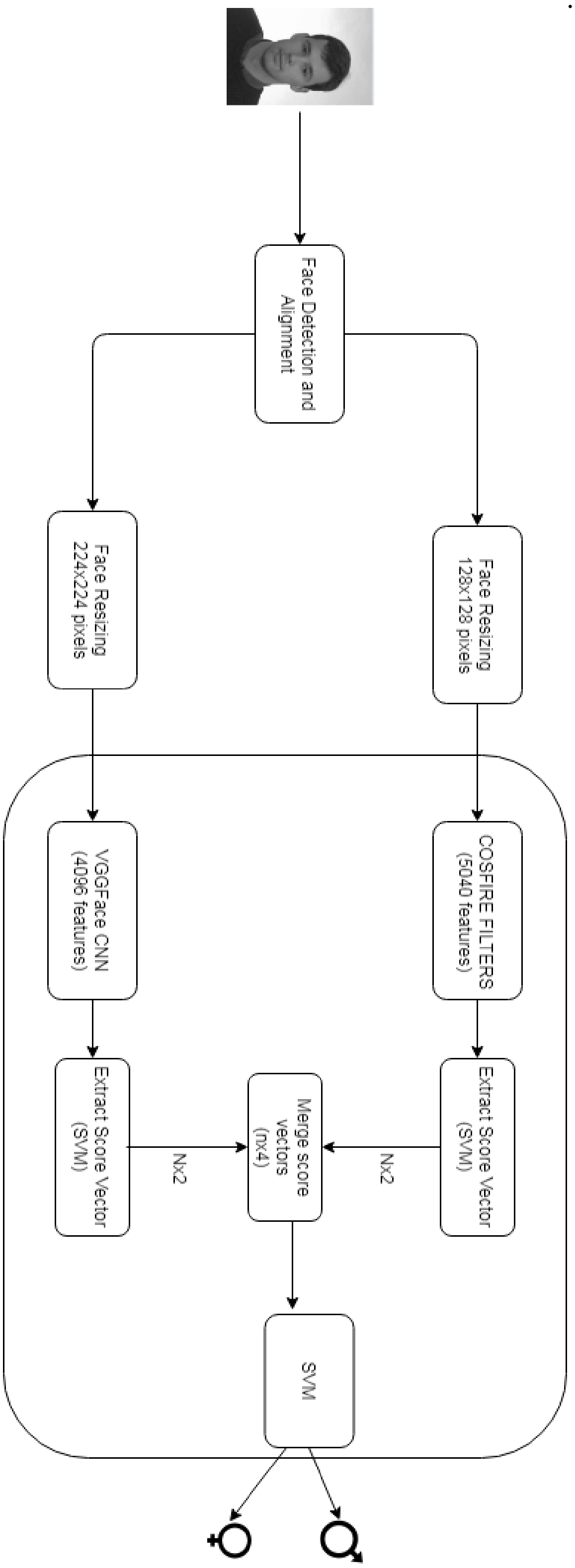

Face Detection and Alignment
Face Resizing 224x224 pixels
Face Resizing 128x128 pixels
VGGFace CNN (4096 features)
COSFIRE FILTERS (5040 features)
Extract Score Vector (SVM)
Extract Score Vector (SVM)
Nx2
Nx2
Merge score vectors (nx4)
SVM

Figure 4.2: Stacked technique.

# 5 EXPERIMENTAL RESULTS

In this chapter we report the experimental setup and summarize the results. First, we provide details on the datasets used for the evaluation of the proposed methods namely GENDER-FERET (GF) and Labeled Face in the wild (LFW) data set. Then, we briefly explain the pre-processing steps of the corresponding experiment.

Moreover, we report the results regarding the performance of each method and the fusion of both CNNs and COSFIRE. We explain the results based on the proposed architectures explained in the previous section.

## 5.1 DATASETS

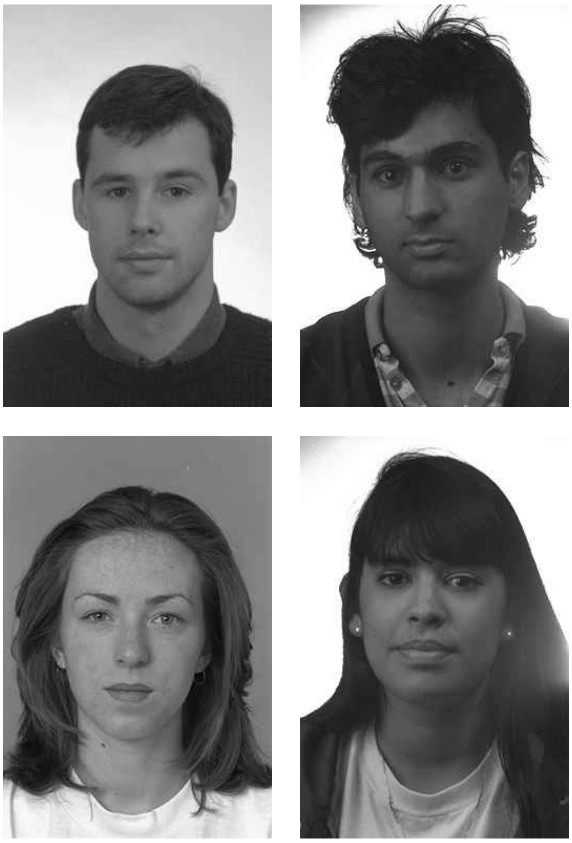
In this study we use two data sets namely GENDER-FERET [29] and Labeled Face in the wild [33] data sets. These data sets are two of the standard data sets used by most researchers to evaluate the performance of the proposed methods and to be able to directly compare the results with the state-of-the-art.

The GENDER-FERET dataset or GF was collected by Dr. Harry Wechsler at George Mason University which consists of 946 grayscale images [47]. It is classified as a contrained data set since the illumination and the background of the images are well controlled. This data set consists of the images of people with different expression, age, race, and pose is almost similar compared to one another. It is also considered as a controlled data set because it contains only one face in the frame with less noise. These conditions help the classifiers to improve its performance in classifying images.

In the conducted experiment, we use 946 GF grayscale images which has been divided into two parts: training and testing images. A balanced number of training and test sets is applied on the division of data sets which were published in [8], [13], and [5]. The training set consists of 474 images (237 males and 237 females) and the test set contains 472 images (236 males and 236 females). The examples of male and female images from GF data set can be seen in figure 5.1.

Moreover, in order to meet one of the objectives of this study that is validating the models on images with unconstrained environment, we also use Labeled Face in the Wild data set or LFW. This data set is maintained by the university of Massachusetts which were designed for studying the problem of unconstrained face recognition [1]. It consists of 13,000 images of 5,749 celebrity and politician faces collected

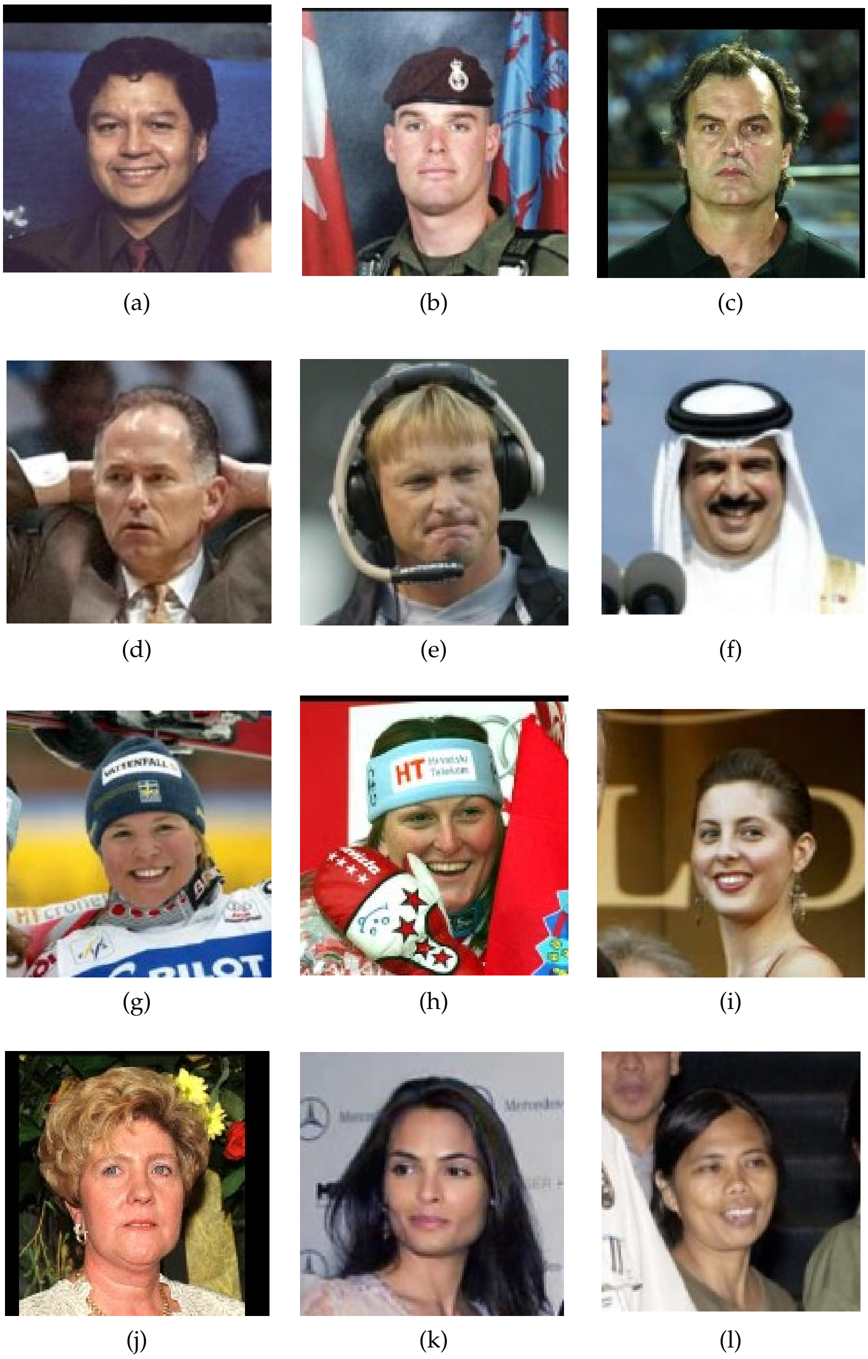
[1] http://vis-www.cs.umass.edu/lfw/



(c)

Figure 5.1: Example male (a,b) and female (c,d) images from GF data set.

from the websites on internet. This data set is considered as one of the most challenging ones in image classification tasks since they were taken when the subjects doing their normal activities such as playing sports, doing a fashion show, giving a speech or campaining, doing an interview, and others. Looking at the facts that the environment of this data set is uncontrolled, the face may appear more than one and also the illumination, background, age, expression, and race are varied. Figure 5.2 shows examples of LFW data set for both male and female. Since LFW images contains lots of noises and not all of



(a) (b) (c)

(d) (e) (f)

(g) (h) (i)

(j) (k) (l)

Figure 5.2: Example male faces (a,b,c,d,e,f) and female faces (g,h,i,j,k,l) from LFW data set.

them are suitable to be used in the experiment, therefore filtering images is needed. Following the recommendation in [49] and [55], 7,443 grayscale images are chosen for the study with the details of 2,943 females and 4,500 males and manually labeled the ground truth for gender of each image as suggested in [1]. All the images were aligned with commercial software [59] and the faces that are not clear or the ground difficult to establish were discarded. Figure 5.3 shows the example images which are not suitable for the experiment. Considering the number of sets between male and female is not balance, we apply 5-fold cross-validation by partitioning images into five subsets of similar size and keeping the same ratio between male and female [49]. Then, we compute the accuracy by taking the average of all folds.

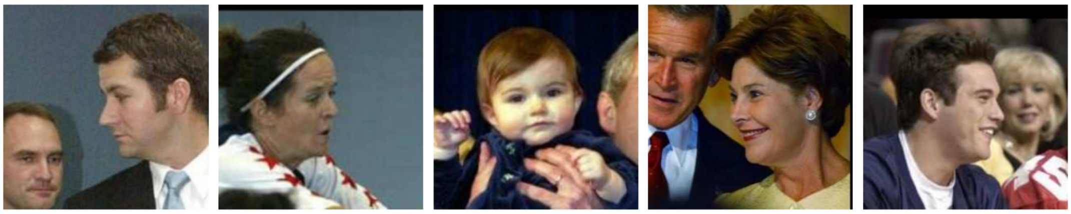


Figure 5.3: Example images which are discarded from LFW data set.

## 5.2 PRE-PROCESSING

As mentioned earlier in chapter 3, we apply Viola-Jones algorithm [58] and facial landmark tracking [56] to every image in order detect face and align the corresponding images. After that, we crop the face images accordingly. We also resize the cropped images to a fixed size of 128 × 128 pixels and 224 × 224 pixels as input for COSFIRE and VGGFace respectively.

Below are listed the steps of pre-processing task using facial landmark tracking and Viola-Jones algorithm:

- First, we align all images using facial landmark tracking algorithm
- Then, we applied Viola-Jones algorithm on the aligned images in order to obtain the most relevant parts of face in the images
- The corresponding images are cropped based on the given positions

## 5.3 EXPERIMENTS

In this section, we report the evaluation of the models applied on GF and LFW data sets. First, we report the results of the COSFIRE-based method followed by the results of the CNNs-based method and then we present the results achieved by the fusion of those methods. We also compare the results of the current study with other methods in the end.

### 5.3.1 *Result with COSFIRE-based Method*

Following the same procedure as explained in [5] and [13], we conducted the experiments with COSFIRE-based method on GF and LFW data sets. However, instead of using 180 filters as suggested in the prior works, we employed 240 COSFIRE filters because it works well with our proposed methods. The total of 120 COSFIRE filters are randomly selected from male training images and another 120 filters from female training images. For each of the training images, we selected a random region of $19 \times 19$ pixels in order to create a prototype to configure a COSFIRE filters. If the pattern consists of at least five features (tuples), then we considered it as a valid prototype. Conversely, if the number of features less than five, we repeated the same procedure over and over again until it meets the condition. As explained in [5], we configured the parameters of the COSFIRE filters with $t_1 = 0.1$, $t_2 = 0.75$, $\sigma_0 = 0.67$, and $\alpha = 0.1$. Moreover, we also configured the responses of the Gabor filters along the concentric circles and center point $\rho = 0{,}3{,}6{,}9$.

The results of the COSFIRE-based method using SVM classifier is shown in table 5.1. It can be seen from the table that the performances of COSFIRE filters applied on GF and LFW data sets are 94.2 % and 93 % respectively and it is 4% below the performance of VGGFace CNNs. However when we employed XGBoost classifier, the accuracy decreases to 87 % on GF and drops significantly to 71.6 % on LFW data set (See table 5.2).

Table 5.1: Results of the COSFIRE and VGGFace CNNs-based method on GF and LFW data sets using SVM classifier.

| Method | Dataset | Accuracy (%) |
|---|---|---|
| COSFIRE filters | GF | 94.2 |
| | LFW | 93.0 |
| VGGFace CNNs | GF | 97.4 |
| | LFW | 98.0 |

### 5.3.2 *Result with VGGFace CNNs-based Method*

Unlike COSFIRE filters, the VGGFace CNNs-based method does not need to configure several parameters because the configuration has been pretty much set up in the architecture. The only thing that we did was to make sure the extracted features were obtained from the second fully connected layer which was done by configuring the parameter output of the VGGFace to *fc7*. After that, the features were extracted by the model from each image followed by the normaliza-

Table 5.2: Results of the COSFIRE and VGGFace CNNs-based method on GF and LFW data sets using XGBoost Decision Tree.

| Method | Dataset | Accuracy (%) |
|---|---|---|
| COSFIRE filters | GF | 87.0 |
| | LFW | 71.6 |
| VGGFace CNNs | GF | 95.3 |
| | LFW | 97.6 |

tion of the corresponding features to values between 0 and 1. The normalized features were then trained using SVM ECOC and XGBoost Decision Tree classifiers.

Table 5.1 and 5.2 depict the performances of VGGFace CNNs-based method validate on GF and LFW data sets using SVM and XGBoostTree classifiers. The result show that the performance of VGGFace are always constant around 95 to 97 %. It outperforms the performance of the COSFIRE filters-based method no matter which classifiers were being employed.

### 5.3.3 *Result with the fusion of COSFIRE and VGGFace-based methods*

We performed several experiments in order to observe the results of the proposed methods. First, we followed the traditional approach by appending the features of VGGFace CNNs to to the fatures of COSFIRE and subsequently employed SVM ECOC and XGBoost Decision Tree classifiers to perform the gender classification. The results of this experiment show that when the features are merged, the performance increases in the range of 0.1 to 2 % in comparison to the best performances achieved by VGGFace CNNs. As can be seen in table 5.3, the performance of both data sets which were validated using SVM ECOC classifier is above 98 % and it almost reached the same accuracy using XGBoost classifier.

Moreover, we also conducted another experiment which follows the second approach, stacked technique. Instead of merging the features, this approach takes the score vectors generated from COSFIRE and CNNs SVM classifiers as an input for a new SVM classifier. Table 5.3 shows the performance of stacked technique using SVM ECOC classifier. We can see from this table that the results of this technique outperforms the traditional technique which were tested on both GF and LFW data sets. It was able to achieve an accuracy of 98.9% on the GF and 98.4% on the LFW data sets.

Table 5.3: Results of the COSFIRE-based method on GF and LFW data sets using XGBoost Decision Tree.

| Fusion technique | Classifier | Dataset | Accuracy (%) |
|---|---|---|---|
| Traditional | SVM ECOC | GF | 98.3 |
| | SVM ECOC | LFW | 98.2 |
| | XGBoost | GF | 97.2 |
| | XGBoost | LFW | 97.8 |
| Stacked | SVM ECOC | GF | 98.9 |
| | SVM ECOC | LFW | 98.4 |

### 5.3.4 *Comparison with other methods*

As mentioned earlier that one of the objectives of this study is to prove the effectiveness of the proposed methods by comparing them with the existing studies. In this occasion, we performed comparative analysis with the ones that use GENDER-FERET and LFW data sets. The comparison of the performance is depicted in below tables.

The results of the performances depicted in table 5.4 shows that both proposed methods outperform the performances of prior studies proposed in [8], [5], and [13] which were validated on the GF data set. The stacked technique is able to achieve an accuracy of 98.9 % which is 4.2 % higher than the accuracy of the best previously state-of-the-art listed in the given table. Moreover, the performance of the traditional technique is also outstanding in which only 0.5% lower than the stacked one.

Table 5.4: Comparison of the results on the GF data set.

| Method | Description | Accuracy (%) |
|---|---|---|
| Azzopardi et al. [8] | RAW LBP HOG | 92.6 |
| Azzopardi et al. [5] | COSFIRE | 93.7 |
| Azzopardi et al. [13] | COSFIRE SURF | 94.7 |
| Proposed 1 (Traditional Technique) | COSFIRE VGGFACE | 98.3 |
| Proposed 2 (Stacked Technique) | COSFIRE VGGFACE | 98.9 |

We also compared the performances of our proposed methods with the existing methods which were validated on the LFW data set. As we can see from table 5.5, the best method was achieved by the stacked technique with an accuracy of 98.4 % followed by the traditional technique at 98.2%. These results outperform the methods proposed in

[55], [22], and [49], however, among all the methods listed in the table, the COSFIRE SURF method proposed in [13] is still leading the way.

Table 5.5: Comparison of the results on the LFW dataset.

| **Method** | **Description** | **Accuracy (%)** |
|---|---|---|
| J.E Tapia et al. [55] | LBP | 92.6 |
| Dago-Casa et al. [22] | Gabor | 94.0 |
| Shan et al. [49] | Boosted LBP | 94.81 |
| Azzopardi et al. [13] | COSFIRE SURF | 99.4 |
| Proposed 1 (Traditional Technique) | COSFIRE VGGFACE | 98.2 |
| Proposed 2 (Stacked Technique) | COSFIRE VGGFACE | 98.4 |

# 6 DISCUSSION

In this section, we discuss the results of the fusion of trainable features VGGFace and COSFIRE to infer gender from face images. We begin by discussing the effectiveness of the proposed methods (traditional and stacking) followed by the discussion of how well the performance of both approaches when applied on the constrained (GF) and unconstrained LFW data sets. We finish this chapter with a discussion about the effectiveness of SVM and XGBoost classifiers during the study.

## 6.1 THE EFFECTIVENESS OF THE PROPOSED METHODS

The results of the study explained in the previous chapter indicate that both proposed methods are demonstrated to be effective in recognizing gender. The traditional approach is able to achieve its best performances with an accuracy of 98.75% on the GF and 98.20% on the LFW data set. When each individual approach is compared, VGGFace is proved to be more effective than COSFIRE by reaching 97% correct classification rate. Nonetheless, COSFIRE also shows its capability in inferring gender by achieving an accuracy of 93.50% on average using SVM classifier and when both methods were combined, the performance increases by 0.1 to 2 %. These findings show that the extracted features from COSFIRE work well with CNNs and looking at the fact the fusion of these methods achieved a great performance, therefore the features are proved to be linear.

Moreover, the results of the stacking method also confirm the effectiveness of the proposed method in gender classification. It outperforms the previously proposed method, the traditional technique by achieving its best performance at 99.10% which were tested on GF followed by the LFW at 98.40%. With the help of SVM classifier, this technique shows that the non linear combination of the features is also demonstrated to be effective in inferring gender. Having said that this method is highly effective in this study, it relies on SVM-ECOC and requires an extraction of score vectors from each CNNs and COSFIRE classifier which are considered to be a downside.

## 6.2 THE PERFORMANCES OF THE PROPOSED METHODS ON THE CONSTRAINED AND UNCONSTRAINED DATA SETS

In this study, two data sets namely Gender Feret (GF) and Labeled Face In the Wild (LFW) were used to confirm the effectiveness of the proposed methods on different data sets. We can see from the results, the proposed methods work very well with the facial images that contain less noises by achieving a remarkable accuracy of 99%. However, when it deals with unconstrained one which by nature has different pose variations, partial occlusion of the face, age variations, different race, and different expression, the performance decreases yet still considerably effective in comparison to the constrained one. Both proposed methods were able to achieve its best performance at 98% on the most challenging data set, the LFW.

However, a downside of these methods is it can't perform well on the original data sets. It requires several pre-processing tasks called: Face detection and alignment. First, they need to detect the face from the facial images, then the images are aligned and cropped accordingly. When these methods were verified on the original data sets without applying any pre-processing task, the performance decreases by 2 to 3 %.

## 6.3 THE EFFECTIVENESS OF SVM AND XGBOOST CLASSIFIERS

Support Vector Machine (SVM) has been proved to be the most effective classifier in face detection and gender recognition. Two SVM classifiers namely Chi-Squared Kernel and ECOC were employed in this study. SVM Chi-Squared Kernel is demonstrated to be effective on COSFIRE while SVM ECOC turn to be an excellent classifier on VGGFace and both proposed methods. On average, both SVM classifiers were able to achieve an accuracy of above 93% which were validated on the GF and LFW data sets.

On the other hand, XGBoost classifier also turns out to perform well by achieving 97.2% and 97.8% classification rate on the GF and LFW data sets respectively. However, when it was employed on each individual approach (COSFIRE and VGGFace), the performance of COSFIRE decreases significantly by 10% and VGGNet drops to 2% in comparison to SVM. Moreover, the results of XGBoost classifier are considered to be less reliable since we might obtain different results on each attempt.

# 7 CONCLUSION AND FUTURE WORK

In this study we have seen that the fusion of the trainable features from COSFIRE and VGGFace is demonstrated to be highly effective in gender recognition which was able to deal with linear and non-linear features. They are able to exhibit different characteristic of the human faces which helps to infer gender.

The experiments were performed over two public data sets namely Gender FERET (GF) and Labeled Faces in the wild (LFW). The GF aims at verifying the method on constrained data set while the latter deals with unconstrained one with different pose variations, partial occlusion of the face, age variations, different race, and different expression. The proposed methods achieved remarkable performances with accuracy above 98%.

Moreover, we also employed two classifiers: SVM and XGBoost Decision tree. SVM has been proved to be the most effective classifier in this study as well as XGBoost Decision tree. However, XGBoost classifier is considered to be less reliable since the results might be different on each attempt.

## 7.1 FUTURE WORK

In order to validate the performance more accurately, further experiments need to be performed on more data sets such as Audience benchmark for age and gender classification [27], The Specs on Faces (SoF) [1],UNISA-public [7], Images of Groups dataset [24], SCface (Surveillance Cameras Face Database) [31] and others. Also, a parallel implementation of COSFIRE is required so it could run on modern GPUs as suggested in [13].

[1] http://bit.ly/sof$_{d}$*ataset*

Part II

# APPENDIX

# A
# DATA SETS

## A.1 GENDER FERET

Table A.1: The division of training and test set of the GF data set.

| Gender | Training | Test |
|---|---|---|
| Male | 237 | 236 |
| Female | 237 | 236 |
| **Total** | **474** | **472** |

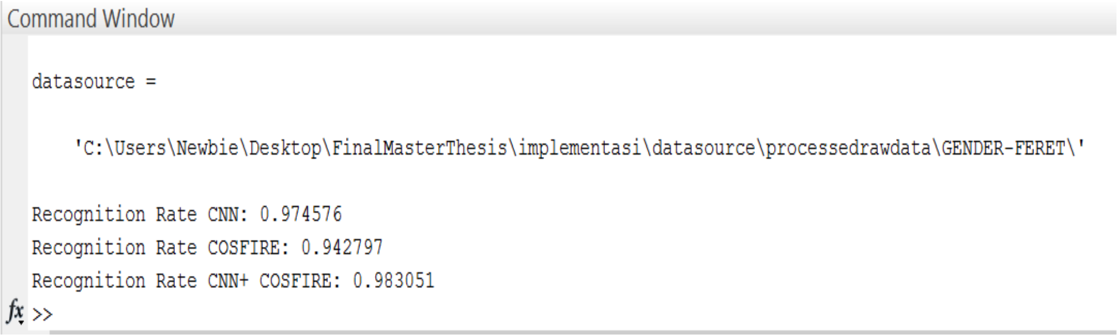
## A.2 LABELED FACES IN THE WILD

Table A.2: The division of training and test set of the LFW data set.

| Fold | Female | Male |
|---|---|---|
| 1 | 589 | 900 |
| 2 | 589 | 900 |
| 3 | 589 | 900 |
| 4 | 588 | 900 |
| 5 | 588 | 900 |
| **Total** | **2943** | **4500** |

# B RESULTS

## B.1 SVM

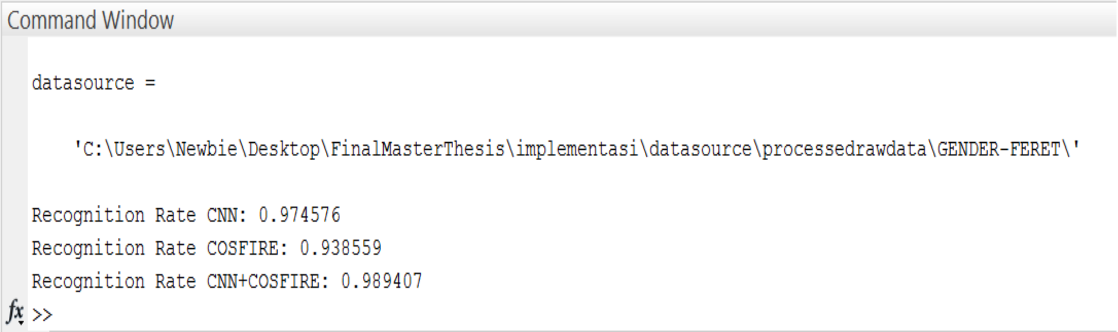


```
datasource =

    'C:\Users\Newbie\Desktop\FinalMasterThesis\implementasi\datasource\processedrawdata\GENDER-FERET\'

Recognition Rate CNN: 0.974576
Recognition Rate COSFIRE: 0.942797
Recognition Rate CNN+ COSFIRE: 0.983051
fx >>
```

Figure B.1: The performance of traditional approach on the GF data set using SVM.



```
datasource =

    'C:\Users\Newbie\Desktop\FinalMasterThesis\implementasi\datasource\processedrawdata\GENDER-FERET\'

Recognition Rate CNN: 0.974576
Recognition Rate COSFIRE: 0.938559
Recognition Rate CNN+COSFIRE: 0.989407
fx >>
```

Figure B.2: The performance of stacked approach on the GF data set using SVM.

Table B.1: The performance of traditional approach on each fold LFW data set using SVM.

| Fold | COSFIRE | VGGFACE | COSFIRE + VGGNET |
|---|---|---|---|
| 1234 | 0.911962 | 0.972446 | 0.974462 |
| 1235 | 0.930780 | 0.981855 | 0.983199 |
| 1245 | 0.944258 | 0.989255 | 0.995299 |
| 1345 | 0.92441 | 0.977166 | 0.971122 |
| 2345 | 0.940228 | 0.982539 | 0.987240 |
| **Average** | **0.9303276** | **0.9806522** | **0.98226447** |

Table B.2: The performance of stacked approach on each fold LFW data set using SVM.

| Fold | COSFIRE + VGGNET |
|---|---|
| 1234 | 0.976478 |
| 1235 | 0.98319 |
| 1245 | 0.994627 |
| 1345 | 0.971122 |
| 2345 | 0.987240 |
| **Average** | **0.9822644** |

## B.2 XGBOOST

Table B.3: The performance of traditional approach on GF data set using XGBoost classifier.

| COSFIRE | VGGFACE | COSFIRE + VGGNET |
|---|---|---|
| 0.870 | 0.953 | 0.972 |

Table B.4: The performance of traditional approach on each fold LFW data set using XGBoost classifier.

| Fold | COSFIRE | VGGFACE | COSFIRE + VGGNET |
|---|---|---|---|
| 1234 | 0.7170 | 0.9684 | 0.9731 |
| 1235 | 0.7043 | 0.9751 | 0.9825 |
| 1245 | 0.6944 | 0.9865 | 0.9852 |
| 1345 | 0.6883 | 0.9717 | 0.9664 |
| 2345 | 0.7803 | 0.98321 | 0.9838 |
| **Average** | **0.7168** | **0.9769** | **0.9782** |

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